ABSTRACT

Title of Document:	Firm Decision Making under Financial Distress: A Study of U.S. Air Fares and an Analysis of Inventories in U.S. Manufacturing Industries
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This dissertation investigates the effects of firm financial distress on two key firm decision variables: sales prices and inventories. These analyses contribute to the Structure-Conduct-Performance paradigm literature. Specifically, the feedback loop between financial distress, a result of poor past performance, and two firm conduct parameters, prices and inventories, is explored in great detail.

The first essay is motivated by the ambiguity of prior research on the relationship between firm financial distress and prices. The extant economics, corporate finance and strategic management literatures differentially approach this relationship, and empirical research has found only limited, at times ambiguous support for any single theoretical contention. These theoretical perspectives are reviewed and an attempt is made to reconcile the apparent conflict by adopting a strategic contingency perspective that

identifies in which way and in what instances firm financial distress may impact prices. The model is empirically tested using data from the U.S. airline industry. The results indicate that firm financial distress and prices are generally negatively related. Moreover, this effect is substantially stronger for firms operating under Chapter 11 protection than for firms approaching bankruptcy. It is further shown that the magnitude of the effect of financial distress on prices depends on firm factors such as operating costs, market power, and firm size, as well as on competitive characteristics such as market concentration and the financial condition of competitors.

The second essay analyzes the impact of firm distress on firm inventories and investigates if this relationship is impacted by a firm's power relative to its upstream and downstream supply chain partners. Building on prior work in the economics field, this research is not only based on microeconomics theory, but also draws on inventory theory as well as on prior work on supply chain relationships. A comprehensive inventory estimation model is specified, and novel measures of inventory determinants and power are developed. The hypotheses are tested using panel data from the U.S. manufacturing industry. It is shown that distressed firms hold less inventory and that a firm's power within the supply chain will determine to what extent inventory ownership is reduced during times of financial distress. Implications for supplier selection and supply chain cooperation are discussed.

In summary, this research significantly enhances researchers' understanding of why, how, and when firm financial distress affects prices and inventories.

Firm Decision Making Under Financial Distress: A Study of U.S. Air Fares and an Analysis of Inventories in U.S. Manufacturing Industries

By

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Dedication

To my parents,
in deep gratitude for all their love and support.

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The completion of this dissertation marks the endpoint of four tremendously exciting years in the doctoral program at the University of Maryland's Robert H. Smith School of Business. Many faculty members, fellow doctoral students, and staff members have contributed to making this time so enriching, enjoyable, and memorable.

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"No matter what the state of the economy, no company is immune from internal hard times—stagnation or declining performance." (Hofer 1980)

"Global competition, technological turbulence, high costs of capital, and other nettlesome factors will cause more and more businesses to face occasional hard times." (Hambrick and Schecter 1983)

1. Introduction

Firm financial distress is an omnipresent phenomenon in manufacturing and service industries. While there is no unique definition of financial distress, distress firms are generally loss-making and suffer from (severe) liquidity constraints. Based on these criteria, Altman (2002, 1968) developed the Z score as a composite measure of a firm's financial condition. Altman suggests that firms with a Z score of less than 1.81 are considered financially distressed and face a high risk of bankruptcy. Following this definition, about one third of all U.S. manufacturing firms[1] and about half of all U.S. airlines (The Economist 2005) were considered financially distressed in 2005. Most recently, car manufacturers such as Ford and General Motors (McCracken 2006), and air carriers like Northwest Airlines and Delta Airlines (Carey and Trottman 2005), to mention but a few examples, have been experiencing financial difficulties. This dissertation investigates the impact of financial distress on managerial decision variables such as prices and inventories.

[1] This estimate is based on the analysis of 2,323 manufacturing firms listed in the Compustat database. Thirty-two percent of these firms had Z scores (Altman 1968) of less than 1.81.

Most research in the broad field of business management is concerned with understanding how managerial decisions come about and how these decisions affect firm and market performance. Many researchers therefore follow the tradition of the structure-conduct-performance (SCP) paradigm which essentially posits that the structure of markets impacts firms' conduct which, in turn, is a key determinant of the performance of firms and markets (Bain 1956, Mason 1949, 1939). The term "structure" thereby refers to structural characteristics of markets that are indicators of the competitiveness of markets. Commonly used measurement variables include industry concentration, the number of firms in the market or barriers to entry and exit (Waldman and Jensen 2001). Firms compete in the marketplace by means of actions that aim at maximizing firm performance. These rivalrous activities are summarized by the term "conduct" which may, for example, refer to pricing and product strategies (Waldman and Jensen 2001). The aggregate performance of firms in a market can be measured in terms of allocative efficiency or production efficiency, for example (Waldman and Jensen 2001). The individual performance of firms, in turn, is typically evaluated based on financial (e.g. profitability) or operating measures (e.g. productivity). *Figure 1* graphically illustrates the structure-conduct-performance paradigm.

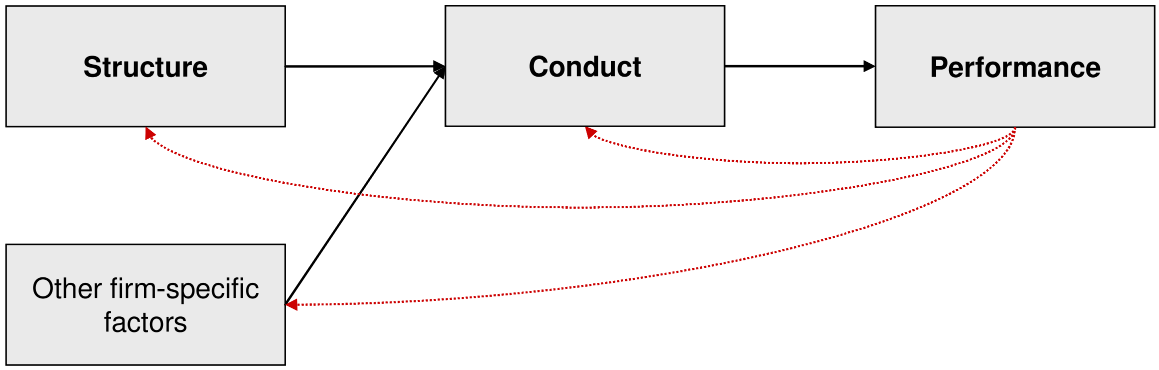

Figure 1: The structure-conduct-performance paradigm

Firm-specific factors are added to the depiction of the structure-conduct-performance paradigm in *Figure 1* to indicate that not only (market) structural, but also other firm characteristics (besides the firm's financial condition) such as operating costs and firm size, for example, may impact a firm's conduct in the market (e.g. Spanos et al. 2004).

The structure-conduct-performance (SCP) paradigm, as presented by Waldman and Jensen (2001), also recognizes that certain feedback loops may exist within the structure-conduct-performance framework. An industry's above-average performance, for example, may attract new entrants, thus affecting the structure of markets. By the same token, a firm's past performance may impact future managerial decisions relating to, for example, prices and sales quantities, thus linking the firm's performance/distress to its conduct. Also, a firm's distress may ultimately impact other firm characteristics such as the firm's size and its cost structure. *Figure 1* illustrates some of these feedback loops within the SCP paradigm[2]. While there are many such feedback mechanisms, one specific link is of particular interest in this dissertation research: The effect of financial distress, a direct result of poor past performance, on a firm's conduct in terms of sales prices and inventories.

Pricing and inventory decisions are important indicators of a firm's competitive conduct in the marketplace. Basic game-theoretic models suggest that firms compete on either price (Bertrand competition) or quantities (Cournot competition) (Gibbons 1992). With inventories being a function of sales quantities, both inventories and prices, thus, are essential decision variables that reflect a firm's competitive behavior. Consequently, numerous researchers have investigated the competitive implications of firms' pricing (e.g. Busse 2002) and inventory (e.g. Cachon 2001, Mahajan and Ryzin 2001) decisions. It is therefore deemed appropriate and relevant to investigate the effects of financial distress on these two firm conduct parameters.

Clearly, a feedback mechanism between financial distress and conduct is intuitively appealing: Managers of distressed firms must turn the situation around and ensure the company's future profitability. Given the widespread occurrence of financial distress, researchers have been interested in understanding the effects of distress on firm conduct. Specifically, researchers have examined the anatomy of corporate turnarounds: What do financially troubled firms do to return to profitability?

[2] Note that the changes in a firm's conduct caused by a deretioration of the firm's financial condition will then impact the firm's performance. The relationship between performance/distress and conduct (as well as structure and firm-specific variables), thus, is iterative over time.

Hofer (1980) notes that price cutting is a popular measure implemented by distressed firms. Arogyaswamy and Yasai-Ardekani (1995) and Sudarsanam and Lai (2001), in turn, suggest that firms frequently reduce inventory levels as a part of their restructuring efforts. While anecdotal evidence and conceptual work suggest that greater levels of distress imply lower prices and inventories, *ceteris paribus*, empirical evidence in support of this contention has been scant. In a similar vein, conceptual and empirical work has arrived at the conclusion that there is no unique turnaround strategy and no single recipe for turnaround success. Rather, different turnaround *gestalts* have emerged: Hofer (1980), for example, distinguishes between revenue-generating, product-market refocusing, cost-cutting, and asset reducing strategies. Both Hofer (1980) and Hambrick and Schecter (1983) suggest that the choice of a turnaround strategy will be contingent on the gravity of financial distress and other firm and market-related contingencies. This contention is illustrated in *Figure 2*: The effect of financial distress (poor past performance) on conduct is moderated by (market) structural characteristics and firm-specific factors.

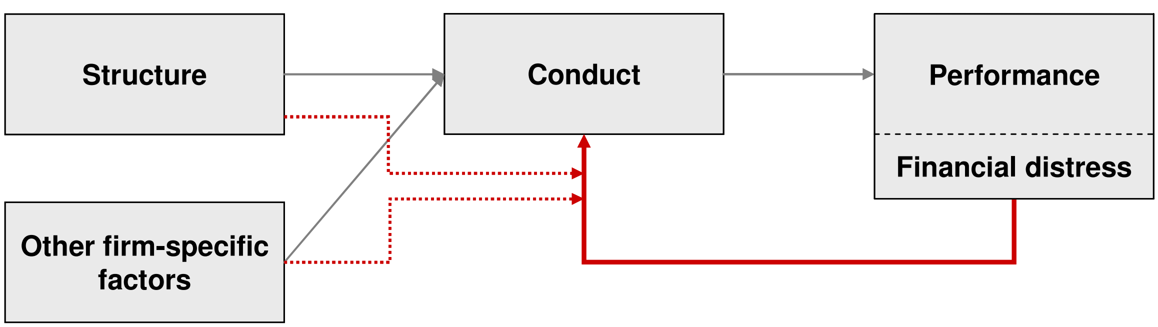

Figure 2: The moderated distress-conduct feedback mechanism

Hofer (1980) and Hambrick and Schecter (1983), thus, contend that the effect of financial distress on firm conduct is contingent on other factors. This contention is consistent with the basic tenet of contingency theory. Contingency theory was originally motivated by the observation that "[p]rominent theorists promote their ascribed frameworks as conceptually valid and pragmatically applicable to all organizations in all situations" (Luthans and Stewart 1977, p.182). This concept of universality, however, has been questioned by researchers on the grounds of both theoretical and empirical counterevidence. Instead, researchers have increasingly recognized the importance and moderating role of situational characteristics in defining causal relationships (Hitt et al. 2004).

Proponents of the situational approach argue "that the most effective management concept or technique depends on a set of circumstances at a particular point in time" (Luthans and Stewart 1977, p.182) and that empirical research based on simple "linear models [has generally] provided disappointing results" (Hitt et al. 2004, p.11). Consequently, researchers have proposed a "general contingency theory of management" (Luthans and Stewart 1977) which rests on the key premise that environmental, resource and management variables intervene in cause-and-effect relationships in the context of strategic management research.

There is, however, no defined set of contingency variables and no universal prescription as to how, when and where contingencies ought to be considered (see e.g. Hofer 1975 for a review of important control variables and contingency factors in the context of business strategy research). Many researchers have therefore criticized contingency theory as an "illusion" (Longenecker and Pringle 1978) and have attacked the theory's vagueness and "lack of clarity" (Schoonhoven 1981). The use of contingency frameworks has nonetheless been popular in the strategic management literature (Hitt et al. 2004).

This dissertation follows this research tradition and defines context-specific contingency variables that are expected to affect the relationship between firm financial distress and prices and inventories, respectively. Specifically, it is suggested that structural and firm-specific factors moderate the effects of firm distress on prices and inventories.

To date, the model shown in *Figure 2* has not been subject to large-scale empirical testing. While some researchers have investigated the effects of financial factors on firm decision parameters such as prices (e.g. Borenstein and Rose 1995) and inventories (e.g. Carpenter et al. 1994), the moderating effects of structural and firm-specific factors on the distress-conduct relationship remain largely unexplored. The sole exception is the work by Ferrier et al (2002): These authors investigate the effect of financial distress on competitive aggressiveness as measured by the number and nature of firms' competitive actions. Ferrier et al (2002) thereby find evidence that the effect of distress on competitive behavior is moderated by industry characteristics[3] and the educational and functional heterogeneity of top management teams. This dissertation builds on the work of Ferrier et al (2002) and extends it to the study of two particular firm conduct parameters: sales prices and inventories.

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[3] Industry growth, industry concentration, and barriers to entry.

Clearly, gaining a better understanding of how financial distress impacts firms' pricing and inventory decision is a timely and relevant research endeavor. Prior research has shown that linear models of the distress-price and distress-inventory relationships may be overly simplistic and do not do justice to the complex nature of decision problems relating to price and inventory management under financial distress (e.g. Singh 1986). While most researchers contend that greater financial distress should result in lower prices and lower inventory holdings, the empirical findings are largely inconsistent and often times statistically insignificant. The basic premise of this research is that structural and firm-specific characteristics moderate the distress-conduct relationship as shown in *Figure 2*, thereby explaining why the distress-conduct effect may be substantial in some instances and insignificant in other cases.

In summarizing, this dissertation investigates the following research questions:

- Does financial distress have an impact on prices and inventories, after controlling for other relevant parameters?
- And how can these effects be characterized, i.e. what factors influence the magnitude of the distress-price and distress-inventory relationships?

This dissertation addresses these questions and thereby makes a number of significant contributions.

This is—to the best of the author's knowledge—the first study to empirically investigate the feedback loop between financial distress (poor past performance) and two key firm conduct parameters: prices and inventories. Particular attention is paid to the moderating effects of structural and firm factors on the distress-conduct relationship. This research, thus, contributes to the SCP literature by analyzing the distress-conduct feedback loop and empirically evaluating the effect of interactions between structural, firm, and financial characteristics on firm conduct parameters.

This framework is empirically tested in two distinct contexts: Prices and inventories are studied in the context of the U.S. airline industry and the U.S. manufacturing industry, respectively. In both instances, context-specific contingency variables are proposed and their moderating effects on the distress-price and distress-inventory relationships are evaluated. This research draws on a broad array of theoretical arguments from the strategic management, economics, and corporate finance literatures to identify these contingency variables and to hypothesize about their impact on the distress-conduct relationship. The validity of the theoretical arguments and models set forth in this dissertation is underlined by solid estimation results. It is shown that financial distress is an important explanatory variable that significantly impacts a firm's sales prices and inventories. This research thus also contributes to furthering empirical research on prices and inventories.

In addition, answering these research questions also paves the way to exploring further managerial implications of financial distress with respect to prices and inventories in greater detail: When are pricing and inventory actions economically viable turnaround strategies? And how will the distressed firm's actions affect competition and inter-firm cooperation?

This dissertation comprises four chapters. Following this introduction (Chapter 1), Chapters 2 and 3 are devoted to the study of the effects of financial distress on prices and inventories, respectively, while Chapter 4 provides a summary of the findings and contributions of this dissertation research.

The impact of distress on prices is discussed in Chapter 2. Two specific research questions are investigated in this essay: How does a firm's financial distress impact its pricing behavior? And what parameters moderate the effect of firm financial distress on the firm's prices? These questions arise upon reviewing a broad set of extant research which is marked by ambiguous empirical findings. This conflict is addressed by developing a contingency framework. It is suggested that firm factors such as operating costs, firm size and market shares, as well as market characteristics such as market concentration and competitors' financial conditions determine to what extent financial distress affects prices. A large-scale empirical analysis using panel data from the U.S. airline industry is conducted. The results provide ample support for the proposed contingency framework.

Chapter 3 focuses on the distress-inventory relationship. This essay is primarily motivated by two observations: First, prior studies have approached the firm finance-inventory link from an economics perspective only, thus ignoring the insights provided by inventory theory. Second, most extant research has failed to put firm inventory decisions into a supply chain context where inter-firm power balances may affect inventory ownership in supply chains. Consequently, two research questions are formulated: Does a firm's financial situation have an impact on its inventories after controlling for other relevant parameters prescribed by inventory theory and supply chain research? And is the magnitude of the presumed effect of financial distress on inventories impacted by power (im)balances in supply chain relationships? To investigate these questions, a thorough review of related economics, inventory, and supply chain research is provided and testable hypotheses are formulated. Based on this theoretical foundation, an empirical estimation equation is specified. Data from U.S. manufacturing industries is used to test the hypotheses. Specifically, it is shown that greater levels of firm financial distress are associated with lower firm inventory levels, *ceteris paribus*. In addition, there is some support for the hypothesis that greater levels of power over suppliers and buyers not only reduce inventory ownership in general, but also increase the effect of financial distress on inventories.

Chapter 4 presents a summary of this dissertation research and highlight its contributions. In addition, a research agenda for further studies of the effects of firm financial distress is outlined.

2. The impact of firm financial distress on prices: A contingency approach

Chapter 2 presents a theoretical and empirical analysis of the relationship between financial distress and sales prices. This chapter is structured as follows: Section 2.1 provides a brief overview of prior research on the financial condition-prices link and clearly states the research questions and contributions of this dissertation essay. In Section 2.2, a comprehensive review of the literature and relevant theories is provided, and hypotheses are derived. The research model is introduced in Section 2.3, the data and variables are discussed, and econometric issues are addressed. In Section 2.4, the regression results are presented. The article concludes with a summary of the study's findings and a discussion of their implications for managers and policy makers (Section 2.5). The study's limitations are noted and directions for future research are provided as well.

2.1. Introduction

The question of how a firm's financial condition impacts the firm's sales prices has been investigated from multiple perspectives. Researchers from the economics, corporate finance, and strategy fields have published a substantial amount of literature on this and related issues (e.g. Borenstein and Rose 1995, Ferrier et al. 2002, Opler and Titman 1994). Yet, in summary, the findings have been largely inconclusive, not only across but also within the respective research streams. Empirical research has found only limited, at times ambiguous support for the contention that distressed firms' sales prices tend to be lower. This study draws on various theories from the economics, corporate finance and strategic management fields to investigate this issue and attempts to reconcile the apparent conflict by adopting a strategic contingency perspective that identifies in which way and under what conditions firm financial distress may impact sales prices.

This research question is of particular interest given that firm financial distress is often argued to lead to and result from price competition: Low market prices may drive firms into bankruptcy, and the latter may, in turn, affect a firm's competitive pricing behavior. The so-called sick industry problem, thus, is intimately associated with the issues of financial distress and price competition as repeatedly evidenced in the U.S. airline industry. In recent years, many U.S. airlines have sought bankruptcy protection under Chapter 11[4], the ultimate manifestation of financial distress. Between 2001 and 2005 alone, seven of the top 20 U.S. carriers took advantage of the provisions of this code to facilitate their restructuring processes[5]. An article in The Economist (2005) noted that "at least half of America's airline industry has now been declared bankrupt" when Delta Air Lines and Northwest Airlines declared bankruptcy in September 2005.

Airlines can achieve significant reductions in labor, leasing, and debt costs under Chapter 11 protection (McCafferty 1995), thus giving bankrupt firms a competitive advantage over their non-bankrupt counterparts. Following Delta's and Northwest's bankruptcy

[4] Title 11 of the U.S. code, commonly referred to as Chapter 11, is a form of interim bankruptcy and grants the filing company protection from its creditors until a reorganization plan is developed and approved by the creditor committees.
[5] The top 20 U.S. commercial carriers were ranked based on 2001 passenger data (available from www.transtats.bts.gov). The following carriers filed for Chapter 11 protection between 2001 and 2005: TWA (2001), United (2002), US Airways (2002, 2004), Hawaiian (2003), ATA (2004), Delta (2005), Northwest (2005).

filings, analysts therefore warned of potentially adverse consequences for other carriers such as American Airlines and Continental Airlines (Trottman 2005). Consequently, researchers (see e.g. Kennedy 2000, Rollman 2004) and managers of non-bankrupt firms have repeatedly criticized the destructive implications of Chapter 11 protection. Gary Kelly, then Chief Financial Officer with Southwest Airlines, for example, notes that “the length of time an airline can go through bankruptcy protection and offer distressed prices is very unsettling” (McCafferty 1995). Similarly, Robert Crandall, the former Chief Executive Officer of American Airlines, argues that “Chapter 11 also undermines responsible managements. In an intensely competitive industry providing a commodity product, the ‘dumbest competitor’—unrestrained by fear of failure—sets the standard” and hence calls for “bankruptcy laws designed to incentivize success and penalize failure” (Crandall 2005). The criticism of Chapter 11 protection as unfair and destructive is all but new: a 1989 article published in The Economist discusses the “uses and abuses” of Chapter 11 and concludes that “what was designed as a shield has become a sword” (Anonymous 1989).

Most of the previous statements make the explicit or implicit assumption that financially distressed firms sell at lower prices than their healthier competitors. This contention, however, has not found consistent theoretical and empirical support.

In the economics stream of research, Borenstein and Rose (1995) find that air fares slightly decrease prior to bankruptcy filings, but do not further change in the time period thereafter. Kennedy (2000) and Brander and Lewis (1986) assert that a firm’s financial condition affects its market conduct, and Busse (2002) supports this contention, indicating that financially distressed firms are more likely to start price wars than their healthier competitors. The traditional economics literature, however, negates a relationship between financial condition and firm output market behavior (e.g. Modigliani and Miller 1958)[6], and stresses the importance of demand fluctuations in instigating price reductions.

From a corporate finance perspective, Baker (1973) argues that highly leveraged firms are more risk-seeking than relatively profitable firms which take some of their "returns in the form of reduced risk" (Hall and Weiss 1967, p.328). Along the same lines, Maksimovic and Zechner (1991) suggest that financially distressed firms are more likely to choose riskier (pricing) strategies. Opler and Titman (1994), in contrast, attribute the lower performance of troubled firms to the (predatory) aggressiveness of competitors and the costs of financial distress rather than to the firm's own pricing behavior.

The strategy literature, finally, has focused the attention on the link between performance distress and competitive behavior in general. Bowman (1982) contends that troubled firms may be more risk-assertive (i.e. inclined to compete more aggressively) than healthy firms, and Miller and Chen (1994) also relate past financial distress to competitive aggressiveness. Ferrier et al (2002), however, find "that poor-performing firms were less likely to exhibit aggressive competitive behavior" (p.311) when looking at the direct relationship between performance distress and competitive aggressiveness. It

[6] See also Brander and Lewis (1986) and Kennedy (2000).

is noteworthy that none of the studies in the strategy field have examined the link between financial distress and prices in particular. Rather, competitive behavior has typically been measured by counting and categorizing competitive actions and reactions (Chen et al. 1992, Ferrier et al. 2002, Smith et al. 1991, Young et al. 1996).

These examples illustrate the inconclusiveness of prior research and suggest that the link between financial distress and prices may be more complex (Singh 1986). The general questions, thus, remain:

- How does a firm's financial distress impact its pricing behavior?
- What parameters moderate the effect of firm financial distress on the firm's prices?

As the research results referenced in the preceding paragraphs demonstrate, the answer to these questions cannot be a straightforward one. There are multiple theoretical perspectives and contingencies that may partly explain the variability of a troubled firm's pricing behavior. Focusing on competitive actions in general, Ferrier et al (2002) have presented a first attempt to reconcile these conflicting views. They stress the importance of context-specific contingencies such as industry growth and concentration, as well as top management team heterogeneity in defining the relationship between performance distress and competitive behavior. In fact, the strategy literature offers rich insights into the contingencies that may moderate this relationship. This research builds on the work of Ferrier et al (2002) in drawing on a broad theoretical basis and proposing a comprehensive contingency framework that aims at characterizing the relationship between financial distress and prices, and identifying factors that may affect the magnitude of this relationship. In addition to developing and empirically testing this contingency framework in the context of the U.S. airline industry, this research extends the extant body of knowledge in three important respects:

First, price is used as a criterion variable. As mentioned earlier, none of the studies published in strategic management journals examine the impact of financial distress on prices. Yet, price is probably the single most important and relevant measure of competitive behavior: From a consumer perspective, for example, prices are decisive in determining consumer welfare – the lower the prices, the greater the consumer surplus. Consequently, prices are – under the assumption that the products and services offered by firms are sufficiently homogenous – the primary driver of purchase decisions. From a firm perspective, price is a key managerial decision variable affecting revenues and a firm’s bottom line. Low prices may allow a firm to gain market share and obtain an advantage over competitors, while a differentiation strategy may enable a firm to skim the market and achieve higher prices (Porter 1980). Moreover, price is of interest from a public policy point of view. Regulatory government bodies, such as the former Civil Aeronautics Board (CAB) in the airline industry, and consumer interest groups survey and screen markets for evidence of predatory pricing and intervene when free market mechanisms of demand and supply fail to produce satisfactory market outcomes. Using price as a dependent variable, rather than count and categorical variables such as number and type of competitive actions, also allows for a more detailed evaluation of the *magnitude* of a firm’s reaction to changes in its financial condition.

A second contribution lies in examining firm financial distress in more detail than has been evident in most prior empirical work. While some studies focus on bankruptcy filings (e.g. Borenstein and Rose 1995), others use measures such as Altman's Z score (Altman 1968) to evaluate a firm's financial situation (e.g. Ferrier et al. 2002). There is, however, substantial evidence that financial distress may differentially impact firm behavior before, during, and after a Chapter 11 filing occurs (Borenstein and Rose 1995, Busse 2002, Kennedy 2000). Therefore, both measures (a Z score-based distress measure and bankruptcy dummy variables) are included in the empirical analyses to more precisely sort out the effects of financial distress and bankruptcy per se. Furthermore, a firm's financial standing *relative* to its competitors in the market is considered. In fact, financial distress in absolute terms may not necessarily imply any pricing actions if competing firms find themselves in similar financial situations. More specifically, it is expected that such pricing actions will be more pronounced when a distressed firm's financial situation is significantly different from that of its rivals.

Finally, this study is unique with respect to its empirical detail. A panel data set from the U.S. airline industry is used to investigate the relationship between financial distress and price. Unlike in many previous studies, the unit of observation in the analyses is a specific route (i.e. "product") market rather than a firm year or firm quarter (Busse 2002, Chattopadhyay et al. 2001, Ferrier et al. 2002). This allows for a much more fine-grained and statistically robust examination of the hypotheses.

This essay reports a comprehensive effort to understand if, when, and how firm financial distress impacts prices. The empirical results suggest that financially distressed firms offer lower prices than their healthier competitors, *ceteris paribus*. The magnitude of the effect of firm financial distress on prices, however, is shown to decrease with unit operating costs, increase with firm size, and decrease with firm market shares. The price effects of financial distress are also stronger in more concentrated markets and when a firm's competitors are in significantly different financial situations. The insights provided by this research will be useful to both firms and policy makers. Distressed firms and their competitors gain a better understanding of how financial conditions typically impact pricing decisions and customer demand. Managers of financially distressed firms may benefit from this knowledge when developing turnaround strategies. Competing (healthy) firms, on the other hand, can more accurately anticipate distressed firms' pricing actions and act accordingly. For policy makers, the findings of this study will help clarify if, when, and to what extent financial distress and Chapter 11 protection impact sales prices and the competitive behavior of firms. The findings presented here may help clarify if current bankruptcy laws serve the purpose they were intended for, and contribute to maintaining or improving the allocative efficiency of markets.

2.2. Theoretical background and hypothesis development

As briefly outlined above, there are competing perspectives on the relationship between financial distress and prices. In this section, an overview of these theories from the strategy, economics and corporate finance fields is provided and hypotheses are derived. The research hypotheses are developed in two steps: In line with the Structure-Conduct-

Performance paradigm (see *Figure 1*), it is expected that there is a relationship between financial distress and firm conduct in terms of prices. Several theories which further support this contention are discussed in Section 2.2.1. Theories that may negate this relationship are reviewed in Section 2.2.2. A contingency framework is proposed which suggests that the relationship between firm financial distress and a firm's pricing behavior may be moderated by certain firm and structural characteristics (Section 2.2.3).

2.2.1. Financial distress as a driver of competitive pricing behavior

The strategy literature offers two theories, prospect theory[7] and organizational learning theory that may support a negative relationship between financial distress and a firm's prices. Both theories are discussed in turn before empirical evidence and arguments from standard microeconomic and corporate finance theory are set forth.

Prospect theory posits that decision makers are more risk seeking when facing situations of likely loss while the inverse is true for decision makers operating in the domain of profitability (Kahneman and Tversky 1979). Prospect theory can, thus, readily be applied to evaluate the risk-taking behavior of financially troubled firms: Managers of low-performing, troubled firms may be risk-assertive in their strategic choices in the expectation of positive long-term returns to risk (in terms of increased market shares, revenues, or profits, for example).

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[7] While prospect theory has its origins in the economics field, its concepts have been widely adopted by strategic management researchers.

There is substantial support for the contention that troubled firms choose riskier strategies in the strategic management literature (Bowman 1982, Moses 1992, Singh 1986, Wiseman and Bromiley 1996). Chattopadhyay et al (2001) further investigate firms' responses to threats such as declining organizational performance by considering elements such as organizational characteristics and strategic type, and Wiseman and Gomez-Mejia (1998) examine managerial risk taking across different governance modes. While extending the basic framework of prospect theory, both papers still support the hypothesized relationship between a firm's level of distress and risk seeking behavior. Authors have, thus, based their arguments on prospect theory when investigating the relationship between organizational decline and risk taking behavior in general (Bowman 1982, Chattopadhyay et al. 2001, Shoham and Fiegenbaum 2002, Singh 1986, Wiseman and Gomez-Mejia 1998), organizational adaptation (McKinley 1993) or innovation (Mone et al. 1998).

With the connection between financial distress and risk taking behavior established, the relationship between the latter and a firm's pricing strategy can be characterized as follows: As noted by Ferrier (2001), pricing actions represent a particular type of competitive actions which have been associated with organizational risk taking (Ferrier et al. 2002). Similarly, (Borenstein and Rose 1995) equate bankrupt firms' "preference for greater risk" (p.397) to competitive aggressiveness. Moses (1992) further notes that low price strategies "sacrifice short-run profits in an attempt to establish a market and generate profits over the long run" (p.40). He concludes that penetration strategies are high risk strategies because the firm might incur further losses if costs fail to decrease below price levels in the longer term. Pricing actions also entail the risk of imitation or retaliation by competing firms. LeBlanc (1992), for example, suggests that low-cost incumbents may choose to price aggressively in response to firms entering their (low-price) markets. In more general terms, authors have investigated the dynamics of competitive actions and responses and have found that a firm's actions drive competitors' responses (Chen et al. 1992), which in turn, determine the effectiveness and performance effects of the focal firm's actions (Chen 1996, Peteraf 1993, Smith et al. 1991). The risk of choosing low price strategies in a homogenous competitive environment, thus, lies in the possibility of unbalancing the competitive equilibrium (Xu and Tiong 2001) and the potential loss resulting from aggressive competitive responses (Young et al. 1996). In summary, prospect theory supports the argument that financial distress induces firms to commit to a riskier, more aggressive pricing behavior, i.e. to lower prices.

Organizational learning theory also provides support for a positive relationship between performance distress and strategic change or competitive aggressiveness (Ferrier et al. 2002). Lant et al (1992) argue that previously unsuccessful firms undergo a learning process which may lead to strategic reorientation, and Ferrier (2001) suggests that the discrepancy between an organization's goals and its actual performance provides motivation for future actions and increases the likelihood of strategic change. To the extent that pricing actions reflect changes in the underlying firm strategy, one may thus argue that financially distressed firms are more likely to change their prices than are healthy firms. Ferrier et al (2002), for example, note that "poor performance provides the firm with strong incentives to aggressively search out new approaches to compete more effectively in the marketplace" (p.304). It is thereby implicit that potential price changes will typically involve *lower* prices (see also e.g. Ferrier 2001).

From a **microeconomics** and **corporate finance** perspective, Brander and Lewis (Brander and Lewis 1986) argue that a firm's "output market behavior will, in general, be affected by [its] financial structure" (p.957, brackets added). Investigating the linkages between financial and product markets, they demonstrate that highly leveraged firms will likely compete more aggressively by increasing their output since riskier strategies with (potentially) higher returns are more attractive to equity holders as a result of the limited liability effect of equity financing, than are conservative strategies which primarily appeal to debt holders. In a similar vein, Maksimovic and Zechner (1991) suggest that highly leveraged firms choose technologies which are riskier in terms of their expected cash flows. Hendel (1996) supports this assertion, arguing that "firms under financial distress use aggressive pricing to generate cash" (p.309) and that prices are a function of a firm's liquidity.

A number of authors have empirically examined the relation between firm financial condition and pricing behavior. Borenstein and Rose (1995) regress the change in prices on a set of Chapter 11 indicator variables[8] and use a panel dataset from the U.S. airline industry (1988-1992 data) to estimate their model. They find support for the theoretical contentions summarized above, indicating that air fares drop by five to six percent in the months preceding the carrier's Chapter 11 filing. Kennedy (2000) demonstrates that a

[8] As noted by the authors, the effects of many other variables typically included in price estimation equations are assumed negligible and are excluded from the model specification.

distressed firm's sales revenues and profits (and that of its rivals) decrease prior to bankruptcy as a result of its altered product market conduct. He analyzes 51 bankruptcy filings and uses Chapter 11 indicator variables and a small set of market and firm-specific control variables to predict revenues and profit margins. Analyzing U.S. airline data from the 1985 to 1992 period, Busse (2002) finds that highly leveraged firms are more likely to start price wars. Busse also argues that "firms in poor financial condition discount future revenues more heavily than do financially sound firms" (p.298), thus focusing on boosting short term sales (by cutting prices, for example).

Taken together, there is theoretical and empirical support for the contention that financially distressed firms choose riskier strategies and price more aggressively, i.e. follow a low-price strategy in an effort to gain market shares and boost sales[9]. *Hypothesis 1* is stated as follows:

Hypothesis 1: Financial distress negatively impacts prices.

It may also be argued that a firm's prices will affect firm financial condition. If prices are consistently below marginal costs, the firm's financial situation will deteriorate. Prices above marginal costs, in turn, will positively impact firm financial condition as long as marginal costs are larger than average costs. The possibility of such reverse causality is not further explored in this research. Firm financial condition is, of course, a firm-level phenomenon while prices are market-specific. A firm's financial distress may, as argued

[9] See also Ferrier et al (2002) for a definition of competitive aggressiveness.

here, impact a firm's pricing behavior in all markets, but the sales price in an individual market will not necessarily affect the firm's financial standing. In fact, the latter may only be true if *all* prices are *systematically* lower (or higher) than marginal costs. This is, however, a strong assumption which requires empirical and theoretical substantiation. Such work is not within the scope of this analysis and is left for future research. This research uses firm level financial distress to estimate multi-market firms' market level prices. It is therefore assumed that problems of endogeneity, caused by reverse causality, do not arise.

Hypothesis 1 implies that financially distressed carriers may be expected to sell at lower prices, all else equal. Prior research, however, suggests that the above hypothesized price effect of firm financial distress may intensify as bankruptcy occurs. As Borenstein and Rose (1995) and Kennedy (2000) have shown, firms try to prevent insolvency by generating cash through aggressive competition prior to bankruptcy filings. Once these firms operate under Chapter 11 protection, however, they benefit from lower operating costs as debt payments are paused (Barla and Koo 1999, Rose-Green and Dawkins 2002) to support the restructuring of the firm. This lower cost base may allow bankrupt firms to charge even lower prices. Moreover, soft demand may force carriers to cut fares once they operate under bankruptcy protection since the latter signals uncertainty to consumers (Hofer et al. 2005). Barla and Koo (1999) further suggest that firms "under protection of Chapter 11 are more likely to adopt short term profit maximization behaviors" which equate to "prices that are well below long run marginal costs" (p.104) when demand is low (see also Hofer et al. 2005).

In summary, there are three rationales which support the contention that the effect of financial distress on prices should be stronger during bankruptcy than prior to the Chapter 11 filing (see also Hofer et al. 2005): First, when operating under bankrupt protection, firms benefit from lower costs and may pass these savings on to consumers in the form of lower prices. Second, bankrupt firms may experience lower demand due to the uncertainty concerning the firms' future operations. Third, bankrupt firms may focus on short term profit maximization and thus offer lower prices, *ceteris paribus*. Consequently, the following hypothesis is suggested:

Hypothesis 2: The negative impact of financial distress on prices is greater during bankruptcy than prior to the Chapter 11 filing.

As indicated previously, a different set of theories suggest that a firm's financial distress may not significantly impact its prices. These perspectives are reviewed below, and hypotheses that suggest that the relationship between financial distress and prices is moderated by other factors are formulated.

2.2.2. Conflicting theoretical arguments

In this section, theoretical arguments and empirical results from the industrial organization economics, game theory and finance literatures that do *not* provide support for the financial distress-price relationship are reviewed.

The **threat-rigidity model** has emerged as a counterhypothesis to prospect theory. Staw et al (1981) argue that individuals, groups, and organizations exhibit restrictive information processing patterns, centralize control and conserve resources when faced with threatening situations. These mechanisms result in increased rigidity which reduces an organization's ability to change and adapt to its environment (McKinley 1993). As noted by McKinley (1993) and Mone et al (1998), there is broad empirical support for the threat-rigidity model: Smart and Vertinsky (1984), for example, find that executives consult fewer information sources during crises, and Chattopadhyay et al (2001) present some evidence that organizations respond to control-reducing threats with low risk, internally directed actions. From this perspective, firms in poor financial conditions may, thus, be expected to not reduce prices in the short-term, but to behave passively and conservatively (Ferrier et al. 2002).

Similar rigidity arguments can be found in the **industrial organization economics**, **game theoretic** and **finance** literature. First, the kinked demand curve theory suggests that firms in oligopolistic markets with few sellers and rather homogenous products face highly inelastic demand for price decreases (Waldman and Jensen 2001). Put differently, firms will refrain from price competition given that their rival firms may be expected to match these moves, thus offsetting any profit gains (Scherer 1980). This argument is further supported by game theory: Derfus et al (forthcoming) argue that pricing actions are negative-sum actions since all competing firms will be worse off after implementing successive price reductions. Consider, for example, a sequential game between duopolists: Firm Two observes Firm One's move and subsequently acts in response to Firm One's action. Firm One, in turn, observes Firm Two's action and may choose to react, etc. (Gibbons 1992). When such moves consist of price reductions, the price may fall below average cost levels in the course of this competitive interaction of moves and countermoves (see also Dasgupta and Titman 1998). These theories are, thus, in line with the imitation/retaliation argument discussed earlier (Busse 2002, Chen 1996, Chen et al. 1992, Peteraf 1993, Smith et al. 1991).

In summary, the threat-rigidity model and arguments from the industrial organization, game theoretic, and finance literatures suggest that financially distressed firms may refrain from lowering prices as information processing and decision making processes are altered in the face of threats or for fear of retaliation.

2.2.3. The contingency approach

This essay attempts to reconcile the apparent theoretical and empirical conflict that has shaped previous research on the relationship between financial condition and prices. Each of the groups of theoretical arguments – those supporting and those denying a negative impact of financial distress on prices – may be valid under specific circumstances. As will be discussed below, there are a number of contingencies that may impact the relationship under investigation. Similar to Ferrier et al (2002), a contingency framework which suggests moderating effects of *organizational* and *market structural* characteristics is developed. This framework aims at defining in what instances the price effects of financial distress are largest.

As shown in *Figure 2*, two groups of contingencies are hypothesized to impact the relationship between financial distress and prices are presented: organizational characteristics and market characteristics. Both groups of variables are discussed in turn, and hypotheses are formulated.

Organizational characteristics

It is suggested that the relationship between firm financial distress and prices is moderated by certain organizational characteristics. More specifically, a firm's operating costs, its size and market shares are hypothesized to influence the extent to which firm financial distress impacts the firm's pricing behavior. The importance of these factors has been shown in prior research.

Prior research has suggested that a firm's particular strategic type may impact its behavior. Chattopadhyay et al (2001), for example, find that a firm's propensity to respond to threats with externally as opposed to internally oriented actions is impacted by its strategic focus. They present empirical support for the contention that firms focusing on product-market development (prospectors) are more likely to act externally (by changing prices, for example) since the "effectiveness of a product-market development strategy depends to a large extent on controlling or modifying the external environment" (p.940/941). Firms focusing on domain defense (defenders), in turn, "are more likely to act within themselves to become more efficient through standardizing organizational processes" (p.941). Therefore, a differential impact of financial distress on a firm's prices by strategic type is expected, given the firms' differential inclinations to act externally versus internally in response to changes in financial situation.

Although there are multiple definitions and classifications of strategic types (see e.g. Shoham and Fiegenbaum 2002), these can be simplified and synthesized as follows (see also Chattopadhyay et al. 2001): Defenders are those firms that operate in a stable, well-defined set of market segments, tend to act conservatively, and are characterized by deadlocked organizational structures and operating routines. Prospectors, in turn, are those firms that constantly seek opportunities to expand their business and whose most distinctive features are their innovativeness and cost-leadership.

In the empirical practice, many operationalizations of strategic types have been suggested, ranging from simple dichotomies (e.g. Peteraf 1993) to multidimensional clusters (Smith et al. 1997). There is, however, substantial agreement in the literature that a firm's costs are an important differentiator with respect to its strategic type (see the above definitions of prospectors and defenders). This is particularly true in the U.S. airline industry: Both the academic and trade presses frequently refer to specific airlines as either *high-cost* carriers or *low-cost* carriers. Peteraf (1993), for example distinguishes between pre- and post-deregulation air carriers, the former being mostly high-cost firms[10] while the latter are virtually all low-cost airlines. A firm's strategic type is therefore identified by means of its **operating costs**. In fact, an airline's relative cost

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[10] Southwest Airlines being a notable exception.

(dis)advantage may impact its choice of strategy. Assuming that lower operating costs also imply higher profit margins, low-cost firms have some financial flexibility to allow for price reductions and potentially ensuing price wars. Higher operating costs (and lower profit margins), in turn, would imply that price cuts likely lead to increased operating losses.

The crucial assumption for this reasoning to be valid is, of course, a negative correlation between operating costs and profit margins. The empirical analyses will be conducted using data from the U.S. airline industry[11]. Accordingly, financial data on U.S. airlines were collected for a total of eight quarterly time periods (1992 and 2002) from the Bureau of Transportation Statistics. An analysis of these data indicates that the correlation coefficient between *operating costs per available seat-mile* and *operating profit per available seat-mile* is equal to $r = -0.1481$ and is statistically significant at the five percent level ($p = 0.0485$)[12]. This result provides some support for the contention that firms with lower operating costs tend to achieve higher profits and may be able to operate profitably even if prices are cut. Firms with higher costs and lower profit margins, in turn, do not have this flexibility and may tend to refrain from lowering prices. The negative effect of financial distress on prices may thus be expected to decrease with the magnitude of the firm's operating costs as depicted in *Figure 3* below. The coefficient of the associated interaction term is, thus, expected to be positive.

[11] Further information about the data sources and the nature of the data set is provided in Chapter 2.3.
[12] This correlation analysis is based on firm-level 228 observations.

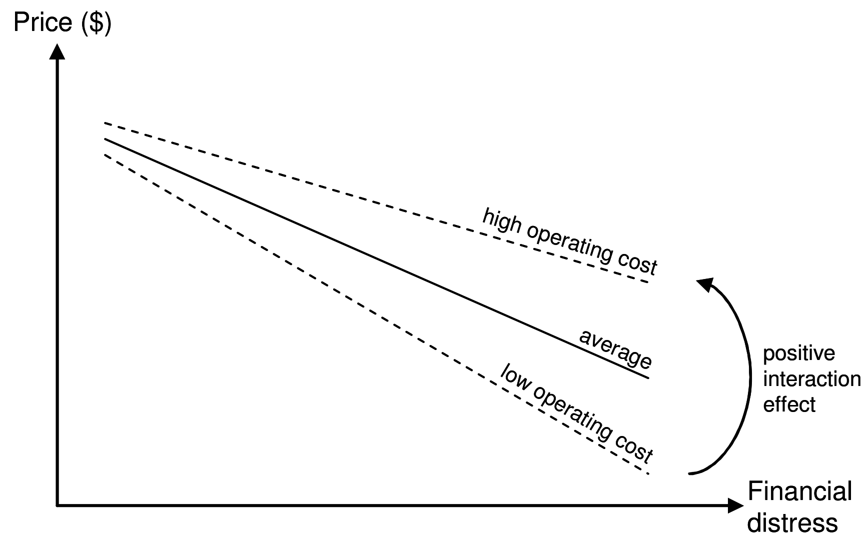

Figure 3: The moderating effect of operating costs on the distress-price relationship

Accordingly, *Hypothesis 3* is proposed as follows:

Hypothesis 3: The negative effect of financial distress on prices decreases with the magnitude of the firm's operating costs.

The effect of firm financial distress on prices may also be impacted by the **firm's size**. Commenting on the survivability of large firms, Tiras (2002) notes that creditors have greater confidence in the turnaround performance of large distressed firms and thus grant them more favorable loan conditions than to small firms. In a similar vein, Smith and Graves (2005) suggest that "larger firms are likely to have a higher probability of survival, as the potential losses to stakeholders are greater. Also, such firms are likely to have a higher profile and therefore more likely to be kept alive" (p.306).

Looking at bankrupt firms, in particular, prior research suggests that larger bankrupt firms have a bankruptcy cost advantage due to scale effects in reorganization costs (Campbell 1996). The costs of bankruptcy consist of both direct and indirect costs, where the former "include lawyers' and accountants' fees, other professional fees, and the value of managerial time spent in administering the bankruptcy", and the latter "include lost sales, lost profits, and possibly the inability of the firm to obtain credit or to issue securities" (Warner 1977, p.338)[13]. Numerous researchers have attempted to estimate these costs. Their estimates vary significantly due to differences in cost definitions, variable measurement, sample composition, and estimation methodology. The estimates range from an average of 1.3% of the change in firm value during bankruptcy in the railroad industry (Warner 1977) to 4% of the firm value in the retail business (Altman 1984), and up to 16.35% of the firm value for a cross-section of industries (Branch 2002)[14].

Many researchers note, however, that there are significant scale economies in bankruptcy costs: Warner (1977), for example, finds that bankruptcy costs are linearly decreasing with firm size. His analyses indicate that bankruptcy costs may be as high as about nine percent of the firm's market value for firms with a market value of less than 30 million dollars and as low as two percent for firms with a market value of around 120 million dollars. Analyzing bankruptcies in the U.S. trucking industry, Guffey and Moore (1991) also find a significant negative correlation between firm size (as measured by total asset

[13] A more detailed discussion of the composition of bankruptcy costs can be found in Guffey and Moore (1991) and Branch (2002).
[14] See also Bradbury and Lloyd (1994) for a summary of prior research estimating bankruptcy costs.

values) and bankruptcy costs. Betker (1997), in turn, finds that the relationship between firm size (total assets) and bankruptcy costs follows an inverted U shape: The direct effect of assets on bankruptcy costs carries a positive coefficient while the coefficient of the squared asset value carries a negative coefficient. The observation of the relationship between firm size and bankruptcy costs has led researchers to conclude that such bankruptcy costs may significantly impact smaller firms' decisions while they may not substantially impact large firms (Bradbury and Lloyd 1994). Consequently, it is expected that larger bankrupt firms may be able to offer lower prices than smaller firms due to their bankruptcy cost advantage.

Previous research has also found that larger firms tend to remain in bankruptcy for longer periods of time and exhibit significantly higher survival rates than smaller firms (Queen and Roll 1987, Rodgers 2000). The latter observation may be attributed to lower bankruptcy costs (Campbell 1996), for example. These advantages in terms of credit conditions, stakeholder confidence, and bankruptcy costs may allow larger distressed firms to commit to riskier turnaround strategies that involve more aggressive pricing behaviors. While detrimental in the short term, the latter may drive competitors out of the market and result in greater long term returns. It is expected that the negative effect of firm financial distress on prices will be stronger for larger firms. Consequently, the interaction effect between financial distress and firm size is hypothesized to positively affect prices, as noted in *Hypothesis 4* and illustrated in *Figure 4*.

Hypothesis 4: The negative effect of financial distress on prices increases with firm size.

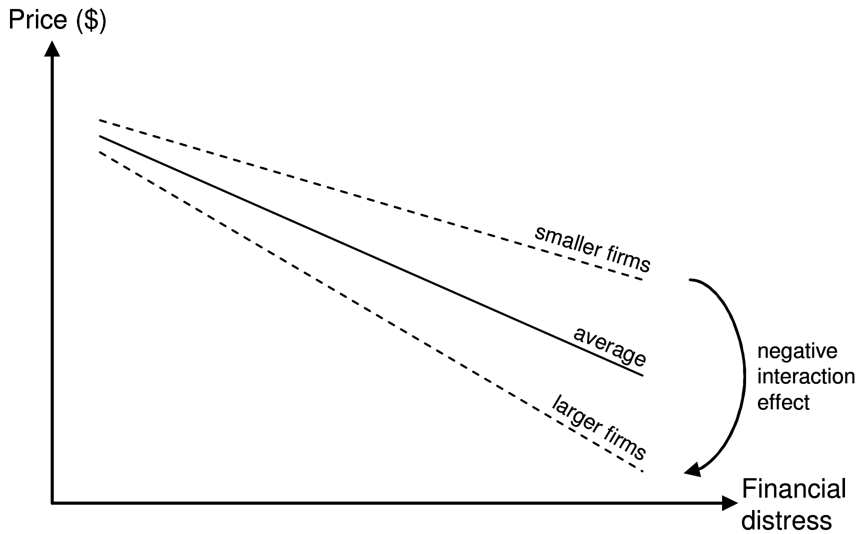

Figure 4: The moderating effect of firm size on the distress-price relationship

The magnitude and direction of the effect of firm financial distress on prices may also depend on the firm's market share in the particular product (i.e. route) market. In the long run, greater **market shares** may result in the achievement of lower marginal costs through economies of density (Ferrier et al. 2002). Furthermore, high market shares may be indicative of barriers to entry and mobility that isolate market-leading firms from intense competition (Caves and Porter 1978, Caves and Ghemawat 1992). From this perspective, high market shares may be considered a valuable firm resource that allows for above-normal returns. Consequently, some researchers have argued that firms will likely try to defend their market power. Busse (2002), for example, presents empirical evidence that firms are more likely to enter price wars the greater their market shares, and

LeBlanc (1992) argues that firms strive to maintain monopoly profits by implementing limit or predatory pricing.

These predictions may, however, not hold when explicitly considering distressed firms. First, note that distressed firms typically focus on short term survival rather than on long term strategic positioning. While the latter is the ultimate purpose of distressed firms' turnaround efforts, generating sufficient cash flows is a mandatory obligation these firms face in the immediate future. In this vein, bankrupt U.S. airlines frequently terminate unfavorable aircraft leases and collective labor agreements right upon entry into Chapter 11 protection. If liquidity is the prime objective, however, price cuts in an effort to maintain market shares may prove counter-productive for high market share firms: Any price reductions will imply lower total revenues since the incremental increase in customer demand likely will not outweigh the detrimental effect of lower sales prices. Assuming (quasi-)fixed production costs in the short run, these revenue losses directly affect the firm's bottom line. Low-market share firms, in turn, may see a substantial increase in customer demand when reducing prices. The prospect of increased volume may, thus, offset the negative effect of lower sales prices. This implies that engaging in price competition is more appealing to firms with smaller market shares: The potential market shares to be gained are greater, and any pricing actions hurt the market leading firm(s) significantly more than the smaller firm. This reasoning reflects the concepts of Judo economics (Gelman and Salop 1983) and Judo strategy (Yoffie and Kwak 2002), which essentially posit that a firm's market shares (and/or size) may constitute a competitive disadvantage when adequately leveraged against it by smaller firms (in terms of market shares).

Standard microeconomic theory further suggests that firms with greater market shares possess market power and can charge price premiums (see e.g. Borenstein 1989). Extending this argument to the present research context, it is expected that distressed firms with higher market shares have higher degrees of market power and will be required to compete on prices to a lesser extent than firms with lower market shares and little market power. Firms with higher market shares may be able to retain greater shares of market demand due to customer retention instruments such as loyalty programs which create higher switching costs for consumers. The latter may thus be reluctant to switch to financially stronger competitors even though they may seem more reliable or offer lower prices. From this perspective, demand inelasticity confers firms with greater market shares greater degrees of market power. And such market power, in turn, enables even distressed firms to maintain higher price levels, *ceteris paribus*.

In summary, these arguments thus suggest that higher market shares reduce the negative effect of firm financial distress on prices (see *Figure 5*), and the associated interaction effect is expected to be positive. *Hypothesis 5* below formally states this contention:

Hypothesis 5: The negative effect of financial distress on prices decreases with the firm's market share.

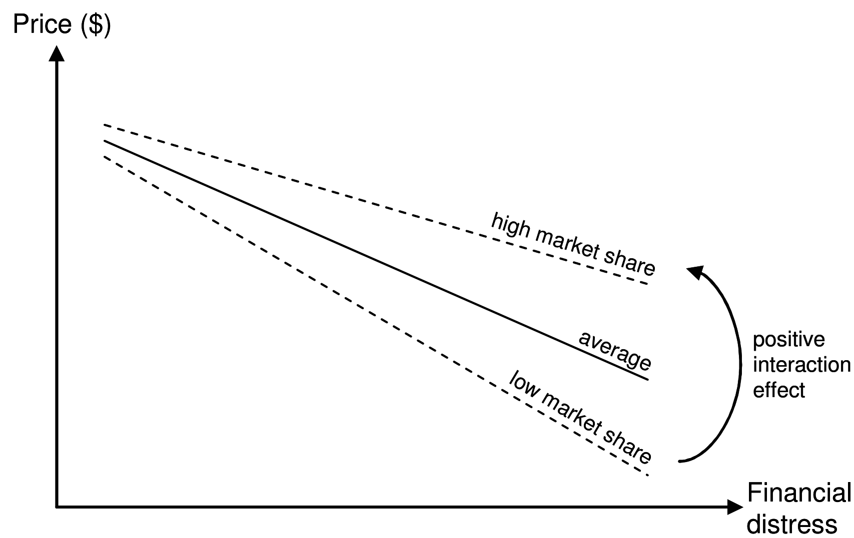

Figure 5: The moderating effect of market shares on the distress-price relationship

A second set of contingencies, those relating to market characteristics, are discussed below.

Market characteristics

Besides organizational characteristics, select market characteristics are hypothesized to impact a distressed firm's pricing strategy. Market concentration is one of the most widely used measures of the competitiveness of markets in the extant literature. While there are many alternative measures of market structure—the number of sellers in the market and multi-market contact measures, for example, have been used to characterize the structure of markets in prior research (e.g. Mazzeo 2002, Scott 1982)—the degree of market concentration is likely highly correlated with these alternative measures and appropriately captures the structural characteristics of a market. The second market-specific factor included in this study is the financial condition of all the firms in a market. This variable is included to evaluate how a firm's financial condition differs from the average distress level of the other firms in the market and how this relative difference impacts the magnitude of a firm's pricing actions.

First, **market concentration** will likely affect a firm's pricing decision. More specifically, the expectation of competitive responses and retaliatory moves in highly concentrated markets impacts a firm's valuation of the effects of any price changes. The structure-conduct-performance paradigm posits that industry concentration reduces the level of competition (Scherer 1980, Waldman and Jensen 2001). Young et al (1996) find empirical support for this contention, noting that firms in concentrated markets or industries carry out fewer competitive moves. The underlying assumption of this reasoning is, however, that the competing firms are similar to one another and that their products are largely homogeneous. Waldman and Jensen (2001) list a variety of factors that violate this homogeneity assumption and may hinder effective collusion between firms in concentrated markets. Cost differences between competing firms, for example, may negatively affect the ease of collusion.

A deterioration in a firm's financial position, and bankruptcy in particular, may bring about such cost differences: firms operating under Chapter 11 protection, in particular, may pause debt payments and shed financial obligations such as contributions to pension plans, for example (Rose-Green and Dawkins 2002). This new cost structure may then lead to the firm's repositioning in the product market. Specifically, a change in a firm's operating costs changes the firm's profit maximization problem, and consequently its optimal price levels. The interaction of market concentration and financial distress may therefore lead to a destabilization of collusive arrangements and increase pricing competitiveness (Barla and Koo 1999). While market concentration is expected to be positively related to prices, this research contends that this positive relationship will diminish in magnitude in the light of an aggravation of a firm's financial condition. Put differently, the interaction of financial distress and market concentration is expected to negatively affect prices, ceteris paribus (*Hypothesis 6*).

Hypothesis 6: The impact of financial distress on prices is greater, the higher the level of market concentration.

Figure 6 illustrates the differential effect of financial distress on prices as a function of the degree of market concentration.

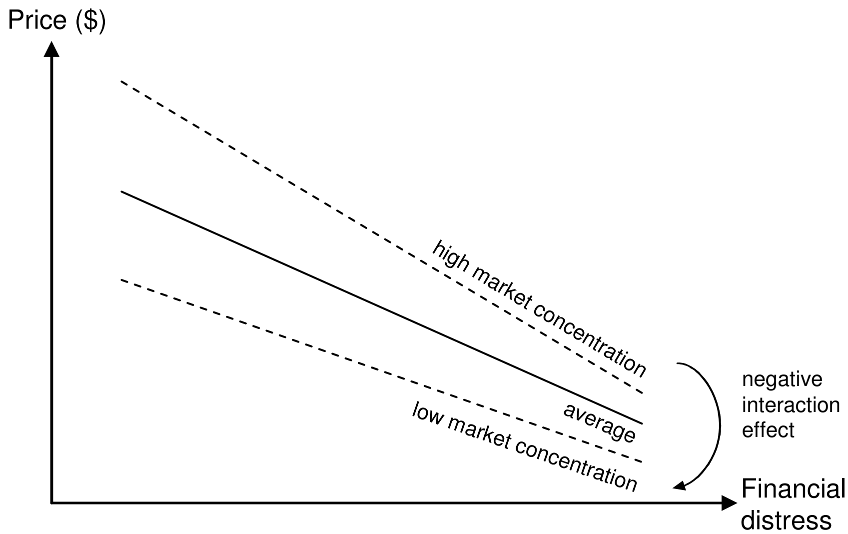

Figure 6: The moderating effect of market concentration on the distress-price relationship

A distressed firm's pricing decisions will, in part, also depend on its **competitors' financial situations**. If a firm's rivals experience similar degrees of distress as the focal firm does (and assuming that the firms' products are undifferentiated), then these rivals may be expected to exhibit comparable or symmetric pricing behaviors. A focal firm's price reductions would then be matched by the other firms, and no single firm could gain a competitive advantage. In fact, game theory suggests that in a perfectly competitive setting each firm will always have an incentive to slightly undercut its competitor's prices, thus eroding profit margins to zero (Gibbons 1992). Financially distressed firms will, therefore, avoid competing on price when their competitors find themselves in similar financial conditions. Conversely, *Hypothesis 7* is stated as follows:

Hypothesis 7: The greater a firm's financial distress relative to its competitors, the lower the firm's sales prices.

In summarizing, a set of hypotheses on the link between firm financial distress and firm prices has been formulated based on a variety of theoretical perspectives. Conflicting viewpoints that may suggest the absence of any significant relationship respectively are presented, and a contingency framework that more precisely defines for what type of firms and under what circumstances changes in a firm's financial situation may indeed cause changes in the firm's pricing behavior is proposed. The resulting model is shown in *Figure 7*.

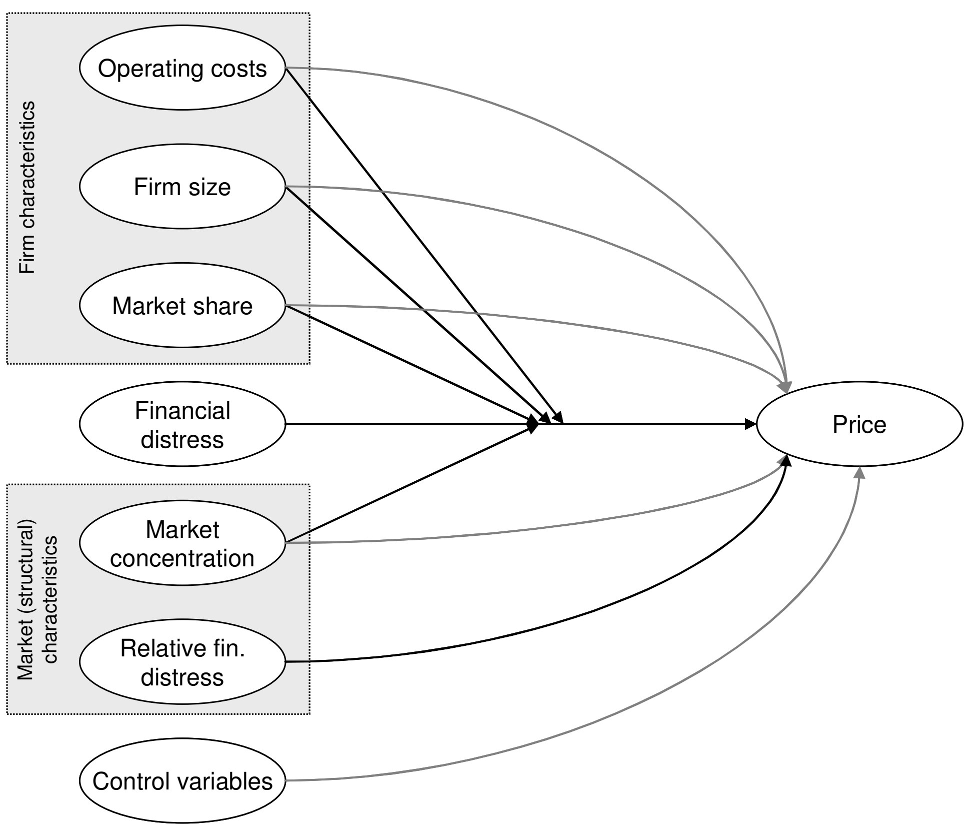

Figure 7: Research model

In the following section, information about the sample data that is used for the empirical analyses is provided, and measurements of the variables in the research model as well as methodological issues are discussed.

2.3. Data and methodology

The U.S. airline industry provides the setting for the empirical analyses. This selection is particularly suitable for a number of reasons. First, the markets are clearly defined (Smith et al. 1991), and all firms operating in these markets are dominant-business firms (Peteraf 1993), i.e. firm-specific data reflect the firms' aviation activities and are not diluted by non-aviation business activities. Second, the U.S. airline industry is highly competitive and encompasses a large cross-section of routes that differ significantly with respect to their market characteristics (Peteraf 1993, Smith et al. 1991). Third, the industry has experienced periods of severe financial distress (Borenstein and Rose 1995), but is sufficiently heterogeneous with respect to the airlines' financial conditions. Finally, there is a wealth of publicly available data on the U.S. airline industry due to the U.S. Department of Transportation's reporting requirements[15].

[15] Some sections of this chapter, particularly the sample data and variable descriptions, are similar or equal to the corresponding sections of a related paper published by Hofer et al (2005).

2.3.1. Data sample

Data were collected on the top 1000 U.S. domestic origin and destination route markets[16], for all quarters in 1992 and 2002. These years were chosen because the airline industry experienced serious distress in the early nineties (Barla and Koo 1999) and in the aftermath of the 9/11 attacks. At the same time, limiting the analyses to two years only allowed keeping the dataset at a manageable size. The sensitivity of the empirical results with respect to the selection of these particular time periods is investigated by re-estimating the regression models using an extended data set that also includes 1997 data. These results will be discussed in Section 2.4.3.

Quarterly data are used to capture the short-term effects of financial distress and Chapter 11 filings on air fares. The top 1000 route markets cover a wide range of route characteristics in terms of traffic volume, distance, and intensity of competition. The unit of observation is a specific carrier's fare on a particular route market in a given time period.

The raw data were purchased from Database Products Inc. (DPI), a reseller of the Department of Transportation's DB 1A data which contain a 10% sample of all U.S. domestic origin and destination tickets. DPI downloads the DB 1A data and screens them for erroneous and redundant data entries. These entries and data points from non-revenue

[16] Based on 2002 traffic figures, 48 contiguous states only.

transactions[17] are removed from the dataset. The data obtained from DPI thus are filtered and quality-controlled and provide airline and route specific information on fares, nonstop and itinerary miles, the number of passengers, and the number of coupons. Additional air traffic and airline operating and financial data were gathered from the DOT's T-1[18] and Form 41[19] databases. Other data sources include the American Transport Association (ATA; U.S. airline bankruptcy data), the Bureau of Labor Statistics (BLS; income data and inflation indexes) and the Bureau of Economic Analysis (BEA; population statistics).

Observations from carriers with less than five percent route market share were deleted from the data set to keep the data set at a manageable size[20]. Furthermore, a total of 577 observations were excluded because of unidentified carriers[21], or unavailable airport and airline-specific data. A total of 23,039 observations were retained for the analyses. Each observation indicates data for a specific carrier on a specific route market in a specific time period.

2.3.2. Variables and measurement

This section provides detailed information on the variables used in this research model.

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[17] E.g. personnel travel and frequent flyer award travel.

[18] Table T-1 provides summaries of T-100 data by carrier, aircraft type and service class and includes information on available seat miles (ASM) and revenue passenger miles (RPM).

[19] Form 41 (financial schedule) contains financial information on large U.S. certified air carriers including data from balance sheets, income statements, and information on cash flows, and aircraft operating expenses.

[20] This is common practice: Borenstein and Rose (1995), for example, exclude all observations of carriers with less than ten percent route market shares.

[21] "XX – unduplicated commuters" and "UK – unknown carrier".

The purpose of this research is to investigate the effect of financial distress on prices. Consequently, ticket prices (fares) are used as the dependent variable. Among those factors that may explain and predict variations in ticket prices, firm financial distress is of particular interest here. Other independent variables include not only the aforementioned moderating factors—operating costs, firm size, market shares, and market concentration (see also *Figure 7*)—but also a set of airline-specific, route-specific, and airport-specific characteristics that have been shown to impact air fares in prior research (Hofer et al. 2005). The dependent variable is discussed first, followed by the independent variables of interest. In addition, information on the set of control variables included in the empirical estimation model is provided. Descriptive statistics and a correlation table are provided in Section 2.3.3.

2.3.2.1. Dependent variable

Previous studies published in the strategic management literature have measured the impact of financial condition on firm behavior in terms of the number and type of competitive actions, response speed and delay, for example (Chen et al. 1992, Ferrier 2001, Ferrier et al. 2002, Smith et al. 1997, Smith et al. 1991, Young et al. 1996). While price data are commonly used as dependent variables in the economics literature, this is, to the best of the author's knowledge, the first study to investigate the impact of financial distress on *prices* from a strategic management perspective. More specifically, $Fare_{kij}$ is the average price carrier k charges on the route between airports i and j[22]. All fare values

[22] Fare values are averages across all booking classes and do not include taxes and fees.

are one-way fares based on roundtrip purchases and are given in real 1992 U.S. dollars[23].

2.3.2.2. Independent variables

The measurement of financial distress is of particular interest in the context of this study. Previous studies of financial condition have generally relied on one of two measures. Ferrier et al (2002) and Chakravarthy (1986), for example, relied on a composite measure to evaluate a firm's financial situation. Altman's (1968) Z score is the most prominent member of this group of measures and takes into account the firm's past and present profitability, its liquidity and its degree of activity. Other researchers have focused on Chapter 11 filings[24], the most visible and definite sign of financial distress, to investigate the effects of firm financial distress (e.g. Borenstein and Rose 1995, Kennedy 2000). While both measures have their merit, it is important to note that they capture different aspects of financial distress. Z score-type measures are indicators of a firm's financial health (or distress), while Chapter 11 filings refer to a specific point in time at which the firm is no longer able to meet its debt obligations. The model builds on both of these indicators and includes four measures of financial distress to more precisely sort out its effects on firm behavior in terms of pricing:

- $Distress_k$ is a measure of Airline *k*'s financial distress. The *Distress* variable is the inversion of firms' Z scores. More specifically, Z'' scores (Altman 2002) are used, a revised version of Altman's original Z score formulation (1968) which is particularly suitable for firms operating in service industries (such as the airline industry). The

[23] All nominal values were converted to real 1992 dollars using the appropriate price indexes published by the Bureau of Economic Analysis.
[24] See Daily (1994) for a comprehensive explanation and discussion of the U.S. Code Chapter 11.

more recent Z'' scores (Altman 2002) are also preferred over the original Z score formulation (Altman 1968) since it has been shown that "the relation between financial ratios and financial distress changes over time" (Grice and Ingram 2001) such that more recent formulations are more reliable and effective in predicting a firm's financial distress. Based on discriminant analysis, Altman (2002) developed the following model to estimate a firm's financial fitness:
$Z'' = 6.56 * X_1 + 3.26 * X_2 + 6.72 * X_3 + 1.05 * X_4$ where X_1 = working capital / total assets; X_2 = retained earnings / total assets; X_3 = Earnings Before Interests and Taxes (EBIT) / total assets; X_4 = book value of equity / total liabilities. All airline financial data needed to compute the Z'' scores were obtained from the Department of Transportation's Form 41 data which are available online on a carrier-time period basis. High Z'' scores indicate financial health, while low and negative scores indicate (serious) financial distress. Specifically, it has been suggested that scores of 2.60 or above indicate financial health, while scores of 1.10 or lower indicate severe distress. To facilitate the interpretation of the estimation results, the Z scores are inverted, i.e. $Distress = (-1) \cdot ZScore$, such that higher (positive) *Distress* scores indicate financial distress (see also Ferrier et al. 2002). This variable is used to test *Hypothesis 1*. Moreover, the airlines' *Distress* scores are used to test the moderating effects from *Hypothesis 3*, *Hypothesis 4*, *Hypothesis 5*, and *Hypothesis 6*, respectively.

- *Chpt11Ops*$_k$ is a binary (0/1) variable that identifies those carriers that operate under Chapter 11 protection ("1"). It thus is an alternate, though rather coarse, measure of a firm's financial distress. All bankruptcy data were obtained from WebBRD, a bankruptcy research database that is accessible online at http://webbrd.com/. This database is maintained by Professor Lynn M. LoPucki with the University of California at Los Angeles. This database specifies the dates at which firms (airlines) entered into and exited from Chapter 11 protection. These data were also double-checked with the bankruptcy data which are available online at the Air Transport Association's website (http://www.airlines.org/econ/). No discrepancies were found.

- *Pre4Chpt11*$_k$, identifies those carriers that will face bankruptcy within the following four quarters. In the latter case, this binary variable takes on the value of "1". This variable is based on the same sources as the *Chpt11Ops* variable defined above. A four-quarter period (prior to the Chapter 11 filing) is selected to best capture price reactions to aggravating financial distress in the time period immediately preceding bankruptcy.
- *Post4Chpt11*$_k$ is similar to the *Pre4Chpt11*$_k$ variable, but identifies those carriers that filed for Chapter 11 within the past four quarters ("1"). This variable is based on the same sources as the *Chpt11Ops* variable defined above. The inclusion of the *Pre4Chpt11*$_k$ and *Post4Chpt11*$_k$ variables allows capturing the differential impact of financial distress over time as stated in *Hypothesis 2*.
- The *Chpt11*$_k$ variable is an indicator variable which is equal to "1" if the focal carrier filed for bankruptcy protection in the current quarter. The number of observations in which this is the case is small such that this variable is only used for descriptive purposes (see *Figure 9*) and is not included in the regression analysis. An overview of the Chapter 11 dummy variables is provided in *Figure 8* below. Note that the *Pre4Chpt11*, *Chpt11*, and *Post4Chpt11* variables are mutually exclusive.

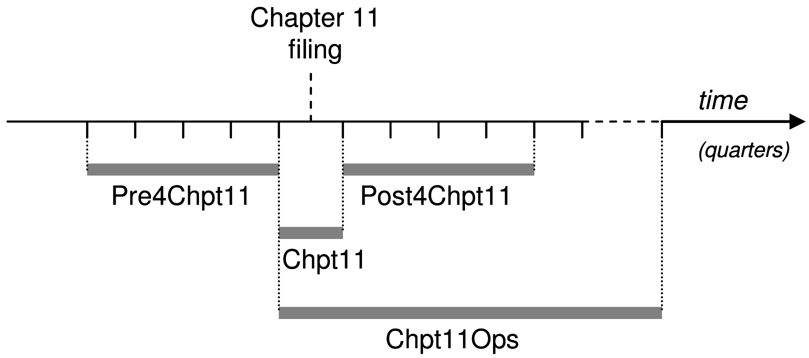

Figure 8: Overview of Chapter 11 indicator variables

- $DistressDiff_{kij}$ is an indicator of an airline's financial standing relative to its route competitors. It is based on Altman's Z'' score and is computed for each carrier in each route market for each time period. It is the difference between the focal carrier's Z'' score and the route market share weighted average of its route competitors' Z'' scores: $DistressDiff = Distress_{focal} - \frac{\sum\left(Distress_{competitors} * route\ shares_{competitors}\right)}{\sum route\ shares_{competitors}}$. Higher scores, thus, indicate that the focal carrier is financially better off relative to its route competitors and vice versa. The $DistressDiff_{kij}$ variable is designed to test *Hypothesis 7* which refers to an airline's financial standing relative to its competitors. This variable, thus, differs from the *Distress* and *Chpt11* variables in that it indicates an airline's *relative* financial standing, i.e. the focal firm's *Distress* relative to the market share weighted average *Distress* of its competitors, rather than its *absolute* financial distress. Positive *DistressDiff* values indicate that the airline is financially worse off than its route competitors, while negative values indicate relative financial wellbeing.

Further, a set of moderating variables is included as suggested in *Hypothesis 3* to *Hypothesis 6*. More specifically, it is hypothesized that the impact of financial distress on prices varies by strategic type/operating costs (*Hypothesis 3*), firm size (*Hypothesis 4*), firm market shares (*Hypothesis 5*), and market concentration (*Hypothesis 6*). These moderating variables are operationalized as follows:

- $AirlineCost_k$ is an indicator of an airline's operating efficiency. It is defined by the ratio of operating expenses to available seat miles (ASM).
- $Size_k$ indicates the firm's size in terms of its total assets (measured in 000s of U.S. \$).
- $RouteShare_{kij}$ measures an airline's market share on a route market (based on its share of route passengers).
- $RouteHHI_{ij}$ is a measure of route market concentration. It is based on the Herfindahl-Hirschmann Index (HHI), the sum of the squared market shares of all firms competing in the route market. The route HHI is computed on an airport-to-airport basis rather than on a city-to-city basis. This allows capturing airport-specific effects.

These variables are interacted with the *Distress* variable to estimate their moderating effects in the relationship between firm financial distress and prices.

2.3.2.3. Control variables

A set of firm and market specific control variables that have been shown to impact prices in previous research (see e.g. Borenstein 1989) is included in the empirical model. The firm-specific variables are the following:

- $MaxAirportShare_{kij}$ indicates an airline's market share in the airport market *i* or *j*, whichever is highest. The rationale for this approach is that a higher market share at an airport conveys an airline some degree of market power in that airport market which may be expected to impact fares in route markets involving that airport (Borenstein 1989). Higher airport market shares likely imply higher fares.

- $Circuity_{kij}$ is another measure of the quality and convenience of carrier *k*'s service between airports *i* and *j*. Circuity is the ratio of itinerary miles; i.e. the distance actually flown, and nonstop miles between airport *i* and *j*. The higher this ratio; i.e. the larger the detour, the lower the quality of the transportation service. At the same time, however, higher circuities mean higher operating costs. The impact on fares is, thus, undetermined.
- $AirlinePass_{kij}$ is the number of passengers carried by airline *k* between airports *i* and *j* in a given time period. Higher numbers of passengers may be associated with economies of density, and, thus, lower costs and lower fares. On the other hand, high traffic volumes reflect high demand levels which may result in high prices.
- $Loadfactor_k$ is the average fill rate of a carrier *k*'s passenger aircraft during a given time period. Note that this variable is not route specific since data were not available on a route basis. Higher load factors may imply economies of density and utilization, and fares may be expected to be lower for carriers with high load factors. At the same time, high load factors may be associated with poorer service quality (e.g. possibly lower frequency of service, less space for each traveler in a fully booked cabin, less attentive/personalized cabin service) and lower fares.

The group of market specific control variables consists of the following variables:

- $Distance_{ij}$ is the distance (in miles) between airports *i* and *j*. In general, fares may be expected to rise as distance increases.
- $DistanceSquared_{ij}$ is the square of the $Distance_{ij}$ variable. Its inclusion allows for a nonlinear relationship between distance and fares.
- $SlotRoute_{ij}$ is a binary variable that indicates whether one or both airports i, j are slot-controlled[25]. Such airports are typically highly congested and access is limited. Fares are therefore expected to be higher on routes to or from these airports.
- $MaxAirportHHI_{ij}$ indicates the degree of concentration of an airport market. Rather than including two values for both airports *i* and *j*, only the higher HHI value is retained in this analysis. The rationale for this approach is that the more concentrated airport is more likely to be the "bottleneck", and fares on routes involving this airport may be expected to be higher than fares on routes between "unconcentrated" airports.
- $LCCCompForHCC_{ij}$ is a binary variable. It takes on the value "1" when the carrier in the observation is a high cost carrier and faces route competition by a low-cost carrier. While some studies focused on Southwest Airlines only (e.g. Morrison, 2001), others employed a wider definition of low-cost carriers and defined all carriers that started operations after deregulation as low-cost carriers (e.g. Dresner et al. 1996). In an effort to rigorously define LCCs in this research, financial data on all airlines included in this analysis were collected. To account for the fact that operating expenses per available seat mile (ASM) are likely higher for airlines operating predominantly short haul flights, a carrier's operating expenses per ASM were regressed on its average stage length. The error terms, thus, reflect differences in

[25] Presently, JFK, LGA, and DCA are the only slot-controlled airports in the U.S.; ORD was slot controlled until June 2002

operating costs that cannot be attributed to differences in average stage length and are indicators of an airline's operating efficiency. A ranking of these error terms revealed consistent patterns across all time periods considered in this research, and twelve airlines were identified as low-cost carriers (see Appendix 1): Southwest Airlines, Reno Air, Sun Country Airlines, Spirit Air Lines, JetBlue Airways, Western Pacific Airlines, Airtran Airways, American Trans Air, Braniff Int'l Airlines, America West Airlines, Frontier Airlines, Valujet Airlines.

- *LCCCompForLCC*$_{ij}$ is a binary variable which takes on the value "1" when the carrier in the observation is a low-cost carrier and competes with another low-cost carrier in the route market. *LCCCompForHCC*$_{ij}$ and *LCCCompForLCC*$_{ij}$ specify the presence of low-cost carrier competition. These two variables are used to allow for differential impacts in terms of pricing on LCCs and high cost carriers.
- *AltRouteLCC1M*$_{ij}$ is another dummy variable which indicates if there are one or more adjacent route markets that are served by one or more low-cost carriers. The inclusion of this variable builds on the work by Dresner, Lin and Windle (1996) and Morrison (2001) who analyzed the impact of adjacent route competition on fares. Based on the population statistics (i.e. PMSA, CMSA, MSA) published by the Bureau of Economic Analysis (BEA), the following markets have been defined as metropolitan multi-airport markets in this research: Boston (BOS, MHT, PVD), Chicago (ORD, MDW), Cleveland (CLE, CAK), Dallas (DAL, DFW), Detroit (DTW, FNT), Houston (HOU, IAH), Los Angeles (BUR, LAX, LGB, ONT, SNA), Miami (MIA, FLL), New York (EWR, JFK, LGA, ISP, HPN), Norfolk (ORF, PHF), Philadelphia (PHL, ACY), San Francisco (OAK, SFO, SJC), Tampa (TPA, PIE), Washington (BWI, DCA, IAD).

- Time variables are also included in the analysis to capture macroeconomic changes as well as seasonal fluctuations (quarter dummies *Quarter2*, *Quarter3*, *Quarter4*) and general trends over time (year dummy *2002*).
- $Population_{ij}$ is used as a first-stage instrument and is the product of the metropolitan area populations around airports *i* and *j*: $Population_{ij} = Population_i \cdot Population_j$. A first stage estimation of the *AirlinePass* variable is required to address the endogeneity of the *Fare* and *AirlinePass* variables (see Section 2.3.4 for further detail on this endogeneity issue). For econometric reasons, the first-stage estimation of the endogenous variable (*AirlinePass*) requires the use of at least one instrumental variable. *Population* is one of two instrumental variables used in this research.
- $Income_{ij}$ is also used as a first-stage instrument and is the population-weighted average income in the metropolitan areas around airports *i* and *j*:

$$Income_{ij} = \frac{\left(Income_i \cdot Population_i\right) + \left(Income_j \cdot Population_j\right)}{\left(Population_i + Population_j\right)}.$$

2.3.3. Descriptive statistics

Correlations are presented in *Table 1* below. Due to the large number of observations, most correlations are statistically significant at the five percent level. Few correlations coefficients, however, are larger than 0.50. The market share and market concentration measures are highly correlated[26], as are the measures of firm financial distress[27].

[26] Airport market shares (*MaxAirportShare*) and route market shares (*RouteShare*), for example, have a correlation coefficient of 0.72.
[27] The correlation coefficient for the *Distress* and *DistressDiff* variables is 0.79, for example.

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	Fare																			
2	Distance	**0.52**																		
3	SlotRoute	**0.13**	**-0.04**																	
4	RouteHHI	**-0.19**	**-0.59**	0.01																
5	MaxAirportHHI	**0.15**	**-0.21**	**-0.10**	**0.50**															
6	RouteShare	**-0.12**	**-0.40**	**0.04**	**0.52**	**0.25**														
7	MaxAirportShare	**0.05**	**-0.34**	-0.01	**0.44**	**0.46**	**0.72**													
8	Size	**0.20**	**0.11**	**0.06**	**-0.06**	**0.01**	-0.01	**0.20**												
9	LCCCompForHCC	**-0.10**	**0.19**	**-0.12**	**-0.29**	**-0.19**	**-0.18**	**-0.14**	**0.28**											
10	LCCCompForLCC	**-0.27**	**-0.04**	**-0.10**	**-0.04**	**-0.11**	**-0.02**	**-0.06**	**-0.31**	**-0.20**										
11	AltRouteLCC1M	**-0.06**	**0.06**	**0.26**	**0.02**	**-0.03**	**0.04**	**-0.01**	**0.02**	**0.07**	0.00									
12	Circuity	0.00	**0.03**	**-0.07**	**-0.06**	**-0.08**	**-0.37**	**-0.28**	**0.11**	**0.11**	**-0.07**	**-0.14**								
13	Distress	**0.10**	**0.06**	**0.06**	**-0.05**	0.01	**-0.13**	**-0.16**	**-0.37**	**0.06**	**-0.13**	-0.01	0.00							
14	DistressDiff	**-0.03**	0.00	0.00	0.00	0.00	**-0.10**	**-0.13**	**-0.32**	**0.12**	**-0.06**	0.00	0.00	**0.79**						
15	Chpt11Ops	**0.08**	**0.04**	0.00	**-0.04**	-0.01	**-0.09**	**-0.10**	**-0.23**	**-0.03**	**-0.03**	**-0.01**	0.00	**0.43**	**0.33**					
16	Pre4Chpt11	**-0.06**	**0.03**	**0.02**	**-0.02**	**-0.02**	**-0.03**	0.00	**0.11**	**0.14**	**-0.06**	**0.07**	-0.01	**0.18**	**0.16**	**-0.08**				
17	Post4Chpt11	**0.03**	0.00	**0.02**	**-0.01**	0.00	**-0.06**	**-0.08**	**-0.18**	**-0.04**	0.00	-0.01	-0.01	**0.23**	**0.18**	**0.55**	**-0.04**			
18	Loadfactor	**-0.17**	**0.12**	**0.03**	**-0.07**	**-0.07**	**-0.03**	0.00	**0.32**	**0.24**	**-0.05**	**0.10**	**0.05**	**-0.12**	**-0.02**	**-0.18**	**0.18**	**-0.14**		
19	AirlineCost	**0.43**	0.00	**0.09**	**-0.03**	**0.06**	**-0.05**	**0.06**	**0.20**	**0.06**	**-0.37**	**-0.10**	**0.05**	**0.20**	**0.06**	**0.09**	**0.05**	**0.07**	**-0.31**	
20	AirlinePass	**-0.32**	**-0.41**	**0.12**	**0.35**	**0.08**	**0.71**	**0.56**	**-0.05**	**-0.10**	**0.09**	**0.18**	**-0.47**	**-0.10**	**-0.06**	**-0.10**	**0.02**	**-0.07**	**0.08**	**-0.17**

(correlation coefficients in bold are significant at the 5% level)

Table 1: Correlation matrix (n = 23,039)

The change of firms' *Distress* during bankruptcy is illustrated in *Figure 9*: For each possible state with respect to bankruptcy, the airlines' unweighted mean *Distress* scores are graphed. The averages are computed for all carriers and across all time periods (eight quarters in 1992 and 2002) included in the dataset. The sample size *n* indicates the number of firm-quarter observations the respective statistics are based on. As can be seen in *Figure 9*, non-bankrupt (i.e. comparatively healthy) carriers have a mean *Distress* score of 0.8, with the minimum and maximum *Distress* scores being -3.0 and 18.6, respectively. Financially sound airlines are thereby assumed to have negative *Distress* scores while troubled (yet non-bankrupt) carriers have positive *Distress* scores. Mean *Distress* scores for carriers approaching bankruptcy (*Pre4Chpt11*) are substantially higher (12.2) and always positive, ranging from 0.4 to 69.5. A Welch-Aspen two-sample t test for independent groups[28] is performed to evaluate whether these differences are statistically significant. The test statistic is t = 2.55 with 15.1 degrees of freedom (*df*). This result is statistically significant at the five percent level, indicating that firms approaching bankruptcy have significantly higher distress scores. Carriers' *Distress* scores average 1.7 during the quarter in which the Chapter 11 filing occurs (*Chpt11*). It should be noted, however, that this statistic is based on four carrier observations only[29]. Bankrupt carriers' *Distress* scores averaged 7.7 in the four quarters following the entry into bankruptcy (*Post4Chpt11*). In this latter case, the *Distress* scores range from 0.4 to 26.8. Based on these descriptive statistics it is concluded that financially distressed carriers will always have positive *Distress* scores. Financially sound airlines, in turn, have negative *Distress* scores.

[28] Given the difference in sample sizes, unequal variances are assumed.
[29] TWA filed for Chapter 11 in the first quarter of 1992, Markair filed in the second quarter of 1992, US Airways filed in the third quarter of 2002, and United Airlines filed in the fourth quarter of 2002.

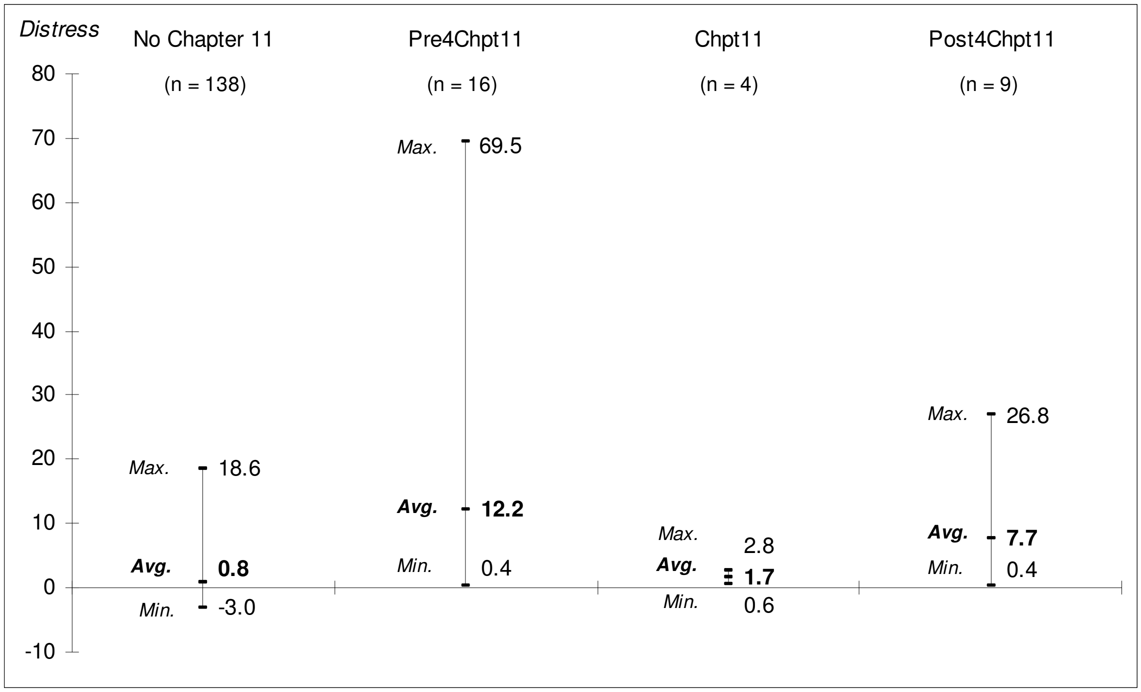

Figure 9: Distribution of Distress scores prior to and during bankruptcy

Table 2 provides the mean and standard deviation, minimum and maximum values for some selected variables included in the model. The mean *Distress* score of 0.59 indicates that most carriers experienced some level of financial distress in 1992 and 2002[30]. While there is no direct interpretation for this value, it implies that a significant proportion of passengers used (severely) troubled carriers. This contention is further substantiated by the mean of the *Chpt11Ops* variable (0.11) which suggests that eleven percent of all passengers traveled with bankrupt airlines. It is further noted that approximately seven percent of all passengers traveled with near-bankrupt carriers (*Pre4Chpt11*, 1571 observations), while approximately five percent of all passengers used airlines that filed

[30] The mean of the *Distress* variable is significantly different from 0. A one-sample mean comparison test yields a test statistic of $t = 43.74$ which is statistically significant at the one percent level.

for Chapter 11 protection within the past year (*Post4Chpt11*, 1196 observations). Moreover, the data set contains 2,414 carrier-route market observations (out of a total of 23,039 observations) with *DistressDiff* values larger than 2.86 (one standard deviation above the mean), indicating an airline's severe financial distress relative to its route competitors.

	Variable	Mean	Std. dev.	Min	Max
	Fare (1992 U.S. dollars)	114.26	60.61	25.17	1140.19
Financial distress	Distress	0.59	2.28	-3.02	69.53
	DistressDiff	0.05	2.81	-31.97	68.59
	Chpt11Ops	0.11	0.31	0	1
	Pre4Chpt11	0.07	0.25	0	1
	Post4Chpt11	0.05	0.21	0	1
Moderators	AirlineCost ($)	0.08	0.02	0.04	0.24
	RouteShare	55.47%	27.28%	5%	100%
	RouteHHI	5298.78	2172.02	1259.66	10000
	Size (1,000 $)	11,900,000	8,887,998	3,936	29,300,000
Control variables (selected)	AirlinePass	1570.76	2408.01	1	29368
	Distance (miles)	950.86	643.09	30	2717
	SlotRoute	0.22	0.41	0	1
	MaxAirportShare	46.09%	23.89%	0.015%	100%
	MaxAirportHHI	3966.56	1885.11	1131.37	10000
	Circuity	1.02	0.05	1	2.2
	Loadfactor	67.81%	6.18%	35.1%	84.6%
	Quarter1	0.23	0.42	0	1
	Quarter2	0.26	0.44	0	1
	Quarter3	0.27	0.44	0	1
	Quarter4	0.25	0.43	0	1
	1992	0.42	0.49	0	1
	2002	0.58	0.49	0	1

Mean values weighted based on number of airline passengers, except for "AirlinePass"

Table 2: Descriptive statistics for selected variables (n = 23,039)

2.3.4. Empirical methodology

A log-linear price estimation equation forms the basis of the model used in this research. More specifically, an airline's fare on a route is modeled as a function of a set of route, airport, and carrier specific variables, as well as a number of control variables. The estimation of the model requires the implementation of a two-stage least squares procedure since $AirlinePass_{kij}$ is an endogenous variable; i.e. the number of airline passengers may impact airfares while at the same time the latter may have an effect on the number of passengers. In a first stage regression, the number of airline passengers (*AirlinePass*) is modeled as a function of all exogenous variables including two instrumental variables, *Income* and *Population.* Fitted values for *AirlinePass* are then used to estimate fares (*Fare*) in the second stage model. The basic estimating model is defined as follows:

Equation 1: First-stage regression model

$$
\begin{aligned}
\ln \mathit{Airline\ Passengers} = {} & \alpha_0 + \alpha_1 \ln \mathit{Distance} + \alpha_2 (\ln \mathit{Distance})^2 + \alpha_3\, \mathit{Slot\ Route} \\
& + \alpha_4 \ln \mathit{Route\ HHI} + \alpha_5 \ln \mathit{Max\ Airport\ HHI} + \alpha_6\, \mathit{Route\ Share} + \alpha_7\, \mathit{Max\ Airport\ Share} \\
& + \alpha_8\, \mathit{LCC\ Comp\ for\ HCC} + \alpha_9\, \mathit{LCC\ Comp\ for\ LCC} + \alpha_{10}\, \mathit{Alt\ Route\ LCC} \\
& + \alpha_{11} \ln \mathit{Circuity} + \alpha_{12}\, \mathit{Distress} + \alpha_{13}\, \mathit{Load\ Factor} + \alpha_{14} \ln \mathit{Airline\ Cost} + \alpha_{15} \ln \mathit{Size} \\
& + \alpha_{16} \ln \mathit{Population} + \alpha_{17} \ln \mathit{Income} + \alpha_{18}\, 2002 + \Sigma \gamma_t\, \mathit{Quarter}_t
\end{aligned}
$$

Equation 2: Second-stage regression model

$$\ln Fare = \beta_0 + \beta_1 \ln Airline\ Passengers\ (fitted) + \beta_2 \ln Distance + \beta_3 (\ln Distance)^2$$

$$+ \beta_4\ Slot\ Route + \beta_5 \ln Route\ HHI + \beta_6 \ln Max\ Airport\ HHI + \beta_7\ Route\ Share$$

$$+ \beta_8\ Max\ Airport\ Share + \beta_9\ LCC\ Comp\ for\ HCC + \beta_{10}\ LCC\ Comp\ for\ LCC$$

$$+ \beta_{11}\ Alt\ Route\ LCC + \beta_{12} \ln Circuity + \beta_{13}\ Distress + \beta_{14}\ Load\ Factor$$

$$+ \beta_{15} \ln Airline\ Cost + \beta_{16} \ln Size + \beta_{17}\ 2002 + \Sigma\gamma_t\ Quarter_t$$

The OLS assumptions of homoskedasticity and independence are frequently not met when dealing with cross-sectional time series data (Greene 2003). Therefore, tests to detect the potential problems of heteroskedasticity and autocorrelation of the error terms are implemented.

First, the Breusch-Pagan/Cook-Weisberg Lagrange multiplier test (Breusch and Pagan 1979, Cook and Weisberg 1983) uses fitted values of the dependent variable (*Fare*) to determine whether the residuals vary with the fitted values of the dependent variable; i.e. violate the homoskedasticity assumption. This test is implemented after an OLS regression similar to the second stage model described above (the sole difference being that the actual values of Airline Passengers are used rather than fitted values; see Appendix 2). The implementation of this test yields a test statistic of 614.33 which follows a χ^2 distribution. The null hypothesis of constant variance is clearly rejected with a significance level of less than one percent.

Second, the Wooldridge test for autocorrelation in panel data (Drukker 2003, Wooldridge 2002) suggests the presence of first-order auto-correlation with an F-statistic of $F = 829.37$ which is statistically significant at the less than one percent level. Given the presence of heteroskedasticity, autocorrelation and endogeneity (as discussed previously), a generalized two-stage least squares (G2SLS) procedure is recommended (Greene 2003).

The generalized least squares procedure is typically implemented in one of two distinct econometric specifications: fixed effects or random effects[31]. These two specifications differentially address the heterogeneity of unobserved group and time specific effects, which in the classical ordinary least squares approach, are subsumed in the error term.

In the fixed effects model, the constant term is adjusted for each group and each time period such that the regression model becomes $y_{it} = \alpha + x'\beta + \gamma_i + \delta_t + \varepsilon_{kit}$. The first term on the right-hand side of the equation is the constant term (α), and the second term represents the sum of the products of the regressors (x) and their respective coefficients (β). The third and fourth terms are the group (γ_i) and time (δ_t) fixed effects which effectively adjust the constant term for group and time specific effects. The last term in the model is the individual error term associated with the *k*th observation in group *i* in time period *t* (ε_{kit}).

[31] The reader is referred to any econometrics textbook for a detailed discussion of the econometric issues revolving around generalized least squares models and the choice between fixed and random effects specifications. The overview provided here is based on Greene (2003).

The random effects model proposes a different specification of the error term in the econometric model. In this case, the unobserved individual heterogeneity is assumed independent of the regressors (x), and the group and time specific adjustments to the constant term are assumed to be randomly distributed across cross-sectional units and time. The benefit of the random effects procedure relative to the fixed effects procedure lies in the preservation of a significant number of degrees of freedom since only two random variables are needed (random group and time effects) rather than an exhaustive set of group and time specific dummy variables. If, however, the group and time effects are correlated with the regressors, the random effects procedure may produce inconsistent estimates.

To decide whether it is appropriate to use the fixed effects or random effects procedure, the Hausman specification test (Hausman 1978) is used to test for orthogonality between the regressors and the random effects. If the null hypothesis of no correlation cannot be rejected, the random effects model is both consistent and efficient and preferred over the fixed effects model which, in this case, is inefficient. If, however, the null hypothesis is rejected, only the fixed effects model is consistent and thus preferred over the random effects model. The implementation of the Hausman specification test requires the estimation of the model (*Equation 1* and *Equation 2*) using the fixed effects and random effects procedures, respectively. The test statistic W is based on the covariance matrix ψ of the difference vector of the respective coefficients $[b-\beta]$ and is given by $W=[b-\beta]'\psi^{-1}[b-\beta]$ (Hausman 1978). The test produces a χ^2 distributed statistic of

$W = 995.43$ which is significant at the less than one percent level. The null hypothesis of no correlation is therefore clearly rejected, suggesting that the fixed effects model should be selected.

As noted above, the fixed effects model has the disadvantage of consuming a large number of degrees of freedom due to the inclusion of group and time specific dummy variables in the regression analysis. Greene (2003) and Yaffee (2003) therefore suggest carefully evaluating the benefits of the fixed effects G2SLS procedure relative to the standard 2SLS procedure. The F test of joint significance of fixed effects (Greene 2003) evaluates the contribution of the fixed group and time effects to the fit of the model. To that end, two regression analyses must be performed: The baseline regression which does not include any fixed effects, and the fixed effects regression. The improvement in the fit of the model which is achieved by adding fixed effects is measured by the following F statistic: $F_{fixed\ effects} = \frac{\left(R^2_{fixed\ effects} - R^2_{no\ effects}\right)/\left(n-1\right)}{\left(1-R^2_{no\ effects}\right)/\left(nT-n-k\right)}$ (Greene 2003, Yaffee 2003), where n is the number of groups, nT is the number of observations, and k is the number of regressors.

In this study, the cross-section is defined by route-carrier combinations (a total of 4,508 groups), and there are eight distinct time periods (two years with four quarters each). This implies that 4,514 dummy variables must be added to the baseline 2SLS regression equation[32]. The statistical software package used for this research (Intercooled STATA 8.2) does not support such an operation due to the software's insufficient matrix size. For the purpose of this test, the number of dummy variables is therefore reduced by estimating fixed carrier effects only as opposed to fixed route-carrier effects, thereby reducing the number of cross-sectional indicators from 4,508 to 30. By constraining seasonal (quarterly) effects to be constant over time (in 1992 and 2002), the number of time indicators is reduced to four as specified in *Equation 1* and *Equation 2*. This test is a highly conservative approximation of the full fixed effects test with 4,514 fixed effects and therefore provides a lower bound for the joint significance of the fixed effects[33]. The baseline model (see Appendix 3) yields an R^2 of 0.376, while the reduced fixed effects model (see Appendix 4) yields an R^2 of 0.512. The resulting F statistic is F = 194.22 which is significant at the less than one percent level. It is therefore concluded that the fixed effects generalized two-stage least squares procedure is the most appropriate data analysis technique.

2.4. Empirical results and discussion

The regression results are discussed in two stages: The first-stage regression, in which *AirlinePass* is the dependent variable, is discussed, before the second-stage regression results are presented. The second-stage regression uses *Fare* as the dependent variable and tests the hypotheses set forth in this essay.

[32] Note that this must be done manually to ensure consistency of the R^2 computation (the computation of the R^2 statistic differs between the 2SLS and [fixed effect] G2SLS).

[33] The breakdown of the 30 carrier indicator variables to 4,508 route-carrier indicator variables will necessarily result in an increased R^2 statistic.

2.4.1. First-stage regression

In the first-stage regression, all independent variables (which are assumed exogenous) and the *Population* and *Income* instruments are used to estimate exogenously determined fitted values for *AirlinePass*. *Table 3* presents the coefficient estimates of the first stage regression as specified in *Equation 1*.

Most of the results displayed in *Table 3* are in accordance with prior theoretical reasoning and empirical research: The relationship between the number of passengers and route distance is nonlinear as evidenced by the negative coefficient of the *Distance* variable and the positive sign of the *DistanceSquared* coefficient. This suggests that the number of passengers increases with the distance flown at a rate which increases in route length. The positive coefficient of the *SlotRoute* dummy variable is indicative of congestion and higher passenger volumes on slot-controlled routes. Moreover, greater firm market shares at the route and airport market levels (*RouteShare* and *MaxAirportShare*) imply greater numbers of passengers. Holding market shares constant, an increase in market concentration (*RouteHHI*, *MaxAirportHHI*) then results in lower passenger numbers (see also Ravenscraft 1983). Competition in adjacent route markets (*AltRouteLCC1M*) has a slight negative effect on the number of passengers, while more circuitous routings (*Circuity*) exhibit significantly decreased passenger numbers. Higher load factors (*LoadFactor*) are, of course, associated with more passengers, and higher operating costs (*AirlineCost*), presumably implying higher prices, negatively affect demand. The coefficient of the *Size* variable is statistically insignificant, indicating that firm size per se does not influence passenger demand. The positive coefficients of the quarter dummies indicate seasonal effects (*Quarter2-4*), while the time trend variable (*2002*) carries a negative, though statistically insignificant coefficient, thus hinting at the downturn in the airline industry in 2002. The first instrumental variable, *Population*, carries a positive coefficient indicating that passenger numbers increase as the potential market volume increases. The coefficient of the *Income* variable is statistically insignificant which may be attributed to its limited variability.

There are three variables with unexpected signs: First, the *LCCCompForHCC* and *LCCCompForLCC* variables both have positive coefficients, indicating that the presence of a low-cost competitor *increases* passenger demand for the focal carrier. This result is most likely due to the focal airline lowering its prices as it faces aggressive competition. These lower prices then translate into higher passenger demand. The *Distress* variable carries a positive and statistically insignificant coefficient which suggests a firm's financial distress does not impact passenger demand. A potential explanation may be that distressed carriers mitigate potentially negative demand effects by charging lower prices or that passengers have few or no alternative carrier choices.

In summary, it is noted that the first-stage model is highly significant (F = 1,038.3, significant at the less than one percent level), and that most independent variables are at least marginally significant with most coefficients having the expected signs. Appendix 5 presents the first stage regression results for all five specifications of the model.

Dependent variable: **AirlinePass**	**Coefficient**	**P>|z|**
Constant	444.458	0.000
Distance	-136.296	0.000
DistanceSquared	10.181	0.000
SlotRoute	0.099	0.001
RouteHHI	-0.412	0.000
MaxAirportHHI	-0.367	0.000
RouteShare	0.027	0.000
MaxAirportShare	0.001	0.007
LCCCompForHCC	0.227	0.000
LCCCompForLCC	0.238	0.000
AltRouteLCC1M	-0.022	0.061
Circuity	-2.326	0.000
Distress	0.005	0.190
Loadfactor	0.016	0.000
AirlineCost	-0.095	0.023
Size	0.028	0.150
Quarter 2	0.048	0.000
Quarter 3	0.074	0.000
Quarter 4	0.047	0.000
2002	-0.055	0.315
Population	0.579	0.000
Income	-0.034	0.785
F	1038.3	0.000
R-squared (within)	0.541	

***Table 3: First stage G2SLS regression estimates (n = 23,039)*[34]**

2.4.2. Second-stage regression

In this section, the results from five different second-stage regression analyses are reported. The first and second second-stage analyses test *Hypothesis 1* by including the *Distress* and *Chpt11Ops* variables, respectively. The third regression tests the differential

[34] The carrier fixed effects are omitted in this table.

effect of financial distress over time (*Hypothesis 2*) by estimating the model with the *Pre4Chpt11* and *Post4Chpt11* variables. *Hypothesis 1* and *Hypothesis 2* are tested separately to avoid confounding the results by including both the *Distress* and *Chpt11* variables in a single regression (since all bankrupt airlines have high *Distress* scores). The fourth second-stage regression model tests the moderating effects of firm costs, firm market shares, and market concentration (*Hypothesis 3* to *Hypothesis 6*). These interactions are not included in model 1 to allow for a direct interpretation of the direct effect of the *Distress* variable in model 1. As noted by Aiken and West (1991), when interaction effects are present, a variable's direct effect cannot be assessed by interpreting the variable's coefficient only, but it must be evaluated in conjunction with all its interactions. The fifth and final model tests the importance of a firm's *relative* financial distress as discussed in *Hypothesis 7*. Similar to the argumentation above, the *DistressDiff* variable is tested separately to avoid confounding the effects of absolute (*Distress*) and relative (*DistressDiff*) financial distress. The second-stage regression results are presented in *Table 4*.

Before focusing on the variables of interest in the respective regressions, it is noted that all second-stage models are highly significant (Wald $\chi^2 \geq$ 23,900,000). Caution must be used, however, when interpreting the R-squared statistics[35]. In the generalized least squares (GLS) procedure, the total sums of squares are not broken down as in the ordinary least squares procedure. The GLS R-squared, therefore, is not bounded between zero and one and cannot be interpreted as the percentage of variability explained. In

[35] The information on the use and meaning of R-squared statistics in GLS regressions was obtained from the STATA manuals and the STATA website at www.stata.com.

addition, there are two sources of variation: within variation and between variation. When fixed effects models (i.e. within estimators) are used, only the within R-squared should be used[36]. The R squared for within variation indicates to what extent the model is able to predict a new observation on one of the subjects already in the study. The R squared for total variation indicates the quality of predictions relating to a new observation on a new subject. While all R-squared (within, between, overall) statistics are reported, the reader's attention is directed toward the within R-squared measures which range between 0.741 and 0.783 as reported in *Table 4*.

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[36] This statistic is obtained by fitting a mean-deviated regression model where all the group effects are assumed to be fixed. These group effects are subtracted out of the model and no attempt is made to quantify their overall effect on the fit of the model.

Second-stage G2SLS regression (fixed effects)

Number of obs. *23039*
Number of groups *4508*
Obs. per group: *min.* *1* *avg.* *5.1* *max.* *8*

Dependent variable: **Fare**		**1** Coefficient	P>|z|	**2** Coefficient	P>|z|	**3** Coefficient	P>|z|	**4** Coefficient	P>|z|	**5** Coefficient	P>|z|
Constant		-231.741	0.000	-237.998	0.000	-247.393	0.000	-245.434	0.000	-268.520	0.000
AirlinePass (fitted)		-0.093	0.000	-0.076	0.006	-0.042	0.138	-0.141	0.000	-0.022	0.441
Distance		69.277	0.000	70.705	0.000	73.037	0.000	74.364	0.000	78.903	0.000
DistanceSquared		-5.006	0.000	-5.108	0.000	-5.268	0.000	-5.420	0.000	-5.671	0.000
SlotRoute		0.090	0.000	0.096	0.000	0.083	0.000	0.083	0.000	0.088	0.000
RouteHHI		-0.009	0.495	-0.003	0.795	0.008	0.553	-0.008	0.518	0.021	0.130
MaxAirportHHI		0.055	0.000	0.067	0.000	0.091	0.000	0.030	0.019	0.105	0.000
RouteShare		0.002	0.010	0.001	0.053	0.001	0.437	0.003	0.000	0.000	0.994
MaxAirportShare		0.002	0.000	0.002	0.000	0.002	0.000	0.002	0.000	0.002	0.000
LCCCompForHCC		-0.110	0.000	-0.118	0.000	-0.130	0.000	-0.091	0.000	-0.132	0.000
LCCCompForLCC		-0.024	0.034	-0.014	0.242	-0.001	0.914	-0.011	0.311	-0.005	0.684
AltRouteLCC1M		-0.027	0.000	-0.026	0.000	-0.027	0.000	-0.021	0.000	-0.028	0.000
Circuity		-0.443	0.000	-0.402	0.000	-0.320	0.000	-0.536	0.000	-0.269	0.001
Distress		-0.036	0.000					0.496	0.000		
Chpt11Ops				-0.072	0.000						
DistressDiff										-0.009	0.000
Pre4Chpt11						-0.007	0.179				
Post4Chpt11						-0.042	0.000				
Loadfactor		-0.015	0.000	-0.014	0.000	-0.014	0.000	-0.013	0.000	-0.015	0.000
AirlineCost		0.224	0.000	0.210	0.000	0.235	0.000	0.223	0.000	0.226	0.000
Size		0.055	0.000	0.119	0.000	0.152	0.000	-0.018	0.061	0.130	0.000
Quarter 2		-0.031	0.000	-0.040	0.000	-0.044	0.000	-0.034	0.000	-0.045	0.000
Quarter 3		-0.026	0.000	-0.034	0.000	-0.048	0.000	-0.028	0.000	-0.044	0.000
Quarter 4		-0.034	0.000	-0.046	0.000	-0.054	0.000	-0.027	0.000	-0.053	0.000
2002		-0.257	0.000	-0.306	0.000	-0.332	0.000	-0.208	0.000	-0.314	0.000
AirlineCost*Distress								0.062	0.000		
Size*Distress								-0.013	0.000		
RouteShare*Distress								0.0002	0.000		
RouteHHI*Distress								-0.023	0.000		
Wald χ^2		*26,800,000*		*25,900,000*		*24,500,000*		*28,500,000*		*23,900,000*	
Prob > χ^2		*0.000*		*0.000*		*0.000*		*0.000*		*0.000*	
R-squared:	*within*	0.769		0.761		0.748		0.783		0.741	
	between	0.080		0.084		0.092		0.041		0.101	
	overall	0.087		0.091		0.097		0.049		0.104	

Table 4: Second-stage G2SLS regression estimates

Turning to the control variables first, it is noted that most coefficient estimates are consistent across all five second-stage models and are statistically significant at the less than one percent level: Prices are shown to increase with *Distance*, but at a decreasing rate, as evidenced by the negative coefficient of *DistanceSquared*. As expected, fares tend to be higher in route markets involving one or two slot-controlled airports (*SlotRoute*), and both airport market concentration (*MaxAirportHHI*) and airport market shares (*MaxAirportShare*) are associated with higher fares, *ceteris paribus*. The presence of low-cost carrier competition has a strong negative effect on a high cost carrier's prices (*LCCCompForHCC*), as does the presence of low-cost carriers in adjacent route markets (*AltRouteLCC1M*). Prices for less convenient connecting traffic are shown to be lower than for direct service (*Circuity*), and higher load factors (*LoadFactor*) – indicative of economies of density – also tend to result in lower fares. An airline's operating costs (*AirlineCost*) and size (*Size*), finally, are both shown to positively impact air fares. The time variables capture both seasonal price fluctuations (*Quarter2-4*) as well as a clearly negative time trend (*2002*).

The following variables have either unexpected or statistically insignificant coefficients: While the coefficient of the *AirlinePass* variable is negative as expected in all instances, it is statistically insignificant in models 3 and 5. There is, nonetheless, at least some evidence that higher passenger numbers – implying economies of density – result in lower prices, all else equal. Note that the coefficients of the *RouteShare* variable, while positive as expected, are also statistically insignificant in models 3 and 5. The two variables (*AirlinePass* and *RouteShare*) are highly correlated as expected ($\rho = 0.57$, see

Table 1) with *RouteShare* being the ratio of *AirlinePass* and the total number of passengers in the route market. It is, therefore, likely that multicollinearity between right-hand side variables cause some degree of variance inflation. The *RouteHHI* variable carries a statistically insignificant coefficient in all model specifications, suggesting that route market concentration does not have a direct effect on prices. Also, the presence of LCC competitors does not appear to impact other low-cost carriers' prices as indicated by the insignificant coefficient estimates of the *LCCCompForLCC* variable in models 2-5. Only in the baseline model (1) can the expected negative effect be observed.

The attention is now directed to the variables of interest that test the hypotheses set forth in this paper.

The negative and significant coefficient of the *Distress* variable in the first second-stage regression ($\beta = -0.036$, $p = 0.000$) provides clear support for the contention that greater levels of financial distress result in lower prices, *ceteris paribus* (*Hypothesis 1*). This result thus confirms the basic finding in the extant literature that financially distressed firms behave more aggressively in the output market. More specifically, this result suggests that the reduction of a firm's *Distress* score by one unit leads to a price reduction of 3.6 percent, all else held constant. The second regression presents an alternative test of *Hypothesis 1* using the *ChptOps* variable. The latter carries a statistically significant coefficient of -0.072 ($p = 0.000$) which implies that, on average, airlines operating under Chapter 11 protection charge about seven percent less than their non-bankrupt competitors, *ceteris paribus*. This finding is consistent with the result of the

Distress variable and clearly in support of *Hypothesis 1*.

The third regression presented in *Table 4* tests the differential impact of financial distress prior to and after Chapter 11 filings. The coefficient of the *Pre4Chpt11*, while negative, is statistically insignificant ($\beta = -0.007$, $p = 0.170$) which suggests that there are no significant price changes as an airline approaches bankruptcy. The *Post4Chpt11* variable, however, carries a negative and statistically significant coefficient ($\beta = -0.042$, $p = 0.000$). This indicates that airlines tend to lower prices upon declaring bankruptcy and that the effect of firm financial distress on prices is substantially larger (-4.2%) once the airline operates under bankruptcy protection. This finding supports the contention that passengers may be reluctant to choose bankrupt carriers given the uncertainty about its reliability and future operations. This may entice such firms to cut prices in an effort to stimulate or maintain passenger demand. Moreover, bankrupt carriers may simply pass some of the cost savings that result from operating under bankruptcy protection[37] on to consumers. *Hypothesis 2* is thus supported.

The fourth column in *Table 4* presents a test of the hypothesized interaction effects (*Hypothesis 3* to *Hypothesis 6*). *Hypothesis 3* argues that a firm's operating costs positively moderate the relationship between financial distress and prices, meaning that the effect of firm financial distress on prices will be of lesser magnitude for high-cost firms than for lower-cost firms (see *Figure 3*). The rationale for this contention is that low-cost firms likely have higher profit margins and can more easily (and profitably)

[37] Due to paused leasing and debt payments, for example.

afford price cuts than high-cost firms. The strategic management literature further argues that operating costs are a good proxy for a firm's strategic type: Low-cost firms are often referred to as *prospectors*, and high-cost firms have been termed *defenders*. Prior research has shown that *prospectors* tend to act more aggressively (in terms of prices, for example), while *defenders* tend to behave more conservatively and focus on internally-oriented rather than market-oriented actions which involve price and product changes. The coefficient of the interaction term *AirlineCost*Distress* is positive and statistically significant at the less than one percent level ($\beta = 0.062$, $p = 0.000$). As discussed above, the effect of financial distress on prices is generally negative, implying that distressed firms sell at lower prices, all else equal. The interaction with operating costs (*AirlineCost*) then adds a positive term to the distressed firm's price, where the value of this addition increases in the firm's operating costs. The analyses, thus, present some evidence for the contention that distressed firms will tend to refrain from competing on price when their operating costs are higher, as suggested in *Hypothesis 3*.

It has been suggested in *Hypothesis 4* that firm size will increase a distressed firm's tendency to compete on price (see *Figure 4*). More specifically, it has been argued that larger firms benefit from greater reputation, creditor trust and resource availability which increase their survivability. Consequently, it is expected that larger distressed firms leverage their size advantage and do not avoid price competition to the extent smaller, more fragile airlines do: Larger firms can afford the detrimental short-term effects of price cuts and may pursue such aggressive pricing strategies in an effort to eliminate smaller competitors and thus enhance their long-term profitability prospects. The interaction term between *Distress* and *Size* is negative and statistically significant (β = -0.013, p = 0.000). This result thus implies that larger distressed firms will price more aggressively than smaller distressed firms, all else equal. Consequently, *Hypothesis 4* is supported.

In *Hypothesis 5*, it was argued that the impact of firm financial distress on prices is moderated by firm market shares (see *Figure 5*). Firm with higher market shares may have higher degrees of market power and therefore experience less pressure to lower prices in the light of financial distress. In addition, for firms with high market shares, the potential benefits of cutting prices are limited since the expected gains in terms of market volume may not offset the losses due to lower sales prices. The coefficient of the interaction term of the *RouteShare* and *Distress* variables is positive and significant (β = 0.0002, p = 0.000). Higher route market shares, thus, reduce a distressed firm's pricing aggressiveness as stated in *Hypothesis 5*.

As to the moderating effect of (route) market concentration, it was hypothesized that the interaction of financial distress and route market concentration will positively impact prices (*Hypothesis 6*), *ceteris paribus* (see *Figure 6*). While high market concentration per se may facilitate collusive price fixing among firms, deteriorations in a firm's financial condition and ensuing changes in that firm's cost structure may lead to the breakdown of collusive arrangements with competitors and greater degrees of price competition. The interaction term of *RouteHHI* and *Distress* has a negative and statistically significant coefficient (β = -0.023, p = 0.000). As stated in *Hypothesis 6*, this implies that greater levels of distress and market concentration increase a heavily troubled firm's tendency to compete aggressively and sell at lower prices (after controlling for the moderating effects of route market shares).

Hypothesis 7 suggests that the difference between a focal firm's *Distress* score and that of its (route market) competitors affects the focal firm's prices. This hypothesis is motivated by the fact that firms that are in similar financial conditions may be expected to behave symmetrically. In this case, no single firm would benefit from price reductions and reinforced price competition. It is, therefore, expected that a focal firms pricing actions will be more pronounced the greater the focal firm's financial distress relative to its competitors. To test *Hypothesis 7* the coefficient of the *DistressDiff* variable from the fourth second-stage regression can be interpreted straightforwardly. The negative and significant coefficient ($\beta = -0.009$, $p = 0.000$) indicates that a firm's financial distress *relative* to its competitors negatively impacts the focal firm's prices as stated in *Hypothesis 7*[38].

2.4.3. Second-stage regression: Sensitivity analysis

The results discussed above are based on the analysis of 1992 and 2002 data. These time periods were chosen since the airline industry experienced substantial financial distress during those years. To investigate the sensitivity of the results with respect to the

[38] Recall that positive *DistressDiff* values indicate relative financial distress, while negative values indicate relative financial wellbeing.

selection of the time period studied, the regression models are re-estimated using data from 1992, 1997, and 2002. The addition of 1997 data brings the total number of observations to 34,097. 1997 data were selected since this year is in the middle of the 1992-2002 time period. Also, the airline industry as a whole performed relatively well during that year. It is therefore expected that the findings with respect to the effect of financial distress on prices will be weaker when 1997 data are included in the analyses. Nonetheless, the empirical results should be consistent with the contentions set forth in *Hypothesis 1* to *Hypothesis 7*.

Table 5 presents the second-stage regression results which are based on the analysis of the extended data set (including 1997 data). It is noted that the fit of the regression models is generally inferior compared to the results presented in *Table 4* which were based on 1992 and 2002 data only. Specifically, the R-squared within statistics shown in *Table 5* suggest that the models explain only about fifty to sixty percent of the variability as compared to the seventy to eighty percent variability explained for the 1992 and 2002 data (see *Table 4*). While most variables have statistically significant coefficients with the expected signs, the *Distance* and *DistanceSquared* variables have insignificant coefficient estimates in all models.

The hypothesis testing results can be summarized as follows:

- *Hypothesis 1*: The negative coefficient of the *Distress* variable ($\beta = -0.020$, $p = 0.000$) in the first regression, provides support for the contention that greater levels of financial distress result in lower prices. This contention is further corroborated by the negative and significant coefficient of the *Chpt11Ops* variable in the second regression (β = -0.047, p = 0.000).

- *Hypothesis 2*: The differential effect of financial distress over time (prior to versus during bankruptcy) is empirically examined in the third regression where the *Pre4Chpt11* and *Post4Chpt11* variables are included in the model. While the *Pre4Chpt11* variable carries a statistically significant negative coefficient, the coefficient of the *Post4Chpt11* variable is statistically insignificant. This suggests that, on average, carriers approaching bankruptcy tend to cut prices, while carriers operating under bankruptcy protection do not cut prices. This finding is contrary to *Hypothesis 2* and inconsistent with the results shown in *Table 4*. It is noted that virtually no airline bankruptcies were observed in 1997. As a result, it is not surprising that adding 1997 data to the regression analysis weakens the robustness of the regression results with respect to the effect of bankruptcy on prices.
- *Hypothesis 3*: *Hypothesis 3* suggests that a firm's operating costs positively moderate the relationship between financial distress and prices. The positive and significant coefficient of the *AirlineCost*Distress* interaction effect (β = 0.015, p = 0.000) confirms this expectation. This finding is consistent with the results shown in *Table 4*.
- *Hypothesis 4*: The distress-price effect was hypothesized to be stronger for larger firms than for smaller firms. In line with the regression results reported earlier, this hypothesis is supported even when 1997 data are included: The *Size*Distress* interaction effect carries a negative and significant coefficient (β = -0.009, p = 0.000).

- *Hypothesis 5*: The results shown in *Table 5* suggest that the distress-price effect does not change in magnitude as a firm's route market share increases. The *RouteShare*Distress* interaction effect does not yield a statistically significant coefficient ($\beta = 0.0000$, $p = 0.495$), whereas this interaction effect was positive and significant in the analysis of 1992 and 2002 data (see *Table 4*). Again, the lack of a significant finding may potentially be attributed to the fact that the addition of 1997 data tends to dilute statistical effects of financial distress since the airline industry experienced little distress in that year.
- *Hypothesis 6*: The *RouteHHI*Distress* interaction carries the expected negative coefficient ($\beta = -0.008$, $p = 0.001$), suggesting that the distress-price effect is greater in more concentrated markets than in less concentrated markets. This finding is consistent with *Hypothesis 6* and the previously reported results (see *Table 4*).
-
- *Hypothesis 7*: A firm's financial distress relative to its competitors in the route market is also shown to significantly impact prices ($\beta = -0.003$, $p = 0.000$). *Hypothesis 7* is, thus, supported.

In summary, five out of seven hypotheses are supported when 1997 data are included in the analyses. The lower model fit statistics and smaller coefficient values, however, confirm the contention that adding 1997 data—a period of relative financial health in the airline industry—tends to dilute the results. Nonetheless, the hypothesis testing results are shown to be largely robust.

Second-stage G2SLS regression		*Number of obs.*	*34097*	*Obs. per group:*	*min.*	*1*
(fixed effects)		*Number of groups*	*4798*		*avg.*	*7.1*
					max.	*12*

	1		**2**		**3**		**4**		**5**	
Dependent variable:										
Fare	**Coefficient**	**P>|z|**	**Coefficient**	**P>|z|**	**Coefficient**	**P>|z|**	**Coefficient**	**P>|z|**	**Coefficient**	**P>|z|**
Constant	-30.762	0.477	-16.919	0.707	-27.484	0.531	-40.643	0.364	-29.798	0.489
AirlinePass (fitted)	-0.505	0.000	-0.544	0.000	-0.515	0.000	-0.550	0.000	-0.493	0.000
Distance	13.024	0.318	8.645	0.525	11.527	0.384	16.686	0.217	12.118	0.351
DistanceSquared	-1.025	0.295	-0.690	0.498	-0.895	0.368	-1.315	0.195	-0.936	0.338
SlotRoute	0.188	0.000	0.194	0.000	0.179	0.000	0.183	0.000	0.188	0.000
RouteHHI	-0.161	0.000	-0.177	0.000	-0.168	0.000	-0.172	0.000	-0.157	0.000
MaxAirportHHI	-0.079	0.000	-0.087	0.000	-0.073	0.000	-0.105	0.000	-0.067	0.000
RouteShare	0.013	0.000	0.014	0.000	0.013	0.000	0.014	0.000	0.013	0.000
MaxAirportShare	0.003	0.000	0.003	0.000	0.003	0.000	0.003	0.000	0.003	0.000
LCCCompForHCC	-0.054	0.000	-0.047	0.000	-0.055	0.000	-0.036	0.000	-0.060	0.000
LCCCompForLCC	0.073	0.000	0.087	0.000	0.090	0.000	0.078	0.000	0.084	0.000
AltRouteLCC1M	-0.043	0.000	-0.043	0.000	-0.044	0.000	-0.039	0.000	-0.045	0.000
Circuity	-1.266	0.000	-1.359	0.000	-1.285	0.000	-1.373	0.000	-1.231	0.000
Distress	-0.020	0.000					0.194	0.000		
Chpt11Ops			-0.047	0.000						
DistressDiff									-0.003	0.000
Pre4Chpt11					-0.041	0.000				
Post4Chpt11					-0.005	0.222				
Loadfactor	-0.011	0.000	-0.009	0.000	-0.009	0.000	-0.011	0.000	-0.010	0.000
AirlineCost	0.062	0.000	0.048	0.000	0.056	0.000	0.055	0.000	0.052	0.000
Size	0.049	0.000	0.086	0.000	0.098	0.000	-0.010	0.225	0.094	0.000
Quarter 2	0.005	0.126	0.001	0.796	-0.002	0.582	0.006	0.047	-0.002	0.483
Quarter 3	0.027	0.000	0.024	0.000	0.017	0.000	0.029	0.000	0.020	0.000
Quarter 4	-0.018	0.000	-0.018	0.000	-0.025	0.000	-0.010	0.001	-0.023	0.000
2002	-0.157	0.000	-0.183	0.000	-0.188	0.000	-0.115	0.000	-0.192	0.000
AirlineCost*Distress							0.015	0.000		
Size*Distress							-0.009	0.000		
RouteShare*Distress							0.0000	0.495		
RouteHHI*Distress							-0.008	0.001		
Wald χ^2	*25,300,000*		*23,300,000*		*24,600,000*		*23,600,000*		*25,500,000*	
Prob > χ^2	*0.000*		*0.000*		*0.000*		*0.000*		*0.000*	
R-squared: *within*	0.565		0.528		0.552		0.533		0.569	
between	0.005		0.001		0.007		0.033		0.010	
overall	0.001		0.006		0.015		0.019		0.019	

Table 5: Second-stage G2SLS regression estimates using 1992, 1997, and 2002 data

2.5. Summary and discussion

The study's results are summarized in *Table 6* below. Ample support for the theoretical arguments set forth in this paper is found. The implications of these findings are discussed in this section, and some limitations and directions for future research are noted.

The primary objective of this research is to reconcile the extant theoretical conflict revolving around the impact of firm financial distress on prices. Based on a review of varied theoretical perspectives and numerous empirical studies, it is suggested that financial distress is negatively related to prices. It is noted, however, that this may not be true in all cases. More specifically, it is hypothesized that operating costs, firm size and market shares, as well as market concentration and a firm's financial standing relative to its competitors may impact the magnitude of a troubled firm's pricing actions. A strategic contingency framework which incorporates these moderating effects is developed and tested using a comprehensive panel dataset from the U.S. airline industry.

The empirical results provide clear statistical support for all hypotheses: Firm financial distress negatively impacts prices, and it is shown that these price effects are greatest for carriers that operate under bankruptcy protection. The empirical results further suggest that this is particularly true for firms with lower operating costs and smaller market shares, and for firms operating in highly concentrated markets. The difference between a focal firm's financial distress and that of its competitors is also shown to impact the magnitude of airlines' pricing actions. All hypothesized direct and moderating effects are thus supported.

Hypothesis	Testing variable	Hypothesized effect on prices		Finding	Empirical support for hypothesis?
		Direct	Interaction w/ *Distress* variable		
1	*Distress*	–		–	Yes
2	*(Post4Chpt11 – Pre4Chpt11)*	< 0		< 0	Yes
3	*AirlineCost*		+	+	Yes
4	*Size*		–	–	Yes
5	*RouteShare*		+	+	Yes
6	*RouteHHI*		–	–	Yes
7	*DistressDiff*	–		–	Yes

Table 6: Summary of results

This study's results suggest that passengers traveling on distressed or bankrupt carriers pay nearly four percent less than other passengers, all else equal. This is, of course, a desirable outcome from a consumer perspective as a distressed firm's lower prices implies increases in consumer welfare. Since bankruptcy only sometimes results in a firm's liquidation, there is no indication for longer term negative effects of Chapter 11 protection on consumer welfare through, for example, reduced competition or reduced service levels.

For managers and policy makers, however, this finding may be troubling. Financial distress appears to negatively affect a firm's revenue streams by virtue of lower prices and, in some instances, lower demand[39] and may ultimately reduce the firm's profitability (see also Kennedy 2000). Taken together, these findings raise questions about the rationality of a distressed firm's pricing behavior and the adequacy of Chapter 11 protection. The results suggest that financial distress is both at the beginning and at the end of a vicious circle of literally destructive price competition (see also Moulton and Thomas 1993 for a discussion of the success rates of reorganizations under bankruptcy). Managers and policy makers try to avoid organizational failure by offering lower prices and supporting reorganization efforts respectively, but the very opposite effect may be observed in at least some instances: Financial distress, and Chapter 11 protection in particular, lead to an increase in the competitive pressures, thus increasing the firm's distress and spreading it beyond the firm's boundaries. While it is not an objective of this research to make any managerial or public policy prescriptions, the findings presented in this study may be useful in gaining a greater understanding of the effects of financial distress on prices by considering the moderating effects of firm and market characteristics.

The key message of this study is clear: Microeconomic and corporate finance theory alone cannot fully explain the relationship between a firm's capital structure and its output market behavior. The diversity of firms and circumstantial characteristics have to be considered when investigating the effect of financial distress on prices. Strategic

[39] See *Table 38*: the negative coefficient of the *Post4Chpt11* variable implies that bankrupt firms face lower demand, all else equal.

management research offers an array of theoretical approaches to further explore this issue, and a contingency framework appears to be an appropriate means to do so. In that vein, the hypotheses reflect and the results present evidence for elements of prospect theory, organizational learning theory, and strategic groups research, for example. The author is unaware of any other research that has examined the research question at hand from a strategic management perspective. By combining multiple theoretical perspectives and incorporating them in a single, comprehensive contingency framework, the understanding of the link between firm financial distress and prices is advanced.

Data from the U.S. airline industry are used for the empirical analyses. While this selection has many desirable qualities in terms of the detail and availability of data, one must consider the possibility that these findings may not be generalizable to other industries. The U.S. airline business is particularly competitive and, to some extent, still marked by the era of regulation[40]. The exploration of the effects of financial distress on prices in a cross-section of industries is left for future research. Moreover, the DOT airline data do not contain any information about booking and service classes. As noted by Lee and Luengo-Prado (2005), the failure to recognize these distinctive attributes of the tickets purchased is a potentially critical shortfall of any empirical analysis of air fares.

Research of the impact of financial distress faces a general dilemma: While financial distress is a firm-level phenomenon, prices are clearly market-specific. In this research,

[40] Regulation by the Civil Aeronautics Board ended in 1978, but has shaped the industry in many ways. Although formally deregulated, regulatory controls (e.g. slot controls, antitrust rulings) continue to impact the industry.

the impact of firm-level financial distress on individual product market prices is investigated. This approach presents some challenges in that it is more difficult to isolate statistical effects, and it may be desirable to investigate this research question in the context of single-market firms. The latter are, however, hard to find nowadays.

On a final note, it should be stated that this study's results may also depend upon the measurement of financial distress. This study employed distress measures based on Z scores and Chapter 11 dummy variables given that they have been widely applied in the extant literature. The finance literature offers numerous variations of these measures as well as entirely different ones (see e.g. Gritta 2004 for a comprehensive review of some of these measures). Future research may explore the sensitivity of the results with respect the measurement of financial distress.

This research contributes to the literature on the link between firm financial distress and output market behavior. It is shown that this issue is far from being fully understood and that strategic management theory offers avenues for further exploration of the impact of financial distress on prices. This study has made a first step in this direction by estimating the moderating effect of a number of strategic contingencies on this relationship.

3. The effect of firm financial distress on firm inventories: A supply chain perspective

In this chapter, the effects of financial distress on inventory holdings are discussed and tested empirically. The structure of this chapter is similar to that of Chapter 2 of this dissertation: The subject matter of this essay is introduced in Section 3.1. The latter includes a statement of the research questions and contributions of this research. Section 3.2 presents a review of theories and prior research on the relationship between firm financial condition and inventories, and a baseline hypothesis is formulated. A supply chain perspective is discussed in Section 3.3. It is hypothesized that firm power not only directly impacts firm inventories, but also moderates the effect of financial distress on inventories. Details about the data sample and the empirical methodology are provided in Section 3.4. The empirical results are presented and discussed in Section 3.5, and the study's findings are summarized in Section 3.6. Managerial implications are discussed, and suggestions for future research are provided, while the study's limitations are noted.

3.1. Introduction

Financial considerations play an important role in inventory decision making. The survey results presented by Osteryoung et al (1986), for example, indicate that 73.5% of all respondents consider the firm's cash position, and 57.3% factor in anticipated changes in interest rates when making inventory decisions. It is intuitively appealing to assume that firms under financial distress will shed inventories to generate liquidity. For American car manufacturer Chrysler Corp., for example, reducing inventories was a major component of its turnaround efforts (Stundza and Milligan 2001). Case Corporation, a U.S. manufacturer of construction and agricultural equipment, also drastically cut inventories when it restructured its business in the early 1990s (Buxbaum 1995).

While anecdotal evidence suggests that declining firm financial condition implies lower inventory levels, prior empirical research on this relationship has produced ambiguous results (see e.g. Corbett et al. 1999, Guariglia 1999). Upon closer examination of previously published work, which relies exclusively on finance and economic theory, it becomes clear that the link between firm finances and inventories is not yet well understood, both in theoretical and empirical terms. Insights from inventory theory and supply chain research will be useful to better understand this relationship and to improve upon the specification of empirical estimation models.

A supply chain perspective on the link between financial distress and inventories is of particular interest in this research. More specifically, this research is concerned with the effect of a (distressed) firm's power relative to buyers and suppliers on the firm's inventory decisions. In other words, can a distressed firm with greater levels of power push greater amounts of inventory onto suppliers and buyers? If so, firms may want to pay more attention to the financial condition of potential supply chain partners and be aware of the potentially adverse impact of distressed firms' inventory decisions. The interplay between financial distress, supply chain power, and inventories remains unexplored. The following paragraphs summarize the state of knowledge in this area and outline the agenda of this research.

A sizeable literature in the economics and finance fields deals with the effects of financial parameters on inventories. Some researchers have taken a rather macroeconomic approach, analyzing the impact of monetary policy on aggregate inventory levels across industries (see e.g. Corbett et al. 1999). Another set of research papers has investigated the relationship between firm financial parameters such as bank lending rates or cash flows and firm inventories (see e.g. Carpenter et al. 1998, Gertler and Gilchrist 1994). While approaching the phenomenon from different theoretical and methodological angles, many researchers contend that unfavorable financial conditions are associated with lower inventory levels across an economy and within firms. The empirical findings, however, provide only partial support for the researchers' contentions. Corbett et al (1999), for example, find that interest rates are a significant predictor of inventory levels in certain industries only. Similarly, the results presented by Gertler and Gilchrist (1994) suggest that the coverage ratio, i.e. the ratio of a firm's cash flow and short term interest expenses, explains the inventory behavior of small firms but not that of large firms. A study by Guariglia (1999), finally, establishes a significant relationship between firm finances and firm inventories during recessionary periods only.

The inconsistency of prior findings may, in part, be explained by differences in variable measurement, the composition of data samples, estimation techniques, and perhaps most importantly, variations in model specification. As the relationship between firm financial factors and firm inventories appears to be more complex than previously assumed, important explanatory variables may have been omitted in past research. In fact, most published articles in this area rely exclusively on corporate finance and economic theory. As pointed out by Roumiantsev and Netessine (2007), authors thereby ignore the insights provided by inventory theory. Classical inventory models suggest that firm inventories are a function of factors such as average demand, average lead times, holding costs, demand and lead time variability, for example. Out of these factors, only demand has been incorporated in the models of the articles referenced in the previous paragraph. Potential specification problems encountered in prior research may therefore be alleviated by drawing on inventory theory to a greater extent than has been done before.

Another shortcoming of the extant literature relating firm financial factors to inventories may be the myopic treatment of inventories as firm decision parameters and the neglect of the supply chain context in which most firms operate. While a firm's managers ultimately decide on the amount of inventory they order and sell, firms typically operate within the confines of the terms and conditions negotiated with buyers and suppliers. Some firms, for example, commit to specified service levels and must hold more inventory to meet these performance targets. In other instances, buyers and sellers closely cooperate by implementing Vendor-Managed Inventory (VMI) programs, for example. Under this regime, a firm physically holds inventory that is managed (and possibly owned) by a supplier until items are used in production or sold. Regardless of the inventory policy in place, a firm's bargaining power relative to its buyers and suppliers will significantly impact the extent to which the firm exerts control over its inventories (Wallin et al. 2006). Supply chain considerations, thus, may have a substantial impact on a firm's inventory holdings and on the degree to which a firm's financial distress affects inventories. This research adds to prior work in the firm finance-inventory area by drawing on the supply chain power literature and incorporating associated measures in the empirical analysis.

In summarizing, this essay theoretically and empirically revisits the link between firm financial distress and firm inventories. An objective of this research thereby is to gain a refined understanding of *why* a firm's financial situation may have an impact on inventories. This relationship is also tested empirically. Particular attention is paid to the specification of the regression equation using not only microeconomic theory, but also inventory theory, and insights from supply chain research. Also investigated is how the nature of supply chain relationships, i.e. inter-firm power (im)balances, impact the extent to which firms can reduce inventory holdings when experiencing financial distress. The following research questions, thus, emerge:

1. Does a firm's financial situation have an impact on its inventories after controlling for other relevant parameters prescribed by inventory theory and supply chain research?
2. How does a firm's (supply chain) power impact its inventory holdings?
3. Is the magnitude of the presumed effect of financial distress on inventories impacted by power (im)balances in supply chain relationships?

The contributions of this research are manifold. First, it is shown that firm inventories should respond to changes in firm financial condition. Prior research has not provided such theoretical rationales. This is, to the best of the author's knowledge, the first attempt to investigate the research question at hand from both a microeconomic and an inventory theory perspective, thus providing a broader, more complete theoretical basis for the empirical analyses. Second, the impact of supply chain relationship variables on inventory management is investigated. To date, few researchers have empirically analyzed how the nature of buyer-supplier power balances impact firm inventory levels[41]. In this essay, the role of firm power and concentration in both the upstream (supplier) and downstream (buyer) markets in explaining focal firm inventories is examined. Moreover, the analysis of the relationship between firm financial distress and inventories is extended beyond the boundaries of the firm and is approached from a supply chain perspective, thus more appropriately capturing the external influences on firms' (inventory) decisions (Cox et al. 2003, Dobson 2005). More specifically, it is argued that a firm's buying and selling power moderates the distress-inventory relationship. This contingency framework may help reconcile prior findings by defining when and under what conditions the effect of firm distress on inventories is greatest. This research thus adds to both the inventory and supply chain literatures by analyzing the relationships between firm financial distress, supply chain power, and firm inventories.

Besides its academic theoretical appeal, this research also has potentially important managerial implications for supplier selection. If, for example, distressed firms are shown to use their power to push inventory ownership to buyers or suppliers, firms may want to carefully evaluate a potential partner firm's financial condition and determine how the

[41] Amihud and Mendelson (1989) study how firm market power affects firm inventory. They do not, however, consider a firm's power over suppliers or market concentration measures. Blazenko and Vandezande (2003), in turn, investigate the relationship between market concentration and inventories only and also ignore characteristics of the upstream supplier market.

partner's distress might affect inventory ownership in the supply chain. In addition, Halley and Nollet (2002) note that supplier selection and supplier development become increasingly strategic, long-term firm decisions. An investigation of the role and impact of financial considerations on such decisions, therefore, seems timely and managerially relevant.

3.2. The financial distress-inventory relationship

In this section, the theoretical bases for a link between firm financial distress and inventories are reviewed. Most prior research relied on economic theory when investigating this relationship. This literature and the underlying theoretical rationales are reviewed below. The second subsection discusses the firm finance-inventory link from an inventory theory perspective. It is also suggested that inventory theory offers various determinants of firm inventories that have not been included in prior economics research. This section concludes with the formulation of a baseline hypothesis.

3.2.1. Economic theory

Within the economics stream of research, three articles, all first published in 1994, merit particular attention. Gertler and Gilchrist (1994) are among the first to explore the relationship between monetary policy (interest rates) and firm inventory levels. Kashyap et al (1994) present a very similar study but use firm liquidity rather than security-market interest rates as a measure of financial condition. Both papers support the *lending view* which suggests that a firm's dependence on *external* finance drives the strength of the relationship between firm financial condition and inventories. Carpenter et al (1994), finally, focus uniquely on the availability of *internal* finance as a determinant of inventory (dis)investments and disregard macroeconomic factors such as security-market interest rates. All three papers are discussed in more detail below.

Gertler and Gilchrist (1994) investigate the relationship between monetary policy and firm behavior with respect to sales and inventories. The authors present two theoretical rationales which suggest that tight monetary policy (i.e. an increase in interest rates) negatively affects firm output and inventories. First, it is noted that rising interest rates weaken firms' balance sheet positions by reducing cash flows (net of interest) and lowering the value of collateral assets. Consequently, borrowers reduce their spending which implies output and inventory contractions. Second, monetary policy regulates the pool of funds that is available to bank-dependent borrowers. The effect of monetary policy on firm behavior is argued to be particularly strong for firms with limited access to public capital markets. Both rationales, thus, suggest that monetary policy may affect firm sales and inventories, and that firm financial factors, the access to capital markets in particular, influence this relationship.

Gertler and Gilchrist (1994) use firm size to approximate a firm's access to capital markets and use industry-level time series data disaggregated by firm size classes to estimate the effects of monetary policy on firm behavior. Descriptive analyses and the estimation of structural inventory equations with the firm's coverage ratio (cash flow over total interest payments) as the key independent variable of interest indicate that small firms' sales and inventories decline more significantly during and after periods of tight monetary policy. This result is shown to be significant and quantitatively meaningful for small firms but not for large firms which supports the contention that tight monetary policy particularly affects small firms with limited access to public capital markets.

The work of Kashyap et al (1994) is closely related to that of Gertler and Gilchrist (1994) and is motivated by the observation that there has been little empirical support for a relationship between real interest rates and inventory investment. Yet, the observations that inventory movements explain a substantial portion of the variability in aggregate output, and that economic downturns typically follow periods of tight credit strongly suggest such a relationship.

Kashyap et al (1994) attribute the lack of empirical support to measurement imperfections. More specifically, the authors suggest that measures such as security-market interest rates do not fully capture firm financial conditions or the cost of external finance (e.g. bank loans). The latter, however, is argued to have a greater impact on inventories than security-market interest rates. The authors' key hypothesis thus states that firms that depend on external finance should see their inventories fall more sharply than firms with higher levels of internal funds and better access to public debt markets. This contention is frequently referred to as the "lending view" in extant research.

Kashyap et al (1994) seek to empirically validate their hypothesis by regressing the change in inventories on a set of firm-level determinants which include most notably the inventory/sales ratio, the change in sales over the current and preceding years, and a measure of liquidity (cash and marketable securities over total assets). A series of different regression analyses using time series data indicate that firm liquidity is consistently positively and significantly related to changes in inventory. This is, however, only true for the 1974-75 and 1981-82 time periods when there were substantial liquidity constraints. Data from 1985-86 are used as a control sample, and for this time period the coefficient of the "liquidity" variable is statistically insignificant. In summarizing, the authors thus conclude that financial factors influence inventory movements during tight money (recessionary) episodes but not otherwise.

Most prior research relating inventory investments to financial parameters focuses on the effects of monetary policy (e.g. Gertler and Gilchrist 1994) or financial factors such as commercial paper spread and the mix of bank loans and commercial paper on firm inventories (e.g. Kashyap et al. 1993). Carpenter, Fazzari and Petersen (1994) build on this stream of research and add to it on two accounts: First, they focus on the flow of *internal* finance as opposed to on monetary policy effects (see Gertler and Gilchrist 1994) and external (bank) finance (see Kashyap et al. 1994). Moreover, Carpenter et al (1994) test the importance of financing constraints using high-frequency (i.e. quarterly) panel data and are thus able to observe short term changes in inventory investment levels. The perspective of *financing constraints*, as adopted by Carpenter et al (1994), builds on the notion that external finance (e.g. loans, bonds, commercial paper) is substantially more expensive than internal finance (e.g. earnings and depreciation flows). The latter, thus, is the preferred means of financing (inventory) investments.

Internal finance, however, is extremely volatile over the business cycle as it is immediately affected by a slow-down in sales revenues given fixed or quasi-fixed production costs in the short-run. As a consequence, comparatively liquid assets with relatively low adjustment costs, such as inventories, are likely to absorb most of the internal finance fluctuations of financially constrained firms. Carpenter et al (1994) argue that this is particularly true for small firms whose access to external finance alternatives such as corporate bonds and commercial paper is impeded by the lack of publicly available information and the ensuing information asymmetry, adverse selection and moral hazard problems. Small firms, the authors suggest, are thus forced to rely on expensive bank loans as a last recourse to compensate for fluctuations in internal finance. The effect of internal finance constraints on inventory (dis)investment is therefore expected to be even greater for small firms than for large firms. The authors further suggest that the magnitude of this effect depends on the optimality of inventory levels at the beginning of the period. This contention builds on the idea that the marginal cost of liquidating inventory stocks increases as current inventory levels (negatively) deviate from optimal inventory levels.

Carpenter et al (1994) use Compustat data from the U.S. manufacturing industry (1981-1992) to perform a series of regression analyses. The results generally indicate that the level of cash flows is positively related to inventory investment, or put differently, internal finance flows account for a significant portion of the variability in inventory investment. While this is found to be true for both small and large firms, the authors note that the effect tends to be greater in magnitude for small firms. The general result, thus, is in line with the authors' theoretical expectations. It is further noted, that the movements of cash flows are highly procyclical, which, combined with the identified cash flow-inventory link, provides a rationale for the high volatility of inventory investment over the business cycle.

More recent empirical research also finds partial support for the contention that (firm) financial factors impact firm inventory. Corbett et al (1999), for example, present a study of UK and Japanese industries. They find that interest rates are significant predictors of inventory investments in the paper, chemicals, and non-electric machinery industries (UK), as well as in the Japanese chemicals, steel and iron, and metal manufacturing industries. A study by Guariglia (1999) of UK manufacturing firms further explores the effect of financial factors – Guariglia uses the coverage ratio as a measure of a firm's financial condition – on inventories. Her findings indicate a significant positive relationship between coverage ratios and inventory levels during recessions and periods of tight monetary policy.

In summary, it is noted that researchers in the economics field expect that less favorable financial conditions will result in lower inventory levels. The significance levels of empirical findings, however, vary greatly from study to study, depending on the measures, data sets, and time periods used. It is also noted that researchers have used a broad range of financial variables (interest rates, coverage ratios, and cash levels, for example). No prior research has attempted to more comprehensively measure the multifaceted firm financial distress construct and relate the latter to firm inventories. This essay fills this gap. In addition, it will be argued in this research that previously unobserved factors may also impact firm inventories and moderate the magnitude of the financial distress-inventory relationship.

3.2.2. Inventory theory

Firms hold inventory for at least two reasons. First, delivery and production cycles are typically not perfectly aligned. Natural stocks of raw materials as well as intermediate and finished products therefore occur at various points throughout the production and distribution process. These inventories are typically referred to as *cycle stocks*. Second, inventories buffer against uncertainty. Specifically, unexpectedly high demand or longer than usual lead times may lead to costly disruptions in manufacturing and delivery. *Safety stocks* are a means of mitigating this risk by holding extra inventory that will be used only if the need arises.

Determining the magnitude of cycle and safety stocks is a crucial task in inventory management. While holding inventory is costly due to warehousing and opportunity costs, not holding inventory may result in substantial stockout costs. The latter can take the form of backorder (e.g. expediting) or lost sales costs, for example. Inventory theory has been concerned with developing optimal, i.e. cost-minimizing or profit-maximizing inventory policies. Multiple models have been proposed for different settings and assumptions (see e.g. Tersine 1994). It is not the focus of this research to provide a comprehensive review of these models. Rather, two questions are asked. First, which determinants of inventories are proposed by inventory theory? And second, how may firm financial distress be related to inventories from an inventory theory perspective? To address these questions, two widely used and commonly known inventory models, the *r,Q* model and the *s,S* model are briefly reviewed below. Particular attention is paid to the *r,Q* model, and most of the subsequent discussion refers to this inventory policy. The general results relating to the determinants of inventory levels and the relationship between financial distress and inventory levels do, however, hold for most other inventory models as well.

The *r,Q* inventory model is an extension of the well-known and widely used economic order quantity (EOQ) model which, in its most basic form, balances ordering and inventory holding costs[42]. First developed by Harris (1913), the EOQ and its variants have been prominently featured in inventory management research and practice for over ninety years (see Erlenkotter 1990 for a review of the early history of the EOQ model). This model's appeal lies in its relative simplicity and ease of use, as well as in its robustness (Alstrom 2001). Reuter (1978) surveyed a total of 228 firms in five states in the U.S. and finds that 75.4% of all respondents use the EOQ on a continuing basis with an additional 9.6% indicating occasional use of the EOQ. In a study conducted by McLaughlin et al (1994), 28% out of 236 survey respondents reported using the EOQ. In

[42] See any textbook on inventory management for a detailed discussion of the economic order quantity model and its variants (e.g. Tersine 1994)

a more recent survey, Rabinovich and Evers (2002) find that the EOQ is deemed important in managerial practice and is commonly used by logistics managers to determine optimal order quantities[43]. Zinn and Charnes (2005) note that quick response (QR) inventory policies have become increasingly popular in modern inventory management and therefore analyze the relative merits of the EOQ and QR methods, respectively. Based on a series of numerical analyses, Zinn and Charnes (2005) conclude that the EOQ continues to be the preferred inventory policy when order costs are relatively high[44]. Numerous researchers have conducted sensitivity analyses and have found that moderate deviations from the EOQ's assumptions do not have a substantial impact on order quantities and associated total inventory costs (e.g. Sun and Queyranne 2002). Its popularity, simplicity, and robustness make the EOQ a good starting point for developing an inventory theory perspective on the financial distress-inventory relationship.

The classical EOQ is based on the following assumptions: the demand rate is constant, continuous and known, and lead times are zero. Replenishments are received instantaneously and all at once, and the cost of placing an order as well as unit holding costs are constant. The classical EOQ model considers only a single product and assumes that there are no interactions with other inventory items. Moreover, it is assumed that the firm has sufficient capital and capacity to purchase the economic order quantity. In the *r,Q* model, the rather unrealistic assumptions of constant demand and zero lead times are

[43] On a five point scale (1 = unimportant, 5 = very important) 256 survey respondents ascribe an average weight of 3.27 to the EOQ, and 19.61% report the use of the EOQ for determining finished goods orders.
[44] See Zinn and Charnes (2005) for a summary of their study's results. Table 6 (p.139) identifies the conditions under which QR and EOQ policies are preferred, respectively.

relaxed. With stochastic demand, nonzero but constant lead times, and per-unit backorder costs, the total inventory cost equation is defined by

$TC_I = \frac{\hat{S}}{Q}\left[A + B \cdot E(M > r)\right] + H\left[\frac{Q}{2} + r - \overline{M}\right]$, where $\hat{S}$ is the expected sales volume[45] over the planning horizon, *A* is the order cost[46], *H* is the unit holding cost, and *B* is the unit backorder cost. *M* is lead time demand (i.e. the sales volume during lead time) and *r* is the reorder point which, along with order quantity *Q*, is the decision variable of interest. $E(M > r)$ is the expected stockout quantity, while $(r - \overline{M})$ represents the average size of the safety stock. Taking the derivative of TC_I with respect to *Q* and setting the expression equal to zero yields the cost minimizing order quantity:

$Q^* = \sqrt{\frac{2\hat{S}\left[A + B \cdot E(M > r)\right]}{H}}$. Similarly, the optimal reorder point r^* is obtained by setting the derivative of TC_I with respect to *r* to zero. This yields the cost-minimizing stockout probability $P^*(M > r) = \frac{HQ}{B\hat{S}}$[47]. Under the assumption of normally distributed demand, the latter value converts to standard normal deviate k, and the reorder point is defined as $r^* = \overline{M} + k \cdot \sigma_{LTS} = \overline{S}L + k \cdot \sigma_S \sqrt{L}$ where σ_{LTS} is the standard deviation of lead time sales, and σ_S is the standard deviation of sales[48].

The control parameters of the *r,Q* inventory policy are thus defined by the expected sales

[45] The inventory literature commonly uses the term *Demand* instead of sales volume. It is noted however, that inventory decisions are made a priori based on forecasts.
[46] In a manufacturing context, these order costs may also be thought of as production setup costs.
[47] Since *Q* is a function of *r* and vice versa, the optimal solutions for these parameters are found by iteration.
[48] Lead times are assumed constant. See Tersine (1994) for more detail.

volume, sales variability, lead times, ordering costs, holding costs and backorder costs. Inventory theory suggests that these parameters appropriately predict a firm's inventory decisions and thereby firm inventory levels. *Figure 10* provides a graphic illustration of the *r,Q* policy.

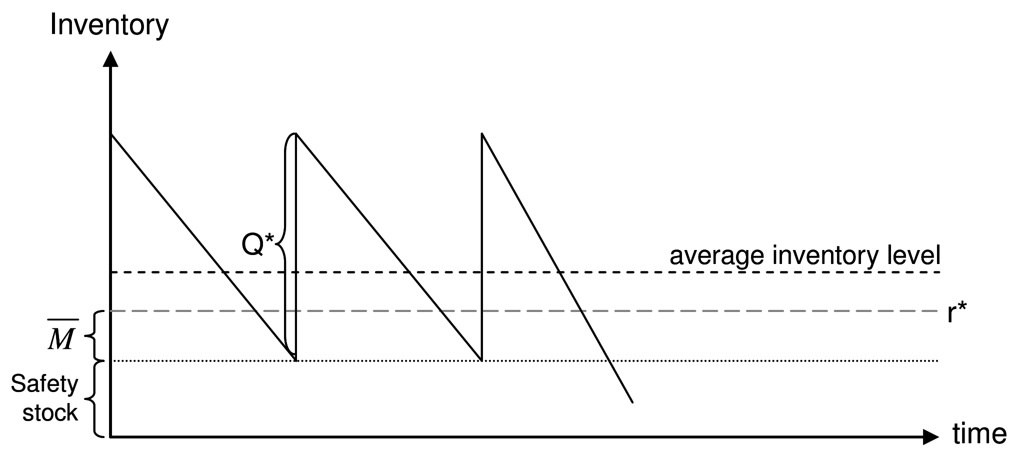

Figure 10: Illustration of the r,Q policy

The *s,S* policy is similar to the *r,Q* inventory policy but may differ from the latter in that the order quantity is variable when inventories are reviewed periodically only, or when demand is lumpy, i.e. does not follow a pure Poisson process with unit demand. Each time the inventory level drops below a threshold level (or reorder point) *s*, on order of size (*S-s*) is placed. For details on the mathematical derivation of the inventory control parameters (*s,S*) the interested reader is referred to Denardo (2003), for example. In this context, it shall suffice to note that the *s,S* policy is defined by the magnitude of demand, the item's unit costs, per-unit holding and backorder costs, as well as ordering costs. Randomness of demand and lead times can also be incorporated in *s,S* type inventory models. The determinants of an *s,S* inventory control policy, thus, are essentially the same as the determinants of the *r,Q* policy.

In summary, inventory theory suggests that firm inventories should be a function of average demand, demand variability, lead times, ordering costs, holding costs and backorder costs (or lost sales costs), regardless of the specific inventory control policy in place.

Next, the potential effects of firm financial distress on inventories are discussed from an inventory theory perspective. Financial costs are most directly reflected in a firm's holding costs. Holding costs include a financial cost component representing the capital cost of inventories (Followill et al. 1990). While holding costs also comprise a noncapital carrying charge[49], Timme (2003) notes that the financial component of holding costs usually exceeds noncapital carrying charges. In accordance with this contention, the survey results presented by Fraser and Gaither (1984) suggest that 68% of all firms approximate inventory carrying costs with borrowing costs. The latter are a function of a firm's financial condition (see e.g. Buzacott and Zhang 2004, Wiersema 2005). Specifically, a deterioration of a firm's financial condition implies higher borrowing costs and thereby higher inventory holding costs. Returning to the inventory control parameters of the *r,Q* policy, it is evident that higher holding costs entail lower inventory levels, all

[49] Noncapital carrying costs comprise the costs of warehousing, obsolescence, pilferage, damage, and insurance, as well as taxes and administrative charges (see Timme, 2003).

else equal[50]. The optimal order quantity $\left(Q^* = \sqrt{\frac{2\hat{S}\left[A + B \cdot E\left(M > r\right)\right]}{H}} \right)$ is decreasing in holding costs $\left(\text{i.e. } \frac{\partial Q^*}{\partial H} < 0 \right)$, as is the reorder point: The optimal stockout probability increases in H $\left(P^*\left(M > r\right) = \frac{HQ}{B\hat{S}} \right)$[51]. This translates to a lower safety factor k and consequently to a lower reorder point r $\left(r^* = \overline{M} + k \cdot \sigma_{LTS} = \overline{S}L + k \cdot \sigma_S \sqrt{L} \right)$. A negative relationship between firm financial distress and optimal firm inventories can therefore straightforwardly be established from an inventory theory perspective.

While the author is unaware of any empirical inventory research relating firm financial condition to inventory levels, there is some analytical research on the relationship between various financial factors in a broader sense and inventory decisions. For completeness, a few examples of such research are discussed below.

One literature stream, for example, investigates the effects of trade credits, permissible payment delays granted by suppliers, on economic order quantities. Haley and Higgins (1973) analyze the interdependence of inventory decisions and credit terms, and determine jointly optimal order quantities and payment schedules. Most subsequent research assumed credit terms as exogenously given (i.e. unilaterally defined by the supplier) and focused on the effects of trade credits on order quantities. Chapman et al

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[50] In addition, higher holding costs may imply lower firm output choices and hence lower demand.

[51] Note that the optimal stockout probability is also a function of Q, which, in turn, decreases in $\sqrt{H}$. P^* therefore increases in H and decreases in $\sqrt{H}$, Overall, the optimal stockout probability increases in $\sqrt{H}$.

(1984), for example, conduct an average cost analysis and conclude that trade credit periods, while significantly impacting total costs, do not affect optimal order quantities. Chand and Ward (1987), on the contrary, find that order quantities increase as payment delay times increase. Rachamadugu (1989) reconciles these contradictory findings and ascribes them to differences in the assumptions and setup of the respective models. In summary, Rachamadugu's (1989) analyses corroborate Chand and Ward's (1987) intuitively appealing findings, as do the results of a more recent study conducted by Chang and Teng (2004). For a review of some earlier works on inventory models with consideration of permissible payment delays the interested reader is referred to Kim and Chung (1990).

Another stream of research is concerned with the impact of budget constraints of inventory decisions. Financially distressed firms are likely to operate under budgetary constraints. Rosenblatt (1981) formulates a constrained inventory optimization problem with limited budget availability. He uses the Lagrangian procedure to demonstrate the intuitive result that the optimal order quantity will be restricted to the maximum affordable level when the budget constraint is tight. A multi-item newsvendor problem with a budget constraint is analyzed by Moon and Silver (2000). The authors' attention focuses on rules for optimally allocating scarce resources to different products. In the context of this research, however, it is sufficient to note that a restriction on total expenditure is shown to lead to lower than optimal order quantities and increased overall costs (Moon and Silver 2000). Abdel-Malek and Montanari (2005) extend Moon and Silver's (2000) work by conducting an analysis of the multi-product newsvendor problem with two (generic) constraints. Rustenburg et al (2000) also present a study similar to that of Moon and Silver (2000) in the context of spare parts logistics, where resupply decisions for multiple items must be made under limited budgets. One of the basic finding's of Rustenburg et al (2000) is that budget constraints result in lower part availability levels.

Empirical inventory research is challenging from a data collection standpoint and therefore rather scarce (examples include Ballou 1981, Roumiantsev and Netessine 2007). Inventory theory is, however, indispensable when empirically explaining inventory levels and analyzing the relationship between firm financial distress and inventories. This research builds on prior work in the economics area by drawing on inventory theory to explain this relationship and by incorporating a set of previously ignored inventory variables in the regression model.

3.2.3. The financial distress-inventory hypothesis

The theoretical link between firm financial distress and inventories has been discussed from both an economics perspective and an inventory theory perspective in the previous subsections. Clearly, both theories suggest that greater levels of financial distress (i.e. less favorable financial conditions) result in lower inventory levels, all else equal. Most prior research argues that budgetary constraints and increased borrowing costs lead distressed firms to hold less inventory. Prior research has found some support for this hypothesized relationship (Carpenter et al. 1998, Carpenter et al. 1994, Gertler and Gilchrist 1994, Kashyap et al. 1994). As Roumiantsev and Netessine (2007) point out, however, this body of work “might contain biases because many important micro-economic data points that affect inventories have been left out, including lead times, demand uncertainty, inventory holding costs, etc.” (p.6). This study reexamines the financial distress-inventory link while controlling for these inventory determinants.

Besides the previously discussed rationale that financial distress results in budgetary constraints and increased borrowing costs, it may be argued that managers of distressed firms have an incentive to liquidate assets (Hofer 1980) such as inventories in an effort to increase liquidity and improve key firm performance measures such as the Return on Assets (RoA). In summary, there appears to be clear theoretical and at least some empirical support for *Hypothesis 8*:

Hypothesis 8: Holding demand constant, greater levels of financial distress result in lower inventories.

So far, the focus has been on firm level determinants of inventories. In the next section, this focus is expanded to include a firm’s supply chain partners. Specifically, the effect of power on inventories and the financial distress-inventory link is discussed.

3.3. The supply chain perspective

In this section, the relationship between distress and inventories is analyzed from a supply chain perspective. Specifically, the role of power in inter-firm relationships and firm (inventory) decision making is reviewed in Section 3.3.1. In line with prior research in the industrial organization economics field, it is suggested that a firm's power position impacts its inventory decisions. The second subsection analyzes the moderating role of inter-firm power in the financial distress-inventory relationship. It is hypothesized that power determines to what extent financial distress affects firm inventories. The resulting contingency framework is subsequently tested using U.S. industry data.

3.3.1. Supply chain considerations in inventory decisions

Many parameters influence managerial decision making. While firm-level variables such as holding and purchasing costs, for example, naturally have a strong impact on managerial decisions relating to sales prices and inventories, market factors and inter-firm relationship variables cannot be ignored.

First, competitors' actions clearly impact a firm's choices. Researchers from both the economics and strategy fields have contended that managers must anticipate competitive reactions and evaluate their implications when deciding on sales prices (see e.g. Chen et al. 1992, Gibbons 1992). By the same token, firms also compete on inventories. Cachon (2001), for example, analyzes competitive inventory policies and, for a given set of assumptions, defines a competitive Nash equilibrium in inventories (see also e.g. Mahajan and Ryzin 2001). As a consequence, a firm's inventory decisions are a direct function of competitors' inventory choices.

Second, firms are typically a part of supply chains that extend across many companies from raw material suppliers to the end customer. As firm decisions impact the functioning of the entire supply chain, supply chain firms are necessarily interdependent (Cox et al. 2001). This interdependence is of particular interest in this research. When the Case Corporation reduced its inventories as a part of its restructuring efforts, for example, suppliers had to bear the burden, but were willing to do so to improve customer service levels (Buxbaum 1995). Chrysler's aggressive cost-cutting measures implemented in 2000 and 2001, in turn, were considered "acts of war" (p.32) by some suppliers who agreed to cooperate only because they had little choice (Stundza and Milligan 2001).

These examples illustrate how firms' (inventory) decision making can be constrained by cooperative arrangements and coercive pressure exerted by buying and supplying firms. The extent to which firms are willing or forced to yield to these constraints is a function of the inter-firm power balance. It is argued in this research that power not only impacts a firm's inventory decision but also moderates the link between financial distress and inventories. Following a brief review of the role of power in inter-firm relationships and some related literature, the corresponding hypotheses are derived below.

3.3.1.1. Inter-firm relationships: The role of power

There exists a sizeable literature base on the nature, drivers, and consequences of power in inter-firm relationships. Gaski (1984) provides a review of the early work in this field and, in summarizing, defines power as the “ability to evoke change in another’s behavior” (p.10). Emerson (1962) relates power to dependence and suggests that Firm A’s power over Firm B equals Firm B’s dependence on Firm A. The sources of (firm) power in (inter-firm) relationships were first analyzed by French and Raven (1959). According to French and Raven (1959) these bases of power include:

- Reward power: A can motivate B by granting rewards;
- Coercive power: A can effectively punish B;
- Legitimate power: A has a legitimate right to prescribe B’s behavior;
- Referent power: A serves as a model to B;
- Expert power: A’s expertise conveys A the power to influence B.

The term *power* often carries a negative connotation (Hingley 2005). French and Raven’s power bases, however, suggest that power may be used both collaboratively and coercively. Along the same lines, Frazier and Antia (1995) suggest distinguishing between the possession and the application of inter-firm power. Frazier and Antia (1995) argue that the channel context and the specific inter-firm power constellation drive the communication style between firms. The latter can be either threatening (as seen above in the case of Chrysler) or collaborative (as evidenced in the previously mentioned example of Case Corp.). Firms with some degree of power can, thus, exert either coercive control or collaborative control to affect other firms’ forced or voluntary behavioral change, respectively (Frazier and Antia 1995, Hingley 2005).

Cox et al (2003) note that power is an element of every buyer-supplier relationship. The authors suggest that each relationship can be characterized by one of four power structures: buyer dominance, supplier dominance, buyer-supplier interdependence, and buyer-supplier independence. Cox (2001) further notes that firms strive to be in a dominant position over buyers and suppliers so as to extract the maximum amount of value generated in the supply chain. Cox et al (2001) have coined the term “value appropriation” to describe this mechanism which can take the form of cost squeezing on the supply side or high-margin pricing on the sales side, for example. As the previously cited examples of Chrysler and Case Corp. (Buxbaum 1995, Stundza and Milligan 2001) have illustrated, firms may also use their dominant power position to shift inventory ownership to suppliers or buyers. In this vein, Wallin et al (2006) contend that “if a firm within a specific buyer-supplier relationship were to hold bargaining power, this would greatly enhance its ability to dictate to and make certain demands of a specific supplier” (p.59) with respect to the inventory management approach used in the supply chain (see also Dobson 2005). This research empirically tests the contention that a firm’s power relative to its suppliers and buyers will impact firm inventory levels, *ceteris paribus*. Prior work in this area is reviewed in the following subsection.

3.3.1.2. Supply chain power and inventory decisions

Few researchers have investigated the effect of power on inventories. Blazenko and Vandezande (2003) ascribe the lack of power-inventory research to the fact that “the academic literature on inventory focuses on production and procurement as the principal determinants of […] inventory […] management” (p.256) while “the principal focus of the study of inventory in the economics literature is on the macroeconomic role of inventory as a stabilizing or destabilizing factor for production in business cycles" (p.256). Much of the research relating dyadic power, i.e. a firm's power vis-à-vis another firm, to inventories remains descriptive in nature and is mostly based on case studies (see e.g. Dobson 2005). Within the supply chain management literature, articles on power and its implications are, for the most part, purely conceptual. The author is aware of only two papers that empirically investigate the effects of power on inventories. Both papers are housed within the industrial organization economics literature and are discussed in turn.

Amihud and Mendelson (1989) suggest that "a firm with market power will use inventory as a wedge between the quantity available for sale and the quantity shipped to market" (pp.269-270). According to Amihud and Mendelson (1989), firms build up inventories when supply exceeds demand in an effort to maintain higher prices and keep production at constant levels. With demand greater than supply, in turn, firms deplete inventories to maximize revenues. A firm's motivation to use inventories to smooth price fluctuations thereby increases with the firm's market power as "greater market power implies a stronger effect of the firm's sales quantity on price" (p.270). Amihud and Mendelson (1989) test the market power-inventory relationship using Compustat data from the U.S. manufacturing industry. The results suggest that firm market power, measured by either the Lerner index ([price – marginal cost]/price) or the firm's market share, positively affects firm inventories after controlling for firm sales, sales trends, sales variability, and average industry inventory levels. The authors therefore conclude that "market power has a sizeable effect on inventory, which has been overlooked so far" (p.275).

Blazenko and Vandezande (2003) build their article on the contention that stockout costs should be represented in inventory estimation models. The authors suggest that greater levels of competition erode profit margins and thereby reduce the amount of profits foregone in case of a stockout, while, at the same time, more competition also increases stockout costs due to the greater availability of alternative sources of supply. According to Blazenko and Vandezande (2003) the effect of market concentration (an indicator of the level of power firms possess in a given market) on inventories is ambiguous and depends on whether the effects of lower foregone profit or increased lost sales costs prevail. The authors empirically investigate the effect of industry concentration (measured by the two-firm concentration ratio) on finished goods inventory levels (at the industry level). The control variables included in the model are, most notably, industry gross-margins and a set of industry indicator variables. Data from the U.S. manufacturing industry are used for the empirical analyses. The results suggest that higher industry concentration levels result in lower inventory levels, *ceteris paribus*. Blazenko and Vandezande (2003) conclude that "a less competitive product market reduces the adverse consequences of stock outs and firms respond by reducing inventories" (p.263).

In summary, Amihud and Mendelson (1989) suggest that greater levels of market power imply higher inventory levels, while Blazenko and Vandezande (2003) find that inventories are lower in more concentrated markets (implying more powerful firms). This conflict may, in part, be explained by different levels of analysis (firm vs. industry), and differences in measurement. In addition, it is noted that both models fail to include variables prescribed by inventory theory, such as lead times and the cost of holding inventory, for example. The results may, therefore, be biased (Roumiantsev and Netessine 2007). Also, neither article attempts to relate focal firm or industry power to the power levels of buyers and suppliers. Yet, power is dyadic in nature (Cox et al. 2001, Emerson 1962, Frazier and Antia 1995, Gaski 1984), and a complete evaluation of power must consider a firm's power *relative* to another firm or industry. Prior research has focused uniquely on downstream power vis-à-vis buyers but has ignored the upstream supply side. Power, however, is "Janus-faced", i.e. double-sided (Cox 2001), as firms are engaged in power relationships with both their buyers and their suppliers (as well as with their competitors). This research addresses this shortcoming in terms of measurement of power and proposes a comprehensive set of power measures (see Chapter 3.4) capturing not only focal firm power, but also power levels in the buying and supplying industries.

3.3.1.3. The power-inventory hypotheses

As outlined previously, prior research on the role of power in supply chain relationships has suggested that greater levels of power allow firms to obtain more favorable terms and conditions in negotiations with their buyers and suppliers (Blazenko and Vandezande 2003, Cox 2001, Cox et al. 2001, Wallin et al. 2006). More powerful firms may thus be able to push the burden of inventory ownership onto buyers and suppliers to a greater extent than less powerful firms. *Hypothesis 9* is therefore proposed as a baseline power-inventory hypothesis:

Hypothesis 9: Greater firm power results in lower inventory levels.

Hypothesis 9 can be refined by distinguishing between firm power relative to suppliers and buyers, respectively. Accordingly, *Hypothesis 10* and *Hypothesis 11* are introduced below.

Wallin et al (2006), for example, argue that a firm with bargaining power may impose item availability targets on suppliers, thus forcing suppliers to hold larger inventories to meet these targets while reducing the need to hold inventory at the buying firm (see also Cox et al. 2001). In addition, a powerful firm may be able to demand inventory consignments from its suppliers, thus providing the buying firm with improved item availability without incurring the cost of inventory ownership (Wallin et al. 2006). *Hypothesis 10* therefore suggests that greater power over suppliers implies lower inventory levels, all else equal.

Hypothesis 10: Greater firm power relative to suppliers results in lower inventory levels.

Hypothesis 11 mirrors the reasoning underlying *Hypothesis 10* and projects it to the downstream relationship between a firm and its buyers. Accordingly, greater levels of power over buying firms are expected to be associated with lower inventory levels, all else equal. While the work of Blazenko and Vandezande (2003) presents some evidence in support of this contention, the results of the study published by Amihud and

Mendelson (1989) appear to contradict this expectation. The latter researchers implicitly assumed that firms can use inventories to mitigate price fluctuations only if they directly own these inventories. Powerful firms in supply chains, however, may be able to dictate the release and buildup of inventories even when these inventories are not under direct ownership and control. From a supply chain perspective, *Hypothesis 11*, therefore, does not necessarily disagree with the arguments and results presented by Amihud and Mendelson (1989).

Hypothesis 11: Greater firm power relative to buyers results in lower inventory levels.

Besides the direct effect of power on firm inventories, it is also contended that firm power impacts the extent to which firms can reduce inventories when experiencing financial distress. These moderating hypotheses are developed below.

3.3.2. Firm power as a moderator of the distress-inventory link

The inconsistency of the results presented by prior research on the link between financial variables and inventories may be an indication that there are factors that affect the magnitude and significance of this relationship. Prior research has suggested that firm size may be such a moderator. This rationale is briefly reviewed below. This essay, in turn, focuses on the moderating role of firm power. The related reasoning is discussed in Section 3.3.2.2 and the corresponding hypotheses are formulated.

3.3.2.1. Prior research: Firm size as a moderator of the distress-inventory link

As discussed in Section 3.2.1, most studies on the link between financial factors and inventories have suggested that the magnitude of this relationship may differ by firm size. Gertler and Gilchrist (1994) and Carpenter et al (1998, 1994), for example, perform separate regression analyses by firm size classes (small vs. large). These authors find empirical support for their contention that smaller financially constrained firms experience stronger inventory contractions due to their limited access to capital markets and, thus, means of financing inventory investments. Kashyap et al (1994) find that the effect of firm liquidity on inventories is stronger for firms without bond ratings than for firms with bond ratings. Since unrated firms typically are smaller firms, their results also suggest that the effect of financial constraints on inventories differs by firm size.

Firm size may be a proxy for a firm's power, with larger firms being more powerful than smaller firms, all else equal. Following this reasoning, the negative effect of firm distress on inventories (as hypothesized in *Hypothesis 8*) may be expected to decrease with the firm's power. It is noted, however, that the arguments set forth in prior research focus uniquely on the operating implications of financial constraints, suggesting that firms with limited resources *must* reduce inventory investments, particularly when external funds can be procured at high costs only. This research, in turn, suggests that financially distressed firms *want* to reduce inventories and will do so to the largest extent possible. In other words, reducing inventories is considered desirable as long as potentially negative consequences of inventory cutbacks, such as stockouts and decreases in customer service levels, can be mitigated by increased buyer and supplier efforts (e.g. in terms of increased inventory holdings, shorter lead times, etc.). This contention is discussed in more detail in the following subsection.

3.3.2.2. The power moderator hypotheses

While firms consistently strive to increase efficiency and profitability, these efforts are reinforced during corporate turnarounds (e.g. Hofer 1980). Tom Sidlik, then Executive Vice President with Chrysler, for example, indicated that "we've accelerated our ongoing cost-reduction programs so that we can take 15% costs out of the system by the end of 2002." (Stundza and Milligan 2001, p. 30). Sidlik continued to note that "in the current business situation, we are counting on our supplier partners to stand with our company […] in these difficult times" (p.31). The importance of concessions and support offered by suppliers during corporate turnarounds is further illustrated by Arogyaswamy and Yasai-Ardekani (1995) who argue that cutting inventory can only be a successful turnaround strategy if potentially resulting delivery delays can be mitigated through suppliers' or buyers' increased efforts, for example. Finkin (1985) also notes that during company turnarounds "[t]erms and conditions of sale are worth fighting over" (p.17) and that a supplier's agreement to shorter lead times may help reduce inventory levels. Clearly, a firm's bargaining power vis-à-vis its suppliers and buyers will determine to what extent such concessions will be made. In a similar vein, Hambrick and Schecter (1983) note that a firm's power might affect its choice of turnaround strategy as "strong channels of distribution […] could allow [the distressed firm] to solve [the] problems at less human and organizational cost" (p.234), with loyal and obedient distributors carrying larger shares of the burden.

These arguments and examples lend support for the contention that distressed firms may be able to reduce inventories to a greater extent when they have higher degrees of power relative to their suppliers and buyers. *Hypothesis 12* is formulated accordingly:

Hypothesis 12: The effect of firm financial distress on inventories increases with the firm's power.

Hypothesis 12 can be specified for a firm's power relative to buyers and suppliers, respectively:

Hypothesis 13: The effect of firm financial distress on inventories increases with the firm's power relative to suppliers.

Hypothesis 14: The effect of firm financial distress on inventories increases with the firm's power relative to buyers.

The moderating effect of firm power on the distress-inventory relationship is graphically illustrated in *Figure 11*. On average, a negative relationship between the magnitude of firm financial distress and inventories is expected (*Hypothesis 8*). This relationship, however, is hypothesized to be stronger the greater the firm's power (*Hypothesis 12*-*Hypothesis 14*).

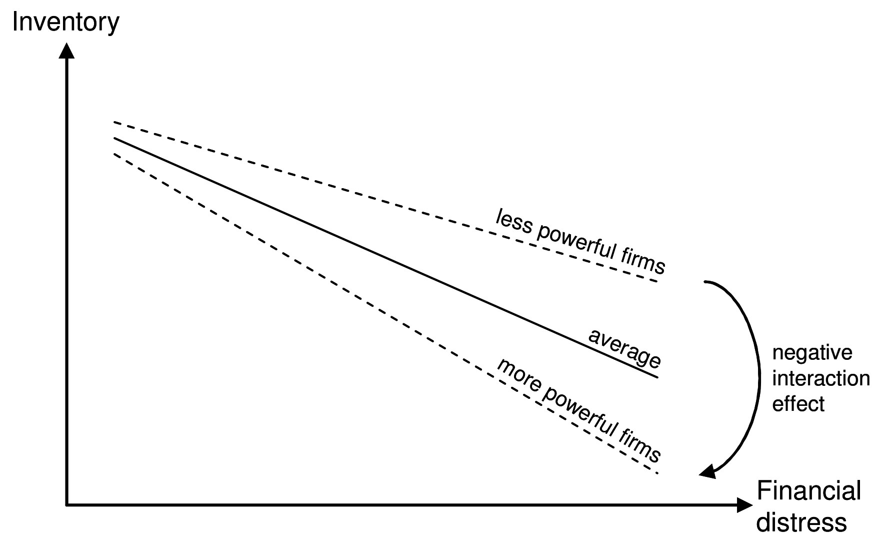

Figure 11: The moderating effect of power on the distress-inventory relationship

An overview of the resulting model is given in *Figure 12*. In summarizing, a set of hypotheses on the link between firm financial distress and inventories has been formulated based on a variety of theoretical perspectives. Particular attention is given to the role of power as a determinant of firm inventories and as a moderator of the distress-inventory relationship.

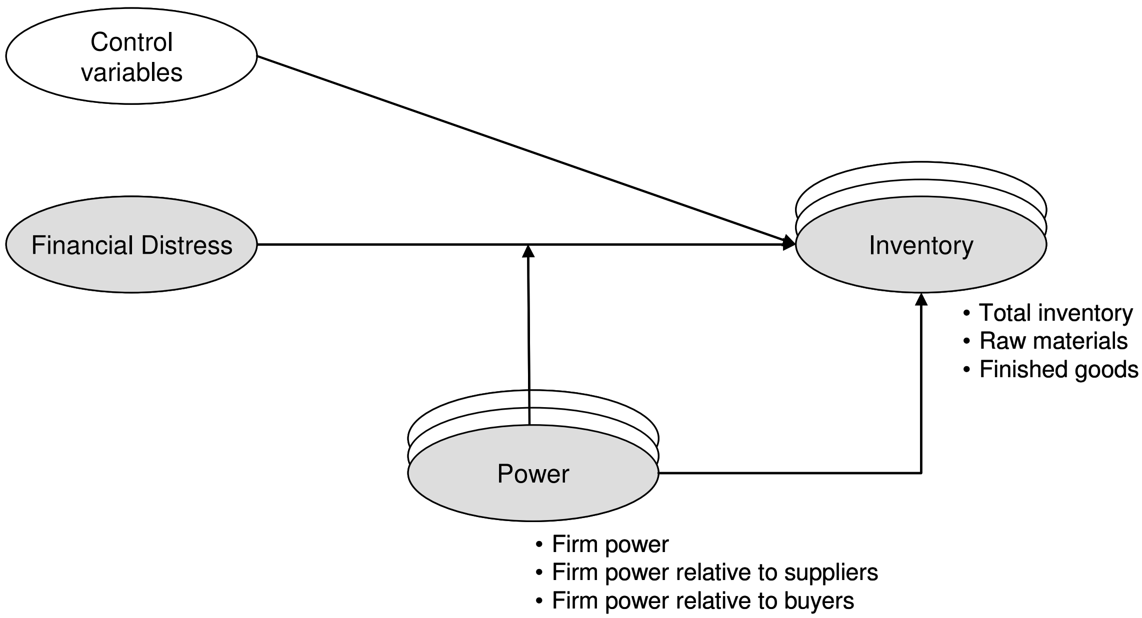

Figure 12: Research model

3.4. Data and methodology

The hypotheses set forth in the previous sections are tested using data sets comprising information on a cross-section of U.S. industries. Details on the data samples, specification of the model, variable measurement, and data sources are provided in the following subsections.

3.4.1. Sample selection

The empirical tests are conducted using data from U.S. manufacturing firms. Two data sets from 1997 and the time period from 1998 to 2004, respectively, are used for the analyses. This subsection provides information on the sample selection criteria.

Industries

Most empirical inventory research has focused on manufacturing industries for the obvious reason that manufacturing firms are likely to hold substantial inventories (Carpenter et al. 1998, Carpenter et al. 1994, Corbett et al. 1999, Gertler and Gilchrist 1994, Guariglia and Schiantarelli 1998, Kashyap et al. 1994, Roumiantsev and Netessine 2007). Manufacturing industries are defined by the North American Industry Classification System (NAICS). The NAICS system has replaced the U.S. Standard Industrial Classification (SIC) system and all U.S. government agencies commonly report industry statistics by NAICS codes. NAICS codes have between two and six digits and are structured hierarchically. The first two digits of a NAICS code designate the "economic sector" and the third digit identifies the "subsector". The fourth, fifth, and sixth digits designate the "industry group", "NAICS industry", and "national industry", respectively. Manufacturing industries are part of the economic sectors 31-33. All firms in these sectors for which complete data are available are included in the empirical analyses.

This study approaches the analysis of inventories from a supply chain perspective and investigates, among other things, the role of a firm's power on firm inventories and on the relationship between financial distress and inventories (see *Figure 12*). Given the dyadic nature of power, the data set also comprises information on the wholesale and retail trade industries[52] as these industries likely are manufacturing firms' principal suppliers and buyers (besides buyers and suppliers within the manufacturing industries). Other industries that may potentially buy from or sell to manufacturing industries are not included in the analysis for the two following reasons:

- Service industries: Service industries[53] are of limited interest in the context of inventory studies and are not considered in this research (see also Roumiantsev and Netessine 2007).
- Insufficient data availability: The remaining economic sectors are Agriculture, Forestry, Fishing and Hunting (11), Mining (21), Utilities (22), Construction (23). While these industries may potentially be involved in the exchange of goods (i.e. inventories) with manufacturing firms, these industries must be excluded from the data analysis due to insufficient data availability at the industry level. Specifically, industry sales data and industry concentration ratios are available at highly aggregated levels only and, thus, are not usable in the empirical analyses.

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[52] NAICS codes 42, 44, and 45.

[53] Service industries are found in the following economic sectors (two-digit NAICS codes are given in parentheses): Transportation and Warehousing (48,49), Information (51), Finance and Insurance (52), Real Estate, Rental and Leasing (53), Professional, Scientific, and Technical Services (54), Management of Companies and Enterprises (55), Administrative and Support and Waste Management and Remediation Services (56), Educational Services (61), Health Care and Social Assistance (62), Arts, Entertainment, and Recreation (71), Accommodation and Food Services (72), Other Services (except Public Administration) (81), Public Administration (92).

Time periods

This research uses data from 1997 to 2004. This time period is selected for two reasons. First, consistent data at the industry level are available for this time period only. More recent data (after 2004) were not available at the time of writing, and older data (prior to 1997) were aggregated differently as the industry classification system was revised in 1997 with the move from the Standard Industry Classification (SIC) system to the NAICS system. Second, the selection of a relatively recent time period is adequate given that inventory dynamics may have been significantly different in earlier time periods prior to the widespread adoption of information systems and Just-In-Time practices, for example (Roumiantsev and Netessine 2007).

In the U.S., an Economic Census is conducted every five years (years ending with "2" and "7"). During the time period considered here (1997-2004), Economic Census data were thus collected in 1997 and 2002. While the 2002 Economic Census data were not available at the time of writing, data from the 1997 Economic Census could be obtained from the website of the Bureau of Economic Analysis (BEA). The Economic Census data provide more detailed industry information, for example on industry sales and concentration ratios, than the data that are collected by the BEA during years in which no Economic Census is conducted. Therefore, the empirical analyses are performed using two different datasets: First, a panel data set is constructed. This panel data set contains information on a cross-section of U.S. manufacturing industries for the time period from 1998 to 2004. Second, a cross-sectional data set using data from 1997 only is constructed.

Using two distinct data sets for the empirical analyses has several advantages. The time series data set, henceforth denoted "data set I", is relatively large with multiple observations per firm. Larger sample sizes generally facilitate the empirical analyses and typically result in more robust coefficient estimates. The 1997 data set, in turn, provides more fine-grained industry level data. This data set, henceforth denoted "data set II", thus is particularly useful when attempting to evaluate the relative power balances between industries. In addition, the robustness and validity of the model are underlined if both data sets produce consistent coefficient estimates.

Frequency

As noted by Carpenter et al (1998, 1994), high-frequency quarterly data may be desirable for the analysis of firm inventories and financial factors due to their dynamic and volatile nature. Many firms, however, report only selected parameters on a quarterly basis. Raw materials and finished goods inventory data, for example, are often available on an annual basis only. In line with prior research and due to greater data availability, annual data are used in this study (Guariglia 1999).

3.4.2. Model specification

The purpose of this section is to derive an empirical inventory estimation model which is grounded in inventory theory and supply chain management research. This research thereby enhances prior economics research which generally modeled inventories as a function of (lagged) sales, financial indicators, and a small set of control variables only.

According to inventory theory, firm inventory decisions should be a function of order quantities (*Q*) and safety stock (*SS*) (see also *Figure 10*). The specific magnitude of end-of-period inventories will then also be a function of sales realization $\left(S_t\right)$. In addition, it is argued in this essay that a firm's distress and power will affect firm inventories. Dummy variables to account for inventory accounting differences (LIFO, AvgCost[54]) are included as well (Carpenter et al. 1994, Gertler and Gilchrist 1994, Kashyap et al. 1994, Roumiantsev and Netessine 2007). This yields the following inventory model:

(1) $Inv = f\left(Q, SS, S_t, Distress, Power, LIFO, AvgCost\right)$.

As seen in Chapter 3.2.2, the order quantity *Q* is a function of expected sales ($\hat{S}_t$), order costs (*A*), backorder costs (*B*) and holding costs (*H*):

(2) $Q = f\left(\hat{S}_t, A, B, H\right)$.

Similarly, safety stocks are shown to be a function of lead times (*L*), sales ($\hat{S}_t$), sales variability (σ_S), and the safety factor *k* which, in turn, is a function of the optimal stockout probability $\left(P^*\left(M > r\right) = \dfrac{HQ}{B\hat{S}_t}\right)$ (see Chapter 3.2.2). Safety stocks can, thus, be represented as follows:

(3) $SS = f\left(L, \sigma_S, H, B, \hat{S}_t\right)$.

The author is unaware of prior empirical inventory research that measured order and backorder costs. For lack of suitable proxy measures, it is common practice to exclude order and backorder costs from empirical inventory analyses (see e.g. Lieberman et al.

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[54] Further detail is provided in Section 3.4.3.2.

1999, Roumiantsev and Netessine 2007). While an attempt is made to approximate order/setup costs (see section 3.4.3.2), backorder costs are not further considered in this research. Holding costs are a function of the cost of the item that is purchased or produced and the holding cost rate. Unit cost measures are not readily available due to a lack of output indicators. Total costs of goods sold, however, are highly correlated with sales, and are therefore not included in the regression model. A proxy for a firm's capital carrying charge will be used to approximate holding costs. Substituting *Equations (2),* and *(3)* in *Equation (1)* and dropping the above mentioned variables, *Equation (1)* can be rewritten as follows:

(4) $$Inv = f\left(S_t, \hat{S}_t, \sigma_S, A, H, L, Distress, Power, LIFO, AvgCost\right).$$

Expected sales ($\hat{S}_t$) and realized sales (S_t) are naturally highly correlated with $S_t = \hat{S}_t + \varepsilon_t^S$, where ε_t^S is the forecast error. To avoid excessive multicollinearity[55], *Equation (4)* is therefore restated as follows:

(5) $$Inv = f\left(\hat{S}, \varepsilon_S, \sigma_S, A, H, L, Distress, Power, LIFO, AvgCost\right).$$

The resulting basic empirical estimation equation is defined in *Equation (6)* below:

(6) $$\begin{aligned} Inventory_{itf} = {} & \beta_0 + \beta_1\, SalesForecast_{itf} + \beta_2\, ForecastError_{itf} + \beta_3\, SalesVariability_{itf} \\ & + \beta_4\, SetupCost_{itf} + \beta_5\, HoldingCost_{itf} + \beta_6\, LeadTime_{itf} + \beta_7\, Distress_{itf} \\ & + \beta_8\, Power_{itf} + \beta_9\, LIFO_{itf} + \beta_{10}\, AvgCost_{itf} + \beta_{11}\, Distress_{itf} * Power_{itf} + \varepsilon_{itf} \end{aligned}$$

The subscripts *i*, *t*, and *f* designate the industry, time period, and firm respectively.

[55] Not only are actual and expected sales highly correlated, but actual sales and the standard deviation of sales are correlated as well.

Inventory$_{itf}$, for example, indicates firm *f*'s inventory level in time period *t*, where firm *f* operates in industry *i*. The interaction term (*Distress*$_{itf}$ * *Power*$_{itf}$) is included to test *Hypothesis 1 Hypothesis 12*, *Hypothesis 13*, and *Hypothesis 14*.

This inventory model specification differs from prior specifications on multiple accounts: First, the model presented here controls for important predictors of firm inventories as prescribed by inventory theory. The author is aware of only one study that controlled for sales variability and lead times (Roumiantsev and Netessine 2007). The latter study, however, does not investigate the effect of financial distress on inventories, nor does it consider the role of firm power in inventory management. Second, measures of a firm's buying power and selling power are included. While few prior studies analyzed the impact of market power on inventories (Amihud and Mendelson 1989, Blazenko and Vandezande 2003), this is the first study to differentiate between power over buyers and power over suppliers. In addition, a more comprehensive measure of financial distress is proposed. Prior research relied on one-dimensional measures such as market interest rates or firm cash flows to estimate holding costs or a firm's financial situation. Market interest rates, however, are poor approximations of holding costs (or firm financial condition, for that matter), as such measures do not account for the heterogeneity of firms' borrowing rates. Measures such as cash flows, in turn, may not comprehensively evaluate firm financial condition. Consequently, this is—to the best of the author's knowledge—the first study to investigate the effects of firm financial distress on inventories from an inventory theory and supply chain management perspective.

3.4.3. Variables and Measurement

Variable measurement has been a major challenge in inventory research and probably is the most important reason for the scarcity of empirical inventory studies. The measures used in this research are in part based on the work of Roumiantsev and Netessine (2007) and Carpenter et al (1994). The dependent and independent variables are discussed in turn.

3.4.3.1. Dependent variable

The dependent variable in this study is firm-level inventory, i.e. firm *f*'s inventory in period *t*. Specifically, three distinct firm inventory measures are used: total inventory, raw materials inventory, and finished goods inventory[56]. Several researchers have previously used these inventory variables in empirical analyses (e.g. Blazenko and Vandezande 2003, Guariglia 1999). In line with prior research, absolute inventory values are used (see e.g. Roumiantsev and Netessine 2007). Total inventories of firm *f* (which is affiliated with industry *i*) in time period *t* are denoted $TotalInv_{itf}$ and are measured in U.S. dollars as reported on the balance sheet (see e.g. Amihud and Mendelson 1989)[57]. Analogously, raw materials inventories and finished goods inventories are denoted $RawMatInv_{itf}$ and $FinGoodsInv_{itf}$, respectively.

[56] Work-in-process inventories are reported by few firms only and are therefore not analyzed separately.
[57] Roumiantsev and Netessine (2007) note that it is generally not necessary to adjust dollar values in time series data since inflation has been at very low levels in the United States over the past decade.

All inventory data are obtained from Standard & Poor's Compustat database. Only, firms with at least $5,000 worth of (total) inventory are included in the dataset to ascertain that only inventory-carrying firms are analyzed. The regression analyses are performed with all three inventory measures.

3.4.3.2. Independent variables

The set of independent variables is discussed next. Variables suggested by inventory theory are discussed first, followed by a review of the measures of firm power. Unless otherwise stated, all data are obtained from Standard & Poor's Compustat database.

- *SalesForecast*$_{itf}$

  Inventory ordering decisions are made based on expected demand. For each firm and time period, annual sales are forecast as follows: $\hat{S}_t = S_{t-1} \cdot \left(1+\bar{g}/2\right)$, where the average growth rate over the past two years $\left(\bar{g}\right)$ is defined as $\bar{g} = \dfrac{\left(S_{t-2}-S_{t-3}\right)/S_{t-3}+\left(S_{t-1}-S_{t-2}\right)/S_{t-2}}{2}$. When only incomplete prior sales data are available or prior sales were impacted by merger and acquisition (M&A) activity, the average growth rate equals the growth rate for the years for which data are available and no M&A activity was observed.

- *SalesSurprise*$_{itf}$

  While firms make inventory decisions based on *expected* demand, the magnitude of inventories at the end of the year is impacted by *actual* demand. If actual demand exceeds expected demand, year-end inventory levels should be lower. Conversely, lower than expected sales should result in larger year-end inventories. The *SalesSurprise* variable provides some control for the difference between expected demand (*SalesForecast*) and realized demand. Following the procedure suggested by Roumiantsev and Netessine (2007), a binary variable is created. Specifically, this variable equals “1” if actual demand is greater than expected demand and is “0”otherwise.

- $SalesVariability_{itf}$

  SalesVariability is measured as the coefficient of variation of sales and is a proxy for demand variability. The more variable firm demand, the more inventory a firm will hold, *ceteris paribus*. While sales may not be equal to actual demand in case of stockouts, demand variability is approximated with sales variability. The coefficient of variation of sales is computed as the ratio of the standard deviation of sales over the past three periods and the mean of sales over the past three periods: $CVS_{itf} = \frac{\sigma_{Sales\ i(t-1,t-2,t-3)f}}{\mu_{Sales\ i(t-1,t-2,t-3)f}}$. The *SalesVariability* variable thus is a standardized measure of the variability of sales.

- $SetupCost_{itf}$

  Information on firms’ average cost of setting up production or placing orders is not readily available. The magnitude of setup costs may, however, be reflected in the magnitude of firms’ order backlogs. Clearly, there are many reasons why firms backlog orders: high demand, long lead times, or manufacturing problems are just a few potential causes of order backlogs. *On average*, however, larger backlogs may simply reflect higher order setup costs: Firms may prefer to accumulate orders before starting production if the cost of setting up production is high. Since the absolute value of backlogged orders is likely highly correlated with sales, the standardized value of order backlogs is used as a proxy for production setup costs:

$$SetupCost_{itf} = \frac{OrderBacklog_{itf}}{Sales_{itf}}.$$

- $HoldingCost_{itf}$

Inventory holding costs consist of warehousing/handling costs and capital carrying costs (Timme 2003). While the former component cannot be estimated based on available accounting information, the latter can be approximated as follows: The capital cost of holding inventory is a function of the capital interest rate which represents either the opportunity cost of internally financed (inventory) investments or the borrowing cost of externally financed (inventory) investments. The firm-specific interest rate is approximated by dividing the firm's interest expenses by total debts: $HoldingCost_{itf} = \frac{InterestExpenses_{itf}}{TotalDebt_{itf}}$.

- $LeadTime_{itf}$

The measure of lead times follows the novel procedure suggested by Roumiantsev and Netessine (2007). Roumiantsev and Netessine propose the following measure:

$LeadTime_{itf} = \frac{365 \cdot AP_{itf}}{COGS_{itf}}$ where AP_{itf} stands for *Accounts Payable* and $COGS_{itf}$

stands for the *Cost of Goods Sold*. While not a measure of physical lead times, this proxy captures the quarterly cash conversion cycle which may, to some extent reflect physical shipment times. Roumiantsev and Netessine (2007) further justify the use of this measure as follows:

"[A]ccounts payable are credited, then [the] product is shipped and is typically debited, then it is received and [payment is made]. Hence, financial transactions are correlated with times of shipment and delivery of inputs and therefore are correlated with the lag a company has to respond to changing market environment by adjusting inventories." (p.13).

Roumiantsev and Netessine (2007) empirically verify "that the lead time proxy is not dominated by standard payment terms (e.g. 30 or 60 days)" (p.14), and that lead times are not merely a function of firm power (as measured by the firm's market share)[58]. In the data sets used here, the correlation coefficients between *LeadTime* and the firm power measures are small and negative ($r_{LeadTime-MarketShare} = -0.06$ and $r_{LeadTime-IndSalesNet} = -0.08$; see *Table 10*), suggesting that more powerful firms tend to have shorter permissible payment delays. It may also be argued that longer payment lead times result from a distressed firm's inability to pay suppliers (implying inflated accounts payable). The correlation coefficients between *LeadTime* and *Distress* are positive and statistically significant in both data sets, although limited in magnitude ($r \leq 0.19$; see *Table 10*). This suggests that the lead time proxy used here may indeed be a function of, amongst other factors, financial distress. Given the lack of suitable alternative lead time proxies and the limited size of the distress-lead time correlation, the *LeadTime* proxy is included in the subsequent analyses. The lead time proxy yields the expected positive sign in Roumiantsev and Netessine's (2007) analyses of firm inventories.

- $Distress_{itf}$

  Distress is a measure of firm *f*'s financial distress. The *Distress* variable is the negative value of a firm's Z score, a measure which was first developed by Altman

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[58] Firms with greater levels of power may be able to squeeze their suppliers and obtain longer permissible payment delays, thus increasing accounts payable.

(1968). Based on discriminant analysis, Altman (1968) developed the following model to estimate a firm's financial fitness:

$$Z = 0.012 * X_1 + 0.014 * X_2 + 0.033 * X_3 + 0.006 * X_4 + 0.999 * X_5,$$

where X_1 = working capital / total assets, X_2 = retained earnings / total assets, X_3 = Earnings Before Interests and Taxes (EBIT) / total assets, X_4 = market value of equity / total liabilities, and X_5 = sales / total assets. The information needed to compute the Z scores is included in the firms' balance sheets and profit and loss statements. These data, as well as stock market data are obtained from Standard & Poor's Compustat database. High Z scores indicate financial health, while low and negative scores indicate (serious) financial distress. Specifically, a score of 2.67 or above indicates financial health, and a score of 1.81 or below suggests (severe) financial distress (Altman 2002). The Z scores are then rescaled to indicate the level of financial distress, i.e. $Distress_{itf} = (-1) \cdot ZScore$, such that higher (positive) *Distress* scores indicate greater financial distress (see also Ferrier et al. 2002). The *Distress* variable is included to test the effect of firm financial distress on inventories as hypothesized in *Hypothesis 8*.

- $DistressDummy_{itf}$

While *Distress* is a continuous variable, *DistressDummy* is a binary variable which indicates whether a carrier is considered financially distressed. Firms are categorized as distressed and non-distressed based on the above-mentioned cutoff levels suggested by Altman (1968). Specifically, firms with Z scores of less than 1.81 (i.e. *Distress* scores of greater than -1.81) are considered financially distressed (*DistressDummy* equals "1"). The sensitivity of the results with respect to the definition of this cutoff value is investigated in Section 3.5. The *DistressDummy* variable is used to investigate if distressed firms, on average, hold less inventory (*Hypothesis 8*), and to split the data samples into distressed and non-distressed firms (see Chapter 3.4.6 for further detail).

This study adds to prior research by investigating the effects of firm buying and selling power on inventories and on the distress-inventory relationship. In the past, researchers have used relatively simple measures of firm power and have ignored the inherently dyadic nature of power (Cox 2001, Cox et al. 2001). Amihud and Mendelson (1989), for example approximate firm power with either the firm's market share or the firm's gross profit margin. Blazenko and Vandezande (2003), in turn, use a market concentration measure to approximate the average level of power firms possess in a particular industry. These measures may not fully capture inter-firm power balances. Unlike prior research, this study uses a set of firm power measures which proxy not only the focal firm's power, but also the power levels in the supplying and buying industries. Since a focal firm's specific supply chain transaction partners (i.e. buyers and suppliers) cannot be identified using accounting data, buyer and supplier industry characteristics are used as proxies of buyer and supplier power. The measures of focal firm, supplier industry and buyer industry power are presented below.

- $IndustrySalesNet_{itf}$

  Many prior studies have used market shares $\left(MarketShare = \frac{FirmSales}{IndustrySales} \right)$ to approximate a firm's power (e.g. Amihud and Mendelson 1989). The regression model established in Section 3.4.2, however, already contains the *SalesForecast* variable and thus controls for the magnitude of firm sales. Including market shares in the regression model would thus entail two potential problems: First, multicollinearity problems may arise given the high correlation between sales forecasts and market shares, thus resulting in inefficient estimates. Second, and perhaps more importantly, the market share variable might then pick up a size effect (larger firms hold more inventory) rather than the firm power effect it is intended to measure. This issue is addressed by transforming the market share variable. Since firm sales are already controlled for by means of the *SalesForecast* variable, the size of the firm's competitors may indicate the level of power a firm exerts in a market. Specifically, the *IndustrySalesNet* variable indicates the sales volume (measured in U.S. $) of all the other firms in the market (excluding the focal firm). To simplify the interpretation of the coefficient estimates, the industry sales volume (net of firm sales) is inverted so as to represent a proxy measure of a firm's power:

$IndustrySalesNet_{itf} = \dfrac{1}{\left(IndustrySales_{it} - FirmSales_{itf}\right)}$. This variable thus indicates the effect of an increase (decrease) in the sales volume of a firm's competitors on the firm's inventory holdings *after controlling for firm sales* (~ *SalesForecast*). Specifically, a positive coefficient estimate of the *IndustrySalesNet* variable would suggest the following: The smaller the firm's competitors, i.e. the more powerful the focal firm, the more inventory the (focal) firm will hold. Conversely, a negative coefficient would confirm the expectation expressed in *Hypothesis 9*: More powerful firms, on average, hold less inventory.

For the empirical analyses, industries are defined at the six-digit NAICS level. While some researchers have computed market shares at the four-digit NAICS level

(Amihud and Mendelson 1989), it is believed that the more fine-grained six-digit NAICS industry data are better suited for the purpose of the analyses. The sensitivity of the empirical results with respect to the granularity of industry definitions will be investigated in Section 3.5. Industry sales data are obtained from the website of the Bureau of Economic Analysis (BEA). These data include the values of exports by U.S. firms, but do not include imports from foreign firms.

- $IndCR4_{it}$

  Researchers in the industrial organization economics area have suggested that the level of market concentration is an indicator of the competitiveness of markets (e.g. Ravenscraft 1983). Specifically, firms in more concentrated markets are believed to be more powerful since there are fewer competitors and collusion between firms is easier to achieve (Waldman and Jensen 2001). While Blazenko and Vandezande (2003) use two-firm concentration ratios (i.e. the sum of sales of the two largest firms divided by total sales in the industry) as a measure of market concentration, the Bureau of Economic Analysis (BEA) publishes 4, 8, 20, and 50 firm industry concentration ratios. Given its widespread use in the extant literature (see e.g. Pryor 2001, Ravenscraft 1983), the four-firm concentration ratio (CR4) is used here. Holding all else constant, greater values of the four-firm concentration ratio imply greater firm power. *IndCR4* thus is one of the measures of firm power used to test *Hypothesis 9* to *Hypothesis 14* in the analysis of the second data set (part II) in which generic industrial supply chains are constructed.

  As with *IndustrySales*, industry concentration is measured at the six-digit NAICS level. Industry concentration data are provided by the Bureau of Economic Analyses and are available in Economic Census years only. The *IndCR4* measure is therefore included in the second data set (part II) only.

- $SupplyCR4_{(i-1)t}$

  Analogous to the *IndCR4* measure, *SupplyCR4* is an indicator of the weighted average concentration levels of those industries that sell to a focal industry. The Input-Output Tables published by the Bureau of Economic Analysis, illustrate the flow of goods (and services) between industries. Specifically, the I-O Tables not only identify those industries that sell goods to another industry, but also indicate the value of the respective transactions. As a result, the relative importance of supplying industries to a focal industry can be evaluated and the weighted average four-firm concentration ratio of the supplying industries can be computed (*SupplyCR4*) as illustrated in *Figure 13* below. As discussed in Section 3.4.1, this study focuses on inventory-carrying industries. The average supplying industry concentration measures, therefore, are based on the four-firm concentration ratios of manufacturing, wholesale and retail trade industries only. Other (e.g. service) industries are not considered in the computation of the *SupplyCR4* measures. Moreover, only domestic suppliers are considered when computing the supplying industry concentration ratio; imports from foreign suppliers are not included.

  Holding all else constant, an increase in the *SupplyCR4* measure, suggests a relative decrease in the focal industry's (and focal firm's) power. This variable is thus used to test *Hypothesis 10* and *Hypothesis 13*.

- $BuyCR4_{(i+1)t}$

  Symmetrical to the *SupplyCR4* measure, the *BuyCR4* measure is the weighted average of the four-firm concentration ratios of a focal industry's buying industries (see *Figure 13*). Holding all else constant, an increase in the *BuyCR4* measure, suggests a relative decrease in the focal industry's (and focal firm's) power. This variable is thus used to test *Hypothesis 11* and *Hypothesis 14*.

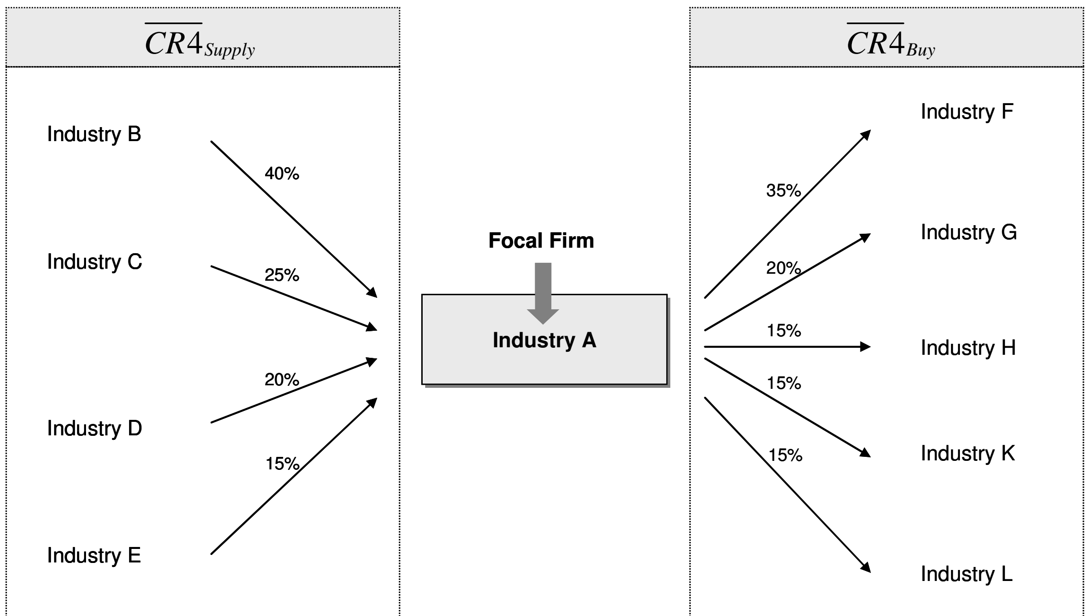

Figure 13: Illustration of the construction of industrial supply chains

There are three widely used methods of inventory accounting: The First In, First Out (FIFO) method values inventories assuming that items are sold out of inventory in the same order they were inventoried. Hence, the cost of the most recently added items determines the value of end-of-period inventories. The Last In, First Out (LIFO) method values inventories assuming that the most recently inventoried items are sold first. Consequently, at the end of the accounting period, the oldest items are left over in inventory. The Average Cost method values inventories at the weighted average cost of all units available for sale during the accounting period. As prices typically change over time, each inventory accounting method results in different inventory valuations at the end of the accounting period. Specifically, with generally increasing prices, the use of the LIFO method will understate the true value of inventories, whereas the FIFO method more appropriately reflects the value of ending inventories. The average cost procedure results in inventory values that lie between LIFO and FIFO. To account for these differences, it is common practice to include an indicator variable which identifies those firms that use one of the "extreme" accounting methods. Following the example of prior research (e.g. Blazenko and Vandezande 2003), two binary variables are included in the model to account for differences in inventory accounting methods:

- $LIFO_{itf}$

  This indicator variable equals "1" if the firm uses LIFO as the primary inventory accounting method and equals "0" otherwise (see also Roumiantsev and Netessine 2007).

- $AvgCost_{itf}$

  This indicator variable equals "1" if the firm uses the average cost method as the primary inventory accounting method and equals "0" otherwise. (see also Roumiantsev and Netessine 2007)

3.4.4. Data sources

All firm-level data are obtained from the Compustat database which is maintained by Standard & Poor's. This database includes accounting information on publicly traded firms. While the focus on public companies excludes smaller, not publicly traded firms from the analyses, this selection also ensures that all reported operating and financial data conform to Generally Accepted Accounting Principles (GAAP) (Roumiantsev and Netessine 2007). The Compustat database contains firm specific accounting data which are commonly found in balance sheets and profit and loss statements, including all the information that is required to construct the firm-specific variables.

Industry level data, most notably industry sales, are obtained from the Bureau of Economic Analysis. Specifically, the BEA provides annual estimates of total industry shipments (in U.S. dollars) for U.S. manufacturing industries. At the time of writing, data were available for the time period from 1998 to 2004[59]. As noted above, the availability of these data thereby defines the timeframe studied in the first part of the data analysis.

Industry level data for the year 1997 were obtained from the U.S. Census Bureau. This agency's website provides access to detailed industry statistics collected through the Economic Census survey (1997). Total industry sales and industry concentration ratios were collected from the Economic Census website.

The information relating focal firms to buying and supplying industries is found in the Input-Output Tables, which are also published by the Bureau of Economic Analysis. The data in these tables summarize the trade flows between industries. Specifically, the "Use" tables indicate from which industries firms in a particular industry purchased goods and

[59] These data are found in the file "GDPbyInd_SHIP_NAICS.xls" available on the BEA website.

services and indicate the respective dollar volumes such that the relative importance of supplying industries can be evaluated. Conversely, the I-O Tables also identify the industries that purchase from firms in a focal industry, and the relative importance of buying industries in terms of the shares of total focal industry sales can be inferred.

The major limitation of using I-O Tables is that these tables focus on U.S. domestic firms only and disregard foreign buyers and suppliers. As a consequence, the industry power proxies used here (concentration ratios) may overstate the true power levels in these industries, particularly when foreign firms hold significant market shares in these industries. By the same token, industry sales data do not include imports from foreign firms. This may result in incorrect estimates of the true size of industries and of firms' market shares. It is believed, however, that the I-O Tables provide at least reasonable estimates of industry characteristics for the purpose of inter-industry comparisons.

3.4.5. Descriptive statistics

This section provides descriptions of the data samples used in this research. Both data sets (Part I and Part II) are discussed in turn.

3.4.5.1. Descriptive statistics: Part I

As discussed in Section 3.4.1, data from U.S. manufacturing industries (NAICS 3xxxxx) for the time period from 1998 to 2004 are used for the empirical analyses. All manufacturing firms for which information on all relevant variables were available for any or all years in the 1998-2004 time period were included in the data set. The firm observations in this data set represent about 8.5% of total sales and 9.9% of total inventory holdings by all publicly traded U.S. manufacturing firms that are included in the Compustat database.

A two-sample Hotelling T-squared test is implemented to evaluate to what extent the firms included in this data set differ from those firms for which data are available in Compustat but which are not included in the analyses due to missing data on one or more variables. Specifically, the Hotelling test compares these two groups on the following variables: Total inventories, sales, cost of goods sold, total assets and total debt. The test yields a test statistic of 2.89. This statistic follows an F distribution and, thus, is statistically significant at the five percent level. This result suggests that the data sample used for the empirical analysis differs significantly from the population of firms included in the Compustat database. Upon closer examination of the data, it becomes apparent that, on average, the sample firms tend to be smaller (in terms of inventories, sales, costs, assets, and debt) than those firms that are not included in the data sample (see Appendix 6). The results of the analyses presented here may, therefore, not be generalizable to firms of all size classes.

The composition of the final data set is shown in *Table 7*. About forty percent of all firm observations are in the computer and electronics industry. The second largest industry in this data set is the machinery industry with 852 observations or about sixteen percent of all observations. While the remainder of the data set comprises firms from a broad array of manufacturing industries, it cannot be ascertained that the empirical results of this study will be generalizable to all manufacturing industries, given the dominance of the computer and electronics, and machinery industries[60].

NAICS	Industry	N	%
334	Computer and electronics	1983	37.9%
333	Machinery	852	16.3%
336	Transportation equipment	341	6.5%
339	Miscellaneous	275	5.3%
335	Electrical equipment	273	5.2%
332	Fabricated metal	252	4.8%
325	Chemical	203	3.9%
315	Apparel	187	3.6%
331	Primary metal	159	3.0%
316	Leather	137	2.6%
326	Plastics and rubber	136	2.6%
337	Furniture	111	2.1%
313	Textile mills	78	1.5%
327	Nonmetallic mineral	69	1.3%
323	Printing	57	1.1%
321	Wood	44	0.8%
322	Paper	36	0.7%
311	Food	26	0.5%
314	Textile products	11	0.2%
312	Beverage and tobacco	6	0.1%
Total		5236	100%

Table 7: Sample composition (Part I)

Table 8 presents the descriptive statistics of this sample. It is noted that raw materials and finished goods data were not available for all firms. Hence, the sample size is smaller for these particular variables. There is substantial variability in all variables. In some instances, however, the standard deviations are larger than the means suggesting skewness in the data. Consequently, all inventory variables, as well as *SalesForecasts*

[60] In future research, within-industry analyses could be performed.

and *DaysPayable* (*LeadTime*) are log-transformed prior to the empirical estimation. It is also noted that, on average, sales forecasts closely approximate actual sales and that about 27 percent of all observations are for financially distressed firms.

Variable	Mean	Std. dev.	Min	Max	N
Inventory Total (million $)	103.9	483.36	0.005	12,207	5236
Inventory RawMat (million $)	24.17	78.74	0.002	1,802	4505
Inventory FinGood (milion $)	43.98	249.23	0.001	7,319	4307
Sales (million $)	835.6	5,164.7	0.05	155,974	5236
Sales Forecast (million $)	847.2	5,149.6	0.01	158,827	5236
SalesSurprise	0.49	0.5	0	1	5236
Coeff. of Variation of Sales	0.20	0.19	0.001	1.73	5236
OrderBacklog/Sales	0.32	1.43	0	90.34	5236
Interest Rate	0.18	0.28	0	1	5236
Days Payable	49.69	50.57	1.32	1,248	5236
Distress	-3.79	13.90	-333.2	220.9	5236
Distress Dummy	0.27	0.45	0	1	5236
Market Share (6 dig. NAICS)	0.07	0.18	0.000001	1	5236
LIFO	0.14	0.35	0	1	5236
AvgCost	0.09	0.28	0	1	5236

Table 8: Pooled descriptive statistics (Part I)

Table 9 presents the descriptive statistics for distressed and non-distressed firms separately. The most striking differences are found in raw materials inventories and days payable outstanding. Specifically, distressed firms appear to hold less raw materials inventory and have larger accounts payable than non-distressed firms. The latter observation can likely be attributed to distressed firms' lower ability to pay. The former observation, however, is interesting and lends some support for the contention that distressed firms try to reduce inventories[61]. This is most easily done with raw materials inventories since extant stock can be reduced by consuming materials while not placing any new raw materials orders.

	Non-distressed firms					***Distressed firms***				
Variable	**Mean**	**Std. dev.**	**Min**	**Max**	**N**	**Mean**	**Std. dev.**	**Min**	**Max**	**N**
Inventory Total (million $)	104.8	388.85	0.011	8,349	3804	101.5	672.94	0.005	12,207	1432
Inventory RawMat (million $)	27.32	85.02	0.005	1,802	3278	15.76	57.99	0.002	993	1227
Inventory FinGood (milion $)	42.44	142.07	0.001	2,209	3180	48.35	424.88	0.001	7,319	1127
Sales (million $)	829.4	3,340.5	0.05	58,198	3804	851.8	8,241.6	0.05	155,974	1432
Sales Forecast (million $)	836.8	3,380.2	0.09	68,849	3804	875.0	8,163.7	0.01	158,827	1432
SalesSurprise	0.51	0.5	0	1	3804	0.42	0.5	0	1	1432
Coeff. of Variation of Sales	0.18	0.16	0.001	1.73	3804	0.25	0.23	0.002	1.73	1432
OrderBacklog/Sales	0.30	0.75	0	34.0	3804	0.40	2.46	0	90.34	1432
Interest Rate	0.18	0.30	0	1	3804	0.15	0.22	0	1	1432
Days Payable	41.74	27.02	1.78	630	3804	70.82	82.46	1.32	1,248	1432
Distress	-6.57	11.82	-333.2	-1.8	3804	3.60	16.14	-1.8	220.9	1432
Market Share (6 dig. NAICS)	0.08	0.19	0.000001	1	3804	0.04	0.12	0.000002	1	1432
LIFO	0.15	0.36	0	1	3804	0.11	0.31	0	1	1432
AvgCost	0.08	0.28	0	1	3804	0.10	0.30	0	1	1432

Table 9: Descriptive statistics (Part I) – distressed vs. non-distressed firms

A two-sample Hotelling T-squared test is performed to assess whether distressed firms are statistically significantly different from non-distressed firms based on the variables listed in *Table 9*. The test yields a test statistic of F = 58.23 which is statistically significant at the one percent level, indicating that distressed firms, on average, differ from non-distressed firms.

[61] An alternative explanation may be that suppliers are reluctant to sell to distressed firms, especially when the latter purchase on credit.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1 Inventory Total (million $)															
2 Inventory RawMat (million $)	**0.89**														
3 Inventory FinGood (million $)	**0.91**	**0.74**													
4 Sales (million $)	**0.94**	**0.85**	**0.87**												
5 Sales Forecast (million $)	**0.92**	**0.83**	**0.85**	**0.98**											
6 Sales Surprise	**0.06**	**0.05**	**0.04**	**0.08**	**-0.06**										
7 Coeff. of Variation of Sales	**-0.25**	**-0.19**	**-0.24**	**-0.25**	**-0.23**	**-0.06**									
8 OrderBacklog/Sales	-0.03	**-0.05**	**-0.05**	**-0.06**	**-0.05**	-0.01	**0.06**								
9 Interest Rate	**-0.11**	**-0.12**	**-0.11**	**-0.10**	**-0.11**	0.00	**0.05**	**0.03**							
10 Days Payable	**-0.14**	**-0.09**	**-0.10**	**-0.17**	**-0.17**	0.03	**0.21**	0.01	-0.02						
11 Distress	**-0.14**	**-0.10**	**-0.07**	**-0.15**	**-0.14**	**-0.05**	**0.04**	-0.01	-0.02	**0.19**					
12 Distress Dummy	**-0.26**	**-0.23**	**-0.21**	**-0.28**	**-0.26**	**-0.08**	**0.17**	**0.03**	**-0.05**	**0.28**	**0.33**				
13 Market Share (6 dig. NAICS)	**0.53**	**0.45**	**0.51**	**0.54**	**0.53**	**0.05**	**-0.12**	0.00	**-0.04**	**-0.06**	-0.02	**-0.11**			
14 Net Industry Sales (inverted)	**0.22**	**0.20**	**0.22**	**0.22**	**0.21**	0.01	**-0.10**	0.00	**-0.03**	**-0.08**	**0.03**	**-0.07**	**0.75**		
15 LIFO	**0.29**	**0.24**	**0.29**	**0.29**	**0.29**	0.00	**-0.18**	**-0.03**	**-0.04**	**-0.15**	0.01	**-0.06**	**0.15**	**0.09**	
16 AvgCost	0.01	-0.03	0.00	0.01	0.00	0.00	0.00	0.01	0.02	0.02	-0.01	0.02	0.01	**-0.03**	**-0.12**

(Values in bold are significant at the 5% level)

Table 10: Pairwise correlations (Part I)

Pairwise correlations are displayed in *Table 10*. Several observations are worth noting:

- As expected, all size variables (inventories, sales, forecasts) are highly and positively correlated. Market shares are also highly correlated with sales and forecasts (as discussed previously in Section 3.4.3.2), with correlation coefficients of up to 0.54. While *NetIndustrySales* (inverted) are also significantly and positively correlated with the size variables, the correlation coefficients are much smaller in magnitude (about 0.20 to 0.22).
- The correlation coefficient of 0.98 between actual and forecasted sales is an indication of the good quality of the sales forecasts.
- In line with the hypotheses presented here, the *Distress* variable is negatively correlated with the inventory variables. There are, however, no excessive correlations between the distress measures and other independent variables.

3.4.5.2. Descriptive statistics: Part II

The second data set (Part II) differs from the first data set (Part I) in that it comprises observations from a cross-section of U.S. manufacturing firms for the year 1997 only. The firm observations in this data set represent about 10.7% of total sales and 12.4% of total inventory holdings by all publicly traded U.S. manufacturing firms that are included in the Compustat database.

A two-sample Hotelling T-squared test is implemented to investigate potential differences between those firms that are included in the data sample and those firms that are not included in the empirical analyses due to missing data. The Hotelling test compares these two groups on the following variables: Total inventories, sales, cost of goods sold, total assets and total debt. The implementation of this test yields a test statistic of 4.15 which is statistically significant at the one percent level. On average, the sampled firms tend to be smaller (in terms of inventories, sales, costs, assets, and debt) than those firms that are not included in the data sample (see Appendix 6). It is therefore noted that the results of the analyses presented here may not be generalizable to firms of all size classes.

The composition of the second data set is very similar to that of the first data set: 446 out of 755 observations are from firms in the computer and electronics, and machinery industries (see *Table 11*). The remainder of the data sample comprises observations of firms from broad variety of U.S. manufacturing industries.

NAICS	Industry	N	%
334	Computer and electronics	291	38.5%
333	Machinery	155	20.5%
335	Electrical equipment	48	6.4%
339	Miscellaneous	47	6.2%
336	Transportation equipment	46	6.1%
332	Fabricated metal	34	4.5%
331	Primary metal	28	3.7%
337	Furniture	21	2.8%
313	Textile mills	16	2.1%
327	Nonmetallic mineral	14	1.9%
325	Chemical	14	1.9%
321	Wood	11	1.5%
323	Printing	8	1.1%
322	Paper	6	0.8%
311	Food	5	0.7%
316	Leather	3	0.4%
326	Plastics and rubber	3	0.4%
315	Apparel	3	0.4%
314	Textile products	2	0.3%
Total		755	100%

Table 11: Sample composition (Part II)

Table 12 presents the descriptive statistics of this sample. The conclusions that can be drawn upon observing these statistics are consistent with what was noted about the first data set. There is substantial variability in all variables. The inventory variables, *SalesForecasts* and *DaysPayable* (*LeadTime*), however, have particularly large standard deviations relative to the means and are log-transformed. It is further noted that the sales forecasts are, on average, substantially larger than actual sales. This result is driven by a relatively small set of observations for which the particular forecasting technique employed[62] here resulted in substantial overpredictions. The log-transformation of the *SalesForecast* variable deemphasizes the impact these outliers have on the regression

[62] Forecasts were calculated based on prior year sales which were progressed using the average sales growth rate over the previous three years (see Section 3.4.3.2 for more detail).

estimates, such that the inferior quality of the sales forecasts is not a great concern[63].

Compared to the first data set, this data sample also contains three new variables: *IndCR4*, *SupplyCR4*, *BuyCR4*. The data in *Table 12* indicate that, on average, the four largest firms in the focal, supplying and buying industries control between 29 and 38 percent of the market.

Variable	Mean	Std. dev.	Min	Max	N
Inventory Total (million $)	110.9	623.42	0.036	12,102	755
Inventory RawMat (million $)	20.92	51.38	0	728	678
Inventory FinGood (milion $)	39.02	296.35	0	7,347	656
Sales (million $)	835.2	6,161.3	0.44	154,329	755
Sales Forecast (million $)	1412.4	17,899.8	0.02	465,806	753
SalesSurprise	0.51	0.5	0	1	755
Coeff. of Variation of Sales	0.23	0.22	0.005	1.72	755
OrderBacklog/Sales	0.38	1.42	0	36.99	755
Interest Rate	0.16	0.58	0	11.33	755
Days Payable	38.26	41.79	2.67	736	755
Distress	-4.80	9.62	-114.4	50.5	755
Distress Dummy	0.18	0.39	0	1	755
Market Share (6 dig. NAICS)	0.05	0.13	0.00002	1	755
IndCR4	37.74	16.37	4.6	94.5	755
SupplyCR4	28.96	6.71	14.8	83.2	755
BuyCR4	37.38	15.08	6.8	86.9	755
LIFO	0.16	0.36	0	1	755
AvgCost	0.08	0.27	0	1	755

Table 12: Pooled descriptive statistics (Part II)

[63] The correlation coefficient between (logged) Sales and (logged) *SalesForecasts* is r = 0.97 (see *Table 36*).

Table 13 presents the split-sample comparison between distressed and non-distressed firms. In this sample, distressed firms appear to be larger than non-distressed firms and therefore tend to hold more inventory. At the same time, distressed firms, on average, have smaller market shares than non-distressed firms. This may be an indication that the distressed firms tend to be concentrated in some (larger) industry sectors.

The result of a two-sample Hotelling T-squared test suggests that, overall, distressed firms are statistically significantly different from non-distressed firms. The test statistic is F = 8.0767 which is statistically significant at the one percent level.

	Non-distressed firms					*Distressed firms*				
Variable	**Mean**	**Std. dev.**	**Min**	**Max**	**N**	**Mean**	**Std. dev.**	**Min**	**Max**	**N**
Inventory Total (million $)	101.0	442.36	0.044	8,967	617	155.0	1121.07	0.036	12,102	138
Inventory RawMat (million $)	22.26	50.21	0	728	561	14.49	56.45	0	509	117
Inventory FinGood (milion $)	31.41	84.39	0	1,078	544	76.01	694.06	0	7,347	112
Sales (million $)	712.7	2,790.0	1.52	45,800	617	1382.9	13,174.0	0.44	154,329	138
Sales Forecast (million $)	1425.7	18,863.6	0.11	465,806	617	1351.9	12,692.2	0.02	147,672	136
SalesSurprise	0.53	0.5	0	1	617	0.42	0.5	0	1	138
Coeff. of Variation of Sales	0.22	0.21	0.005	1.46	617	0.26	0.27	0.01	1.72	138
OrderBacklog/Sales	0.33	0.48	0	5.86	617	0.59	3.17	0	36.99	138
Interest Rate	0.15	0.44	0	6.66	617	0.22	0.98	0.01	11.33	138
Days Payable	34.36	36.43	2.67	736	617	55.70	57.18	5.78	438	138
Distress	-6.38	9.41	-114.4	-1.8	617	2.27	6.98	-1.8	50.5	138
Market Share (6 dig. NAICS)	0.06	0.14	0.00002	1	617	0.03	0.09	0.00003	1	138
IndCR4	38.03	16.20	4.6	94.5	617	36.45	17.09	4.6	88.3	138
SupplyCR4	29.10	6.81	16.1	83.2	617	28.34	6.25	14.8	54.3	138
BuyCR4	37.78	15.15	6.8	86.9	617	35.60	14.68	6.8	83.2	138
LIFO	0.16	0.37	0	1	617	0.12	0.33	0	1	138
AvgCost	0.07	0.26	0	1	617	0.11	0.31	0	1	138

Table 13: Descriptive statistics (Part II) – distressed vs. non-distressed firms

Pairwise correlations are presented in *Table 14*. Again, all size variables are highly correlated, but no excessive correlations between independent variables are found. Given the relatively small sample size, few correlation coefficients are statistically significant.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1 Inventory Total (million $)																		
2 Inventory RawMat (million $)	**0.92**																	
3 Inventory FinGood (million $)	**0.87**	**0.76**																
4 Sales (million $)	**0.94**	**0.88**	**0.84**															
5 Sales Forecast (million $)	**0.91**	**0.86**	**0.81**	**0.97**														
6 Sales Surprise	**-0.12**	-0.04	**-0.10**	**-0.13**	**-0.09**													
7 Coeff. of Variation of Sales	0.05	0.03	0.05	0.05	**-0.09**	**-0.09**												
8 OrderBacklog/Sales	-0.07	**-0.10**	**-0.08**	-0.07	**-0.08**	0.01	-0.01											
9 Interest Rate	**-0.08**	-0.07	-0.06	**-0.10**	**-0.11**	0.01	0.06	0.00										
10 Days Payable	**-0.14**	**-0.11**	**-0.12**	**-0.22**	**-0.21**	**0.27**	-0.03	0.02	0.04									
11 Distress	-0.03	-0.06	0.00	-0.05	-0.05	**-0.15**	0.02	0.02	0.01	**0.16**								
12 Distress Dummy	**-0.31**	**-0.32**	**-0.25**	**-0.33**	**-0.31**	**0.07**	**-0.08**	0.07	0.05	**0.24**	**0.35**							
13 Market Share (6 dig. NAICS)	**0.55**	**0.48**	**0.52**	**0.58**	**0.55**	**-0.08**	**0.09**	0.00	-0.05	**-0.09**	0.03	**-0.09**						
14 Net Industry Sales (inverted)	**0.11**	**0.08**	**0.15**	**0.11**	**0.08**	-0.04	0.05	-0.04	-0.06	**-0.11**	0.04	-0.02	**0.58**					
15 IndCR4	**0.11**	0.04	0.02	**0.11**	**0.11**	-0.02	0.05	0.07	0.04	0.07	-0.06	-0.04	**0.13**	**-0.19**				
16 SupplyCR4	**0.08**	0.07	-0.01	0.07	0.07	-0.01	0.02	**0.09**	0.02	0.03	0.00	-0.04	-0.01	**-0.31**	**0.51**			
17 BuyCR4	**0.15**	**0.12**	0.02	**0.12**	**0.12**	0.00	0.03	**0.09**	0.02	0.04	-0.03	-0.06	0.05	**-0.24**	**0.55**	**0.41**		
18 LIFO	**0.29**	**0.25**	**0.31**	**0.30**	**0.29**	**-0.19**	0.06	-0.05	-0.06	**-0.20**	0.05	-0.04	**0.16**	**0.09**	**-0.11**	-0.04	**-0.14**	
19 Avg. Cost	0.01	-0.01	0.05	0.00	-0.01	-0.01	-0.05	0.01	0.06	0.04	-0.05	0.05	0.02	-0.01	0.04	0.00	0.05	**-0.13**

(Values in bold are significant at the 5% level)

Table 14: Pairwise correlations (Part II)

3.4.6. Methodology

The empirical methodology is discussed in this section. A series of regression analyses are performed to test the hypotheses developed in this essay. An overview of these regressions is presented in the following subsection. Both the panel data set (Part I) and the cross-sectional data set (Part II) present particular econometric challenges that have to be considered when choosing an empirical estimation procedure. The methodologies for the analyses of both data sets are discussed in turn in Subsections 3.4.6.2 and 3.4.6.3.

3.4.6.1. Overview of regression analyses

The hypotheses set forth in this essay are tested by means of a series of regression analyses. *Table 15* provides an overview of the regressions that are performed.

	Data Part I			**Data Part II**		
Dependent variable	Baseline	Split-sample	Distressed firms with interaction effect	Baseline	Split-sample	Distressed firms with interaction effect
Total inventory	R1	R2	R3	R10	R11	R12
Raw materials inventory	R4	R5	R6	R13	R14	R15
Finished goods inventory	R7	R8	R9	R16	R17	R18

Table 15: Overview of regression analyses

As described previously, two separate data sets are used for the empirical analyses. Nine regressions are performed to analyze each data set (R1-R9 and R10-R18). For the analysis of each data set, three lines of regressions are required to estimate the model for three different dependent variables: Total inventory, raw materials inventories, and finished goods inventories. For each dependent variable, a baseline regression using the full data set is implemented first. In a second step, the data set is split into distressed and non-distressed firms, and the regression is implemented for both subsamples separately. The *Distress*Power* interaction effect is included in the third regression model which is implemented using the subsample of distressed firms only and designed to test *Hypothesis 12* to *Hypothesis 14*.

The regression models are further discussed in the following paragraphs. The models below show *TotalInventory* as the dependent variable. The same models are also analyzed with raw materials inventories and finished goods inventories as the dependent variables.

The first regression (R1) estimates the baseline model shown below. This regression is performed using the entire data sample (part I). The measures of financial distress (*DistressDummy*) and of firm power (*IndSalesNet*) are of particular interest. It is expected that, on average, distressed firms hold less inventory than non-distressed firms.

(R1) $\ln TotalInventory_{itf} = \beta_0 + \beta_1 \ln SalesForecast_{itf} + \beta_2\, SalesSurprise_{itf}$

$+ \beta_3\, SalesVariability_{itf} + \beta_4\, SetupCost_{itf} + \beta_5\, HoldingCost_{itf} + \beta_6 \ln LeadTime_{itf}$

$+ \beta_7\, DistressDummy_{itf} + \beta_8 \ln IndSalesNet_{itf} + \beta_9\, LIFO_{itf} + \beta_{10}\, AvgCost + \varepsilon_{itf}$

The second regression (R2) is nearly identical to R1. This regression however, is performed for distressed and non-distressed firms separately, using the *DistressDummy* variable to split the sample into these groups. The continuous *Distress* variable then replaces the *DistressDummy* variable in the model. It is expected that greater levels of financial distress result in lower inventory levels for distressed firms[64].

(R2) $\ln TotalInventory_{itf} = \beta_0 + \beta_1 \ln SalesForecast_{itf} + \beta_2\, SalesSurprise_{itf}$

$+ \beta_3\, SalesVariability_{itf} + \beta_4\, SetupCost_{itf} + \beta_5\, HoldingCost_{itf} + \beta_6 \ln LeadTime_{itf}$

$+ \beta_7\, Distress_{itf} + \beta_8 \ln IndSalesNet_{itf} + \beta_9\, LIFO_{itf} + \beta_{10}\, AvgCost + \varepsilon_{itf}$

The third regression (R3) is similar to R2 for distressed firms, the only difference being that the *Distress***IndSalesNet* interaction term is included to test the contention that the (negative) effect of financial distress on inventories increases with the firm's power.

(R3) $\ln TotalInventory_{itf} = \beta_0 + \beta_1 \ln SalesForecast_{itf} + \beta_2\, SalesSurprise_{itf}$

$+ \beta_3\, SalesVariability_{itf} + \beta_4\, SetupCost_{itf} + \beta_5\, HoldingCost_{itf} + \beta_6 \ln LeadTime_{itf}$

$+ \beta_7\, Distress_{itf} + \beta_8 \ln IndSalesNet_{itf} + \beta_9\, LIFO_{itf} + \beta_{10}\, AvgCost$

$+ \beta_{11}\, Distress_{itf} * \ln IndSalesNet_{itf} + \varepsilon_{itf}$

---

[64] This study focuses on the analysis of financially distressed firms' inventories. The effect of financial health on inventories is not investigated here.

The regression models used to analyze the second data sample (part II) are similar to those described above.

Regression 10 (R10) estimates the baseline model which includes the focal industry's four-firm concentration ratio, as well as the weighted average concentration ratios of the supplying and buying industry in addition to the variables included in R1. The new variables are added to approximate firms' supply chain power. R10 is performed using the entire data sample (part II).

$$\text{(R10)} \quad \ln TotalInventory_{itf} = \beta_0 + \beta_1 \ln SalesForecast_{itf} + \beta_2\, SalesSurprise_{itf} + \beta_3\, SalesVariability_{itf} + \beta_4\, SetupCost_{itf} + \beta_5\, HoldingCost_{itf} + \beta_6 \ln LeadTime_{itf} + \beta_7\, DistressDummy_{itf} + \beta_8 \ln IndSalesNet_{itf} + \beta_9\, IndCR4_{itf} + \beta_{10}\, SupplyCR4_{itf} + \beta_{11}\, BuyCR4_{itf} + \beta_{12}\, LIFO_{itf} + \beta_{13}\, AvgCost + \varepsilon_{itf}$$

Regression 11 (R11) is performed for distressed and non-distressed firms separately, similar to R2. The continuous *Distress* variable then replaces the *DistressDummy* variable in model R10.

$$\text{(R11)} \quad \ln TotalInventory_{itf} = \beta_0 + \beta_1 \ln SalesForecast_{itf} + \beta_2\, SalesSurprise_{itf} + \beta_3\, SalesVariability_{itf} + \beta_4\, SetupCost_{itf} + \beta_5\, HoldingCost_{itf} + \beta_6 \ln LeadTime_{itf} + \beta_7\, Distress_{itf} + \beta_8 \ln IndSalesNet_{itf} + \beta_9\, IndCR4_{itf} + \beta_{10}\, SupplyCR4_{itf} + \beta_{11}\, BuyCR4_{itf} + \beta_{12}\, LIFO_{itf} + \beta_{13}\, AvgCost + \varepsilon_{itf}$$

Building on R11, regression 12 (R12) adds the interaction terms between the *Distress* and *IndSalesNet, IndCR4, SupplyCR4,* and *BuyCR4* variables, respectively.

$$\text{(R12)}\quad \ln TotalInventory_{itf} = \beta_0 + \beta_1 \ln SalesForecast_{itf} + \beta_2\, SalesSurprise_{itf}$$
$$+ \beta_3\, SalesVariability_{itf} + \beta_4\, SetupCost_{itf} + \beta_5\, HoldingCost_{itf} + \beta_6 \ln LeadTime_{itf}$$
$$+ \beta_7\, Distress_{itf} + \beta_8 \ln IndSalesNet_{itf} + \beta_9\, IndCR4_{itf} + \beta_{10}\, SupplyCR4_{itf}$$
$$+ \beta_{11}\, BuyCR4_{itf} + \beta_{12}\, Distress_{itf} * \ln IndSalesNet_{itf} + \beta_{13}\, Distress_{itf} * IndCR4_{itf}$$
$$+ \beta_{14}\, Distress_{itf} * SupplyCR4_{itf} + \beta_{15}\, Distress_{itf} * BuyCR4_{itf} + \beta_{16}\, LIFO_{itf}$$
$$+ \beta_{17}\, AvgCost + \varepsilon_{itf}$$

3.4.6.2. Empirical methodology: Part I

As discussed in Chapter 2, the OLS assumptions of homoskedasticity and independence are frequently not met when dealing with cross-sectional time series data (Greene 2003). Tests for heteroskedasticity and autocorrelation of the error terms are implemented prior to selecting the appropriate empirical estimation procedure.

The Breusch-Pagan/Cook-Weisberg Lagrange multiplier test (Breusch and Pagan 1979, Cook and Weisberg 1983) evaluates the correlation between the residuals of an OLS regression and the dependent variable (e.g. *TotalInventory*). If no such correlation is found, the homoskedasticity assumption is valid and OLS regressions can be assumed to provide efficient and unbiased estimates. The test is implemented after estimating regression R1 (see *Table 15*) using the OLS procedure. The resulting test statistic is 844.18 which follows a χ^2 distribution. This result is statistically significant at the less than one percent level and suggests that the magnitude of the residuals varies with the levels of the dependent variable (heteroskedasticity).

The Wooldridge test for autocorrelation in panel data (Drukker 2003, Wooldridge 2002) is implemented to determine if the residuals are serially correlated over time. This test is particularly suitable for panel data sets since it evaluates serial correlations within panels only. The test statistic is F = 144.745 and is significant at the one percent level. This suggests the presence of first-order autocorrelation.

A generalized least squares procedure (GLS) is recommended for the analysis of panel data with heteroskedastic and serially correlated error terms (Greene 2003). As noted in Section 2.3.4, the GLS procedure can be implemented with the unobserved cross-sectional and time effects modeled as either random or fixed effects. The appropriate procedure (fixed effects or random effects) is determined by implementing the Hausman specification test (Hausman 1978). This test analyzes whether the error terms are independent of the independent variables. If that is the case, the random effects procedure is preferred, while the fixed effects procedure should be selected otherwise. The test produces a χ^2 distributed statistic of W = 845.51 which is significant at the less than one percent level. The null hypothesis of no correlation is therefore clearly rejected, suggesting that the fixed effects model should be selected.

The STATA software package is used for the empirical analyses. This software lets users specify the way in which the first-order autocorrelation of the error terms should be modeled. The default method is to compute the autocorrelation based on the Durbin-Watson statistic. This method is applied here, although the results are found to be largely insensitive to the way in which autocorrelation is computed.

3.4.6.3. Empirical methodology: Part II

The second data set used for the empirical analyses contains firm-level observations from the year 1997. Given that there is only one observation per firm (rather than a time series of firm-level observations), serial correlation of the error terms is not a concern with this data set. Heteroskedasticity may, however, be observed. Therefore, the Breusch-Pagan/Cook-Weisberg Lagrange multiplier test (Breusch and Pagan 1979, Cook and Weisberg 1983) is implemented after an OLS regression (R10, see *Table 15*). The test statistic is 23.81 with a χ^2 distribution. This result is statistically significant at the one percent level. This indicates that the magnitude of the residuals varies with the levels of the dependent variable (heteroskedasticity). This constitutes a violation of the OLS assumption of homoskedasticity.

Robust estimation techniques provide a mechanism to control the heteroskedasticity of errors. While the coefficient estimates themselves remain unchanged relative to the standard OLS estimation procedure, the values of standard errors are adjusted for correlations across observations. The robust regression procedure in STATA uses Huber-

White sandwich estimators to compute robust standard errors (White 1980). The empirical results are presented and discussed in the following section.

3.5. Empirical results and discussion

The empirical analyses are performed for both data sets (Part I and Part II) separately. The regression results are discussed in Subsections 3.5.1 and 3.5.2, respectively, and the empirical support for the hypotheses set forth in this paper is evaluated.

3.5.1. Empirical results: Part I

In this section, the results of the analyses of data set Part I are discussed in four subsections:

- First, the regression results for *TotalInventory* as the dependent variable are presented. Specifically, the baseline regression (R1, see *Table 15*) and the split-sample regression (R2) results are reported, and the interaction between distress and power is evaluated for distressed firms (R3).
- Second, the sensitivity of the regression results (R1) with respect to the definition of the *DistressDummy* variable and the granularity of industry definitions (6-digit NAICS versus 4-digit NAICS) is also evaluated.
- Third, the regression results for *RawMatInventory* (raw materials inventory) as the dependent variable are discussed (R4-R6, see *Table 15*).
- Fourth, the regression results for *FinGoodInventory* (finished goods inventory) as

the dependent variable are discussed (R7-R9, see *Table 15*).

3.5.1.1. Regression results: Total inventory

As discussed previously, the baseline regression is specified as follows:

(R1) $\ln TotalInventory_{itf} = \beta_0 + \beta_1 \ln SalesForecast_{itf} + \beta_2\, SalesSurprise_{itf}$

$+ \beta_3\, SalesVariability_{itf} + \beta_4\, SetupCost_{itf} + \beta_5\, HoldingCost_{itf} + \beta_6 \ln LeadTime_{itf}$

$+ \beta_7\, DistressDummy_{itf} + \beta_8 \ln IndSalesNet_{itf} + \beta_9\, LIFO_{itf} + \beta_{10}\, AvgCost + \varepsilon_{itf}$

This model is tested using the panel data set described in Section 3.4.5.1 and the autoregressive linear regression estimation procedure outlined in Section 3.4.6.2. The empirical estimation results are presented in *Table 16*.

The model's F statistic (F = 135.8) is statistically significant at the one percent level, and the R-squared within statistic is 0.33 indicating that the model explains about one third of the variability in the dependent variable. The coefficient estimates are discussed below:

- *Forecast*: Higher expected demand should result in larger order quantities and larger average cycle stocks. This expectation is confirmed by the positive and significant coefficient $(\beta = 0.361)$. Specifically, this result suggests that a one percent increase in expected demand should result in an increase in total inventory holdings by 0.361%. It is noted that this result is consistent with Ballou's (1981) contention that inventories should increase as the square-root of demand.
- *SalesSurprise*: Greater than expected demand should result in lower end-of-period inventory holdings. This variable's coefficient $(\beta = 0.202)$, however, is positive

and significant. One explanation may be that firms build up inventory once it becomes apparent that demand may exceed expectations.

- *Coefficient of Variation of Sales*: Greater demand variability should result in larger safety stocks and, thus, greater inventory levels. The coefficient estimate $(\beta = -0.027)$, however, is statistically insignificant.
- *OrderBacklog/Sales*: The standardized value of order backlogs is used as a proxy for production setup costs. The higher this cost, the higher production quantities and average cycle stocks should be. The coefficient estimate $(\beta = 0.007)$ is positive as expected although only marginally significant.
- *InterestRate*: The *InterestRate* measure is used as a proxy for inventory carrying costs. Higher carrying costs should equal lower inventory levels. The coefficient estimate $(\beta = -0.038)$ has the expected sign but is statistically insignificant.
- *DaysPayable*: Days payable outstanding is used as a proxy for lead times. The longer the lead times, the more inventory firms should hold. This expectation is confirmed by the positive and significant coefficient estimate $(\beta = 0.120)$.
- *DistressDummy*: As discussed previously, the *DistressDummy* variable identifies those firms that have high *Distress* scores and thus find themselves in situations of financial distress. The key contention of this research is that distressed firms will hold less inventory, all else equal (*Hypothesis 8*). The coefficient estimate is negative and statistically significant $(\beta = -0.065)$. This result suggests that, on average, distressed firms hold 6.5 percent less inventory than financially healthier firms. This finding provides support for *Hypothesis 8*.

- *IndSalesNet*: This variable measures a firm's power in a market relative to its competitors. As stated in *Hypothesis 9*, more powerful firms are expected to hold less inventory, *ceteris paribus*. The coefficient estimate $(\beta = -0.105)$ provides strong support for this hypothesis.
- *LIFO* and *AvgCost*: The coefficient estimates of both the *LIFO* and *AvgCost* variables are not statistically significantly different from 0. The results therefore suggest that in this particular data sample, differences in inventory accounting methods did not significantly affect inventory valuations.

Total Inv	Coef.	P>t
Constant	-0.317	0.000
Forecast	0.361	0.000
SalesSurprise	0.202	0.000
Coeff. of Variation	-0.027	0.621
OrderBacklog/Sales	0.007	0.095
InterestRate	-0.038	0.188
DaysPayable	0.120	0.000
DistressDummy	-0.065	0.003
IndSalesNet	-0.105	0.000
LIFO	-0.005	0.928
AvgCost	0.016	0.803
Number of obs		3,862
F(10,2758)		135.8
Prob > F		0.000
R-sq. within		0.330
R-sq. between		0.806
R-sq. overall		0.781

Table 16: Regression results: Total inventory (R1)

The regression model discussed above is also implemented for both distressed and non-distressed firms separately (R2, see *Table 15*), using the *DistressDummy* variable to split the sample into these groups. In addition, the moderating effect of power (*IndSalesNet*) on the *Distress-Inventory* relationship is evaluated by estimating the corresponding interaction effect for distressed firms (R3). *Table 17* presents these regression results.

	Non-distressed firms		Distressed firms			
			w/o interaction		with interaction	
Total Inv	Coef.	P>t	Coef.	P>t	Coef.	P>t
Constant	-0.121	0.014	-0.689	0.000	-0.691	0.000
Forecast	0.432	0.000	0.191	0.000	0.187	0.000
SalesSurprise	0.197	0.000	0.164	0.000	0.162	0.000
Coeff. of Variation	0.044	0.509	-0.025	0.850	-0.022	0.868
OrderBacklog/Sales	0.077	0.058	0.005	0.387	0.005	0.383
InterestRate	-0.026	0.369	-0.269	0.004	-0.268	0.005
DaysPayable	0.201	0.000	0.014	0.706	0.013	0.724
Distress	-0.001	0.344	-0.011	0.000	-0.015	0.272
IndSalesNet	-0.032	0.009	-0.197	0.000	-0.199	0.000
LIFO	0.002	0.970	0.010	0.954	0.010	0.955
AvgCost	0.076	0.235	0.073	0.688	0.076	0.678
Distress*IndSalesNet					0.000	0.733
Number of obs		2,701		857		857
F		157.0		19.4		17.6
Prob > F		0.000		0.000		0.000
R-sq. within		0.458		0.289		0.289
R-sq. between		0.863		0.627		0.616
R-sq. overall		0.842		0.604		0.593

Table 17: Split-sample regression results: Total inventory (R2, R3)

The leftmost column of *Table 17* shows the regression results for non-distressed, i.e. healthy firms. It is noted that the coefficient estimates are generally consistent with the results for the entire data sample (*Table 16*). The key difference is that the model shown in *Table 17* contains the (continuous) *Distress* variable. It is interesting to note that the level of *Distress* (or financial health in this case[65]) does not appear to impact non-distressed firms' inventory holdings.

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[65] Note that non-distressed firms will have low or negative *Distress* scores, indicating financial health.

The right part of *Table 17* shows the regression results for distressed firms. Given the smaller number of observations (n = 857), the model fit is lower than for non-distressed firms (F = 19.4, 17.6; *R-squared* = 0.289). The coefficient estimates are, however, generally consistent with those for the entire sample (*Table 16*) and those for non-distressed firms (*Table 17*, left column). A few results of the analysis of distressed firms merit further discussion:

- The coefficients of the *OrderBacklog/Sales* and *DaysPayable* variables are statistically insignificant for distressed firms.
- The *InterestRate* variable, on the other hand, has a statistically significant negative coefficient $(\beta = -0.269)$.
- The *Distress* variable carries a negative and statistically significant coefficient $(\beta = -0.011)$ in the model without the interaction effect. This suggests that, for distressed firms, greater levels of distress result in even lower inventory levels. This finding provides further support for *Hypothesis 8*[66].
- The interaction effect between *Distress* and *IndSalesNet* is added to the model in the rightmost column of *Table 17*. The corresponding coefficient estimate is close to zero and does not add any explanatory power to the model. *Hypothesis 12* is, thus, not supported.

In summary, the regression model is of at least reasonable quality and most coefficient estimates have the expected signs. In particular, the results indicate that distressed firms

[66] A squared term of the *Distress* variable was also tested to investigate if the relationship between financial distress and inventories is non-linear. While the results are not reported here, it is noted that the squared Distress variable carries a negative and significant coefficient, suggesting that the magnitude of the effect of distress on prices increases with the severity of financial distress.

hold less inventory than financially healthy firms (*Hypothesis 8*), and that greater levels of distress equate to lower inventory levels. The contention that power moderates the distress-inventory relationship (*Hypothesis 12*) is not supported.

3.5.1.2. Sensitivity analyses

The sensitivity of the regression results with respect to the definition of the *DistressDummy*, *IndSalesNet* and *SalesSurprise* variables is assessed in this section. In addition, it is investigated if the results hold if average inventories rather than end-of-year inventories are used as dependent variables

The *DistressDummy* variable indicates whether a firm has a *Distress* score of greater than -1.81. This cutoff level, initially proposed by Altman (1968), is, of course, somewhat arbitrary. The effect of alternative cutoff definitions on the estimation results is investigated by comparing the regression results for three distinct cutoff levels.

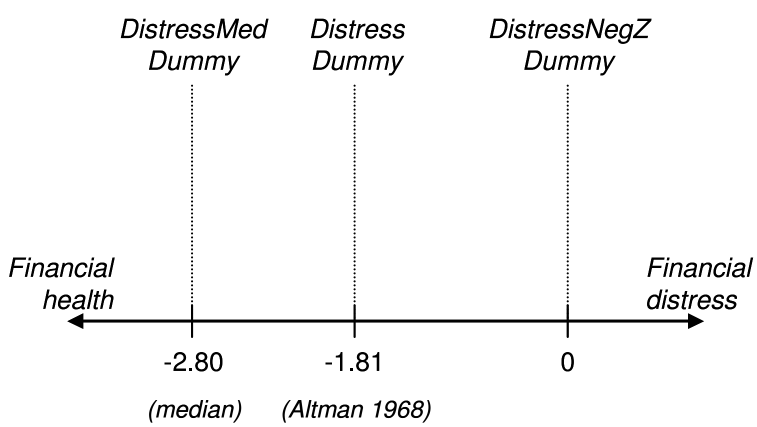

Figure 14: Alternative definitions of distressed and non-distressed firms

Figure 14 illustrates the cutoff levels that are proposed here. The standard cutoff level of -1.81 is shown in the middle of the graph. As seen in *Table 12*, this results in 27 percent of the firms in the full data sample being classified as financially distressed. An equal split into relatively distressed and relatively healthy firm is obtained by using the median *Distress* value (-2.80) as a cutoff level. The resulting indicator variable is named *DistressMedDummy*. Conversely, a stricter definition of financial distress is obtained by moving the cutoff level to the right. The *DistressNegZDummy* variable identifies all severely distressed firms with negative Z scores (i.e. positive *Distress* scores). With this cutoff level, about twelve percent of all firms are considered distressed. *Table 18* juxtaposes the regression results for all three cutoff definitions.

	DistressDummy		***DistressNegZDummy***		***DistressMedDummy***	
TotalInventory	Coef.	P>t	Coef.	P>t	Coef.	P>t
Constant	-0.317	0.000	-0.312	0.000	-0.314	0.000
Forecast	0.361	0.000	0.360	0.000	0.361	0.000
SalesSurprise	0.202	0.000	0.200	0.000	0.203	0.000
Coeff. of Variation	-0.027	0.621	-0.024	0.665	-0.028	0.617
OrderBacklog/Sales	0.007	0.095	0.005	0.203	0.007	0.094
InterestRate	-0.038	0.188	-0.035	0.223	-0.036	0.207
DaysPayable	0.120	0.000	0.121	0.000	0.119	0.000
DistressDummy	**-0.065**	**0.003**	**-0.150**	**0.000**	**-0.033**	**0.113**
IndSalesNet	-0.105	0.000	-0.105	0.000	-0.106	0.000
LIFO	-0.005	0.928	-0.005	0.928	-0.007	0.903
AvgCost	0.016	0.803	0.020	0.760	0.013	0.842
Number of obs		3,862		3,862		3,862
F		135.8		139.0		134.5
Prob > F		0.000		0.000		0.000
R-sq. within		0.330		0.335		0.328
R-sq. between		0.806		0.809		0.804
R-sq. overall		0.781		0.784		0.778

Table 18: Sensitivity analysis: Distressed vs. non-distressed firms

The coefficient estimates are robust across all three cases and there are only minimal variations in the overall fit of the model. Specifically, the only notable result is that the *DistressMedDummy* variable does not yield a statistically significant coefficient. This is not surprising considering that the *DistressMedDummy* variable is based on a very broad definition of financial distress. The alternative variables (*DistressDummy* and *DistressNegZDummy*) both carry negative and statistically significant coefficients. It is therefore concluded that the results are largely insensitive to variations in the definition of financial distress. The *DistressDummy* variable (as defined initially) is retained for the remainder of the analyses.

A second sensitivity analysis is performed to evaluate how the regression results change as the definition of industries changes. Specifically, industries may be defined at different levels of granularity. While a narrow definition based on six-digit NAICS codes is used as a default, the model is re-estimated using the broader four-digit NAICS definition. These definitions affect the magnitude and variability of the *IndSalesNet* variable.

Table 19 presents the regression results for both the six and four-digit NAICS industry definitions. While the broader four-digit NAICS definition provides slightly better results in terms of model fit than the six-digit NAICS definition, the results are robust and consistent across both regressions. The six-digit NAICS industry definition is retained to ensure consistency with the granularity of industry definitions in the second part of the data analysis[67].

[67] The analysis of the second data set (Part II) introduces the concept of supply chain power by adding weighted average industry concentration levels in the buying and supplying industries. To obtain sufficient variability in these variables, industries must be defined at the full six-digit NAICS level.

	6-digit NAICS		***4-digit NAICS***	
TotalInventory	Coef.	P>t	Coef.	P>t
Constant	-0.317	0.000	-0.986	0.000
Forecast	0.361	0.000	0.272	0.000
SalesSurprise	0.202	0.000	0.159	0.000
Coeff. of Variation	-0.027	0.621	-0.076	0.161
OrderBacklog/Sales	0.007	0.095	0.006	0.128
InterestRate	-0.038	0.188	-0.043	0.126
DaysPayable	0.120	0.000	0.077	0.000
DistressDummy	-0.065	0.003	-0.072	0.001
IndSalesNet	**-0.105**	**0.000**	**-0.204**	**0.000**
LIFO	-0.005	0.928	-0.015	0.779
AvgCost	0.016	0.803	-0.003	0.965
Number of obs.		3,862		3,862
F		135.8		151.4
Prob > F		0.000		0.000
R-sq. within		0.330		0.354
R-sq. between		0.806		0.743
R-sq. overall		0.781		0.721

Table 19: Sensitivity analysis: Granularity of industry definitions

Following the example of Roumiantsev and Netessine (2007), the *SalesSurprise* variable is included in the regression to capture the effect of unexpectedly large sales on inventories. Specifically, this indicator variable takes on the value “1” if actual sales exceed forecasted sales. Alternatively, the actual value of the difference between actual sales and forecasted sales, i.e. the forecast error (*ForecastError*), can be included in the regression model as a more finegrained measure of the magnitude of the deviation of actual sales from forecasted sales. The regression results using the *SalesSurprise* and *ForecastError* variables, respectively, are compared in *Table 20*. The model with the *ForecastError* variable is of poorer quality than the model with the *SalesSurprise* variable. The signs of the coefficient estimates, however, are consistent across both models. The *SalesSurprise* variable is retained for all subsequent analyses.

	SalesSurprise		*ForecastError*	
TotalInventory	Coef.	P>t	Coef.	P>t
Constant	-0.317	0.000	-0.082	0.134
Forecast	0.361	0.000	0.234	0.000
SalesSurprise / Error	0.202	0.000	0.000	0.000
Coeff. of Variation	-0.027	0.621	0.001	0.985
OrderBacklog/Sales	0.007	0.095	0.006	0.197
InterestRate	-0.038	0.188	-0.039	0.186
DaysPayable	0.120	0.000	0.132	0.000
DistressDummy	-0.065	0.003	-0.104	0.000
IndSalesNet6D	-0.105	0.000	-0.154	0.000
LIFO	-0.005	0.928	0.015	0.798
AvgCost	0.016	0.803	0.053	0.427
Number of obs		3,862		3,862
F		135.8		97.3
Prob > F		0.000		0.000
R-sq. within		0.330		0.261
R-sq. between		0.806		0.561
R-sq. overall		0.781		0.536

Table 20: Sensitivity analysis: SalesSurprise vs. ForecastError

As noted in Section 3.4.3.1, end-of-year inventories as reported in firms' balance sheets are the dependent variables used in this research. It may be argued that end-of-year inventory values are biased estimates of true average inventory levels as firms may reduce inventory levels toward the end of the year in order to improve key financial and operating performance indicators. This concern is addressed as follows: For each firm in the dataset, an average annual inventory value is approximated by averaging the firm's inventory levels at the end of the first, second, third, and fourth quarters. As shown in *Table 8*, the mean total inventory (end-of-year inventory values) in the panel data set (Part I) is \$103.9 million. The mean *average* total inventory, in contrast, is \$107.78 million. A paired two-sample t test indicates that end-of-year total inventories and average total inventories are statistically significantly different (t = 4.86, p = 0.000). This result, thus, is consistent with the above mentioned contention that end-of-year inventory values may be biased proxies for average inventories. A regression analysis with average total inventories as the dependent variable is performed and compared to the results with end-of-year total inventories as the dependent variable. This comparison in shown in *Table 21* below.

	Total Inventory		***Average Inventory***	
	Coef.	P>t	Coef.	P>t
Constant	-0.317	0.000	-0.279	0.000
Forecast	0.361	0.000	0.376	0.000
SalesSurprise	0.202	0.000	0.174	0.000
Coeff. of Variation	-0.027	0.621	0.007	0.903
OrderBacklog/Sales	0.007	0.095	0.006	0.159
InterestRate	-0.038	0.188	-0.029	0.299
DaysPayable	0.120	0.000	0.060	0.000
DistressDummy	-0.065	0.003	-0.033	0.135
IndSalesNet6D	-0.105	0.000	-0.119	0.000
LIFO	-0.005	0.928	0.022	0.681
AvgCost	0.016	0.803	0.021	0.740
Number of obs		3,862		3,862
F		135.8		135.0
Prob > F		0.000		0.000
R-sq. within		0.330		0.329
R-sq. between		0.806		0.799
R-sq. overall		0.781		0.774

Table 21: Sensitivity analysis: Measurement of total inventories

The coefficient estimates are generally consistent across both the *TotalInventory* and *AverageInventory* regressions. The significance levels, however, are weaker when average inventories are used as the dependent variable. It is noted that there is no indication suggesting that the use of end-of-year inventories results in biased estimation results. As has been done in prior research (e.g. Carpenter et al 1994, Roumiantsev and Netessine 2007), end-of-year inventories are, therefore, retained for the empirical analyses.

The regression results for raw materials inventories are discussed next.

3.5.1.3. Regression results: Raw materials inventory

The full data sample, comprising both distressed and non-distressed firms is used to estimate the regression model using raw materials inventory as the dependent variable (R4, see *Table 15*). The results are reported in *Table 22*.

The estimation results are consistent with the previously presented results for total inventories. The sales variability and production setup cost proxies (*Coeff. of Variation* and *OrderBacklog/Sales*, respectively), as well as the *LIFO* and *AvgCost* control variables are the only variables that have statistically insignificant coefficient estimates. All other variables carry significant coefficients with the expected signs. The *DistressDummy* variable is of particular interest. The negative coefficient $(\beta = -0.096)$ indicates that distressed firms tend to hold less inventory than their healthier counterparts (*Hypothesis 8*).

Raw Mat Inv	Coef.	P>t
Constant	-0.724	0.000
Forecast	0.330	0.000
SalesSurprise	0.164	0.000
Coeff. of Variation	0.013	0.858
OrderBacklog/Sales	-0.001	0.778
InterestRate	-0.136	0.000
DaysPayable	0.073	0.001
DistressDummy	-0.096	0.002
IndSalesNet	-0.063	0.001
LIFO	-0.004	0.951
AvgCost	-0.090	0.331
Number of obs		3,288
F(10,2758)		49.1
Prob > F		0.000
R-sq. within		0.174
R-sq. between		0.709
R-sq. overall		0.675

Table 22: Regression results: Raw materials inventory (R4)

The split-sample regression results for non-distressed and distressed firms are shown in *Table 23*. Focusing on the results for non-distressed firms in the leftmost column first, it is interesting to note that greater levels of financial health (*Distress*) do not impact inventory holdings $(\beta = 0.000)$. In addition, the insignificant coefficient of the *IndSalesNet* variable indicates that financially sound firms do not leverage their power to push inventory ownership up or down the supply chain. The results for distressed firms (without interaction effect), in contrast, suggest that greater levels of financial distress (*Distress*) and greater levels of power (*IndSalesNet*) result in lower raw materials inventory holdings. These findings provide support for *Hypothesis 8* and *Hypothesis 9*, respectively. Moreover, the significant and negative coefficient of the interaction effect between the *Distress* and *IndSalesNet* variables $(\beta = -0.004)$ suggests that the magnitude of the effect of distress on raw materials inventories increases with the firm's power. This result is consistent with *Hypothesis 12*.

	Non-distressed firms		Distressed firms			
			w/o interaction		with interaction	
Raw Mat Inv	Coef.	P>t	Coef.	P>t	Coef.	P>t
Constant	-0.195	0.004	-0.902	0.000	-0.920	0.000
Forecast	0.393	0.000	0.160	0.006	0.139	0.019
SalesSurprise	0.180	0.000	0.082	0.098	0.071	0.154
Coeff. of Variation	0.126	0.176	-0.029	0.872	-0.012	0.948
OrderBacklog/Sales	0.088	0.189	0.001	0.904	0.001	0.866
InterestRate	-0.131	0.001	-0.394	0.001	-0.396	0.001
DaysPayable	0.073	0.006	0.094	0.057	0.091	0.063
Distress	0.000	0.947	-0.013	0.000	-0.054	0.026
IndSalesNet	0.015	0.458	-0.096	0.073	-0.108	0.044
LIFO	-0.012	0.867	-0.044	0.837	-0.046	0.831
AvgCost	-0.018	0.855	-0.047	0.824	-0.027	0.899
Distress*IndSalesNet					-0.004	0.088
Number of obs		2,304		731		731
F		41.1		7.6		7.2
Prob > F		0.000		0.000		0.000
R-sq. within		0.207		0.160		0.166
R-sq. between		0.687		0.591		0.517
R-sq. overall		0.658		0.552		0.481

Table 23: Split-sample regression results: Raw materials inventory (R5, R6)

The regression results for finished goods inventories are discussed in the following subsection.

3.5.1.4. Regression results: Finished goods inventory

In this section, the regression model is estimated using finished goods inventories as the dependent variable. The results for the full data set, consisting of both distressed and non-distressed firms, are provided in *Table 24*.

Fin Good Inv	Coef.	P>t
Constant	-0.677	0.000
Forecast	0.357	0.000
SalesSurprise	0.164	0.000
Coeff. of Variation	-0.271	0.008
OrderBacklog/Sales	0.004	0.561
InterestRate	-0.076	0.151
DaysPayable	0.041	0.172
DistressDummy	-0.035	0.402
IndSalesNet	-0.055	0.025
LIFO	-0.056	0.562
AvgCost	0.285	0.025
Number of obs		3,130
F(10,2758)		29.0
Prob > F		0.000
R-sq. within		0.117
R-sq. between		0.749
R-sq. overall		0.711

Table 24: Regression results: Finished goods inventory (R7)

It is noted that the overall quality of the model is markedly lower for finished goods inventories, than for total and raw materials inventories. The F statistic is 29.0 and the R-squared within is only 0.117. Many independent variables, including the *DistressDummy* variable, carry statistically insignificant coefficient estimates. While financially distressed firms, on average, appear to hold less total and raw materials inventory this is not found to be true for finished goods inventories. *Hypothesis 8*, thus, is not supported for finished goods inventories.

The regression results for non-distressed and distressed firms (without and with interaction effect) are shown in *Table 25*. Surprisingly, the *Distress* variable carries a positive and marginally significant coefficient in the regression analysis of non-distressed firms (leftmost column). For distressed firms, however, the *Distress* variable carries the expected negative sign $(\beta = -0.024)$. The *IndSalesNet* variable also has a negative and significant coefficient $(\beta = -0.200)$. The *Distress*IndSalesNet* interaction effect, however, is not statistically significant (rightmost column).

	Non-distressed firms		**Distressed firms**			
			w/o interaction		with interaction	
FinGoodInv	Coef.	P>t	Coef.	P>t	Coef.	P>t
Constant	-0.402	0.001	-1.889	0.000	-1.833	0.000
Forecast	0.472	0.000	0.173	0.062	0.186	0.045
SalesSurprise	0.184	0.000	0.160	0.036	0.167	0.029
Coeff. of Variation	-0.216	0.088	-0.409	0.127	-0.443	0.099
OrderBacklog/Sales	0.276	0.009	0.001	0.935	0.001	0.953
InterestRate	-0.074	0.183	-0.243	0.217	-0.266	0.178
DaysPayable	0.029	0.450	0.077	0.325	0.077	0.324
Distress	0.003	0.076	-0.024	0.001	0.055	0.340
IndSalesNet	0.022	0.376	-0.200	0.011	-0.192	0.016
LIFO	-0.076	0.460	-0.148	0.621	-0.146	0.627
AvgCost	0.361	0.009	0.147	0.652	0.145	0.658
Distress*IndSalesNet					0.009	0.17
Number of obs		2,228		661		661
F		31.8		4.9		4.7
Prob > F		0.000		0.000		0.000
R-sq. within		0.174		0.123		0.128
R-sq. between		0.730		0.434		0.440
R-sq. overall		0.701		0.410		0.419

Table 25: Split-sample regression results: Finished goods inventory (R8, R9)

The analysis of finished goods inventories, thus, provides only limited support for the hypotheses set forth in this paper. It generally seems as though the hypothesized relationships between financial distress, power and inventories are strongest for total and raw materials inventories. A summary of the empirical results is presented in Section 3.6.

3.5.2. Empirical results: Part II

The second data set (Part II) used for the empirical analyses is described in Section 3.4.5.2. This data set comprises observations from 1997 only, but provides more detailed industry level statistics. Specifically, focal industry, buying industry, and supplying industry four-firm concentration ratios are added to the model.

The analysis of the second data set (Part II) is also conducted in three parts: Total inventories are analyzed, followed by raw materials, and finished goods inventories, respectively. For each of these dependent variables, three regression analyses are performed. First, the model is estimated using the full data set (comprising both financially healthy and financially distressed firms). Then, the model is estimated for healthy and distressed firms, separately. In a third step, the interaction effects between the *Distress* and *Power* variables are added to the model which is then estimated using the subsample of financially distressed firms only. The reader is referred to *Table 15* for an overview of the regression analyses.

3.5.2.1. Regression results: Total inventory

The basic regression model used to analyze total inventories is shown below (R10, see *Table 15*). This model includes the focal industry's four-firm concentration ratio, as well as the weighted average concentration ratios of the supplying and buying industries in addition to the variables included in R1 (see *Table 15*). The new variables are added to approximate a firm's supply chain power.

$$\text{(R10)}\quad \ln TotalInventory_{itf} = \beta_0 + \beta_1 \ln SalesForecast_{itf} + \beta_2\, SalesSurprise_{itf} + \beta_3\, SalesVariability_{itf} + \beta_4\, SetupCost_{itf} + \beta_5\, HoldingCost_{itf} + \beta_6 \ln LeadTime_{itf} + \beta_7\, DistressDummy_{itf} + \beta_8 \ln IndSalesNet_{itf} + \beta_9\, IndCR4_{itf} + \beta_{10}\, SupplyCR4_{itf} + \beta_{11}\, BuyCR4_{itf} + \beta_{12}\, LIFO_{itf} + \beta_{13}\, AvgCost + \varepsilon_{itf}$$

This model is estimated using an OLS regression procedure with robust standard errors. Specifically, the Huber-White sandwich estimator of standard errors is used to provide some control for heteroskedasticity.

The regression results for *TotalInventory* are shown in *Table 26*. The model explains about 86 percent of the variability in total inventories, and the model's F statistic is 215.33 which is statistically significant at the less than one percent level.

While some variables have statistically insignificant or unexpected coefficients (*SalesSurprise*, *Coefficient of Variation*, *OrderBacklog/Sales*, *InteresRate*), many variables have significant coefficients with the expected signs. Specifically, total inventories are shown to increase with forecasted sales ($\beta = 0.868$) and days payable outstanding (the lead time proxy, $\beta = 0.247$). The coefficient of the *DistressDummy* variable is negative ($\beta = -0.182$), thus supporting *Hypothesis 8* which states that financially distressed firms should hold less inventory than their healthier counterparts.

Total Inv	Coef.	P>t
Constant	-1.982	0.000
Forecast	0.868	0.000
SalesSurprise	0.451	0.000
Coeff. of Variation	-0.335	0.168
OrderBacklog/Sales	0.006	0.729
InterestRate	0.036	0.230
DaysPayable	0.247	0.000
DistressDummy	-0.182	0.023
IndSalesNet	0.052	0.005
IndCR4	-0.003	0.091
SupplyCR4	0.004	0.349
BuyCR4	0.007	0.002
LIFO	0.185	0.013
AvgCost	0.204	0.107
N		753
F(13, 739)		215.33
Prob > F		0.000
R-squared		0.863

Table 26: Regression results: Total inventory (R10)

Some of the coefficient estimates of the power variables also have the expected signs: Greater levels of (focal) industry concentration, suggesting greater firm power, are shown to be associated with lower inventory levels ($\beta = -0.003$, *Hypothesis 9*). In addition, the buying industry power (*BuyCR4*) has a positive and statistically significant coefficient ($\beta = 0.007$). An increase in the buying industry's concentration level (holding focal industry concentration levels constant), thus, implies that firms will hold more inventory. This finding supports *Hypothesis 11*. The *SupplyCR4* variable, however, does not have a statistically significant coefficient, and the coefficient of the *IndSalesNet* variable, while significant, does not have the expected sign.

In summary, the analysis of the second data set (Part II) is generally consistent with the results from the analysis of the first data set (Part I, see *Table 16*).

Table 27 shows the split-sample regressions (non-distressed and distressed firms) and the interaction effects between *Distress* and the *Power* variables are included in the regression analysis of distressed firms in the rightmost column.

Despite the relatively small sample sizes all models explain 85 percent of the variability in the dependent variable. Many of the coefficient estimates, however, are statistically insignificant which may be a function of the small number of observations, especially in the case of distressed firms (n = 136).

Focusing on the results for non-distressed firms first (*Table 27*, leftmost column), it is noted that the statistically significant coefficient estimates are consistent with the results shown in *Table 26*. The only unexpected result is the positive and significant coefficient of the *Distress* variable (β = 0.006). The other coefficients, including those of the four-firm concentration ratio variables are statistically insignificant.

	Non-distressed firms		Distressed firms			
			w/o interaction		with interaction	
Total Inv	Coef.	P>t	Coef.	P>t	Coef.	P>t
Constant	-1.909	0.000	-2.780	0.001	-2.715	0.002
Forecast	0.857	0.000	0.829	0.000	0.831	0.000
SalesSurprise	0.384	0.000	0.594	0.000	0.562	0.000
Coeff. of Variation	-0.306	0.308	-0.207	0.659	-0.247	0.613
OrderBacklog/Sales	0.165	0.014	0.365	0.002	-0.016	0.129
InterestRate	0.016	0.733	-0.014	0.151	0.071	0.381
DaysPayable	0.263	0.000	0.069	0.368	0.356	0.003
Distress	0.006	0.026	-0.036	0.015	-0.038	0.799
IndSalesNet	0.054	0.008	0.591	0.039	0.008	0.917
IndCR4	-0.001	0.654	0.143	0.710	-0.010	0.114
SupplyCR4	0.006	0.152	0.010	0.897	-0.009	0.587
BuyCR4	0.002	0.283	-0.012	0.042	0.019	0.007
LIFO	0.136	0.042	-0.006	0.685	0.569	0.050
AvgCost	0.182	0.060	0.020	0.004	0.116	0.771
Distress * IndShipValueNet					-0.014	0.273
Distress * IndCR4					-0.002	0.066
Distress * SupplyCR4					-0.004	0.450
Distress * BuyCR4					0.001	0.464
Number of obs		617		136		136
F		248.02		105.47		90.11
Prob > F		0.000		0.000		0.000
R-squared		0.859		0.851		0.857

Table 27: Split-sample regression results: Total inventory (R11, R12)

The results for distressed firms (second column in *Table 27*) closely resemble the results for non-distressed firms. The significance are, however, generally lower due to the small sample size (n = 136). The *Distress* variable carries a negative and significant coefficient (β = -0.036) which is in line with *Hypothesis 8*. This hypothesis suggests that distressed firms hold less inventory than healthier firms.

The only power measure with a statistically significant coefficient is *BuyCR4*. The coefficient is negative (β = -0.012) which suggests that greater buying industry power results in lower focal firm inventory holding. This finding is surprising and inconsistent with *Hypothesis 11* and the results for the entire data sample (see *Table 26*).

The only distress-power interaction effect that is significant is that of the *IndCR4* variable (β = -0.002, see rightmost column in *Table 27*). This result indicates that the negative effect of (focal) industry concentration—a proxy for a firm's power—on the firm's inventory holdings is greater the more distressed the firm is. This finding lends some support to *Hypothesis 12*. There are, however no statistically significant interaction effects between *Distress* and the *IndSalesNet*, *BuyCR4*, and *SupplyCR4* variables.

3.5.2.2. Regression results: Raw materials inventory

The key results for the analysis of raw materials inventories are similar to those for total inventories. *Table 28* presents the regression results for the entire sample of non-distressed and distressed firms (n = 676).

Again, distressed firms are shown to hold less raw materials inventory than healthy firms (*Distress*, β = -0.206), thus confirming *Hypothesis 8*. It is also interesting to note that all power variables have statistically significant coefficients:

- *IndSalesNet*: Greater levels of firm power, as approximated by the *IndSalesNet* variable, are shown to be associated with greater inventory holdings (β = 0.094). The same unexpected result was found in the analysis of total inventories.
- *IndCR4*: The negative coefficient of the *IndCR4* variable (β = -0.007), in turn, is consistent *Hypothesis 9* and suggests that greater power, as approximated by focal industry concentration levels, should result in lower inventory holdings.

- *BuyCR4* and *SupplyCR4*: Both the *BuyCR4* and *SupplyCR4* variables have positive and significant coefficients (β = 0.009 for *BuyCR4* and β = 0.013 for *SupplyCR4*). These results support *Hypothesis 11* and *Hypothesis 10*, suggesting that, while holding focal industry power levels constant, greater buying and supplying industry power levels result in larger inventory holdings.

Raw Mat Inv	Coef.	P>t
Constant	-2.515	0.000
Forecast	0.786	0.000
SalesSurprise	0.363	0.000
Coeff. of Variation	-0.106	0.648
OrderBacklog/Sales	-0.027	0.014
InterestRate	0.075	0.000
DaysPayable	0.263	0.000
DistressDummy	-0.206	0.034
IndSalesNet	0.094	0.000
IndCR4	-0.007	0.008
SupplyCR4	0.013	0.005
BuyCR4	0.009	0.001
LIFO	0.081	0.384
AvgCost	0.122	0.374
N		676
F(13, 662)		141.38
Prob > F		0.000
R-squared		0.769

Table 28: Regression results: Raw materials inventory (R13)

The results for non-distressed firms only (see *Table 29*) are largely consistent with the results for the entire data set. The analysis of distressed firms (second and third columns in *Table 29*), in turn, yields only few statistically significant coefficient estimates. Specifically, the coefficient of the *Distress* variable (β = -0.034) is not statistically significant in these regressions, and the only power variables with significant coefficients are *IndCR4* (β = - 0.017) and *BuyCR4* (β = 0.015). The *Distress*IndCR4* interaction effect also carries a negative and statistically significant coefficient estimate (β = -0.003). This finding suggests that financial distress only affects firms' raw materials inventories when these firms operate in highly concentrated industries, i.e. when firms possess some degree of market power. This finding thus is consistent with *Hypothesis 12*. There is, however, no support for the contention that the distress-inventory effect increases with the level of buying industry or supplying industry concentration (*Hypothesis 13* and *Hypothesis 14*, respectively).

	Non-distressed firms		**Distressed firms**			
			w/o interaction		with interaction	
Raw Mat Inv	Coef.	P>t	Coef.	P>t	Coef.	P>t
Constant	-1.952	0.000	-6.013	0.000	-5.839	0.000
Forecast	0.759	0.000	0.844	0.000	0.807	0.000
SalesSurprise	0.309	0.000	0.662	0.000	0.595	0.001
Coeff. of Variation	0.056	0.845	-0.260	0.551	-0.260	0.552
OrderBacklog/Sales	-0.033	0.805	-0.027	0.001	-0.033	0.000
InterestRate	0.093	0.002	0.052	0.377	0.037	0.558
DaysPayable	0.213	0.006	0.642	0.000	0.597	0.000
Distress	0.003	0.436	-0.034	0.140	-0.109	0.557
IndSalesNet	0.123	0.000	-0.066	0.481	-0.094	0.313
IndCR4	-0.005	0.114	-0.017	0.002	-0.011	0.082
SupplyCR4	0.014	0.006	0.025	0.140	0.010	0.621
BuyCR4	0.007	0.017	0.015	0.028	0.019	0.011
LIFO	0.073	0.445	0.277	0.397	0.310	0.347
AvgCost	0.108	0.425	0.203	0.613	0.160	0.701
Distress * IndShipValueNet					-0.006	0.746
Distress * IndCR4					-0.003	0.002
Distress * SupplyCR4					0.004	0.576
Distress * BuyCR4					0.000	0.922
Number of obs		561		115		115
F		87.19		136.42		107.48
Prob > F		0.000		0.000		0.000
R-squared		0.731		0.825		0.842

Table 29: Split-sample regression results: Raw materials inventory (R14, R15)

3.5.2.3. Regression results: Finished goods inventory

The results for finished goods inventories are shown in *Table 30* and in *Table 31*. Unfortunately, the estimation results are of generally poorer quality than the results for total and raw materials inventories. None of the hypotheses set forth in this essay are empirically supported for finished goods inventories and few variables carry statistically significant coefficients. The lack of significant findings may be attributable to, among other factors, the particularly small sample sizes.

Fin Good Inv	Coef.	P>t
Constant	-2.885	0.000
Forecast	0.882	0.000
SalesSurprise	0.464	0.000
Coeff. of Variation	-0.504	0.129
OrderBacklog/Sales	0.005	0.926
InterestRate	0.127	0.191
DaysPayable	0.302	0.001
DistressDummy	0.090	0.500
IndSalesNet	0.065	0.044
IndCR4	-0.005	0.209
SupplyCR4	-0.004	0.562
BuyCR4	-0.004	0.352
LIFO	0.465	0.001
AvgCost	0.440	0.052
N		654
F(13, 640)		81.28
Prob > F		0.000
R-squared		0.701

Table 30: Regression results: Finished goods inventory (R16)

Fin Good Inv	Non-distressed firms		Distressed firms			
			w/o interaction		with interaction	
	Coef.	P>t	Coef.	P>t	Coef.	P>t
Constant	-3.231	0.000	-1.578	0.246	-1.393	0.360
Forecast	0.885	0.000	0.847	0.000	0.817	0.000
SalesSurprise	0.445	0.000	0.588	0.028	0.556	0.045
Coeff. of Variation	-0.772	0.061	0.270	0.700	0.308	0.656
OrderBacklog/Sales	-0.645	0.000	0.067	0.000	0.059	0.000
InterestRate	0.088	0.338	-0.099	0.874	-0.139	0.795
DaysPayable	0.388	0.000	0.120	0.547	0.101	0.628
Distress	0.003	0.419	0.015	0.664	0.135	0.630
IndSalesNet	0.057	0.090	0.098	0.491	0.093	0.551
IndCR4	-0.001	0.723	-0.012	0.197	-0.007	0.514
SupplyCR4	-0.001	0.868	-0.012	0.646	-0.025	0.378
BuyCR4	-0.002	0.586	-0.001	0.896	0.002	0.841
LIFO	0.412	0.003	0.631	0.240	0.595	0.266
AvgCost	0.519	0.013	0.415	0.464	0.430	0.468
Distress * IndShipValueNet					-0.006	0.841
Distress * IndCR4					-0.001	0.508
Distress * SupplyCR4					-0.001	0.891
Distress * BuyCR4					-0.003	0.282
Number of obs		544		110		110
F		107.14		15.12		14.7
Prob > F		0.000		0.000		0.000
R-squared		0.717		0.672		0.686

Table 31: Split-sample regression results: Finished goods inventory (R17, R18)

3.6. Summary and discussion

This paper develops a comprehensive theoretical perspective of the firm distress-inventory relationship, drawing on theories and prior research from the economics, inventory theory, and supply chain management fields. Previously, researchers generally ignored the role of firm financial distress when investigating inventories. This study contends that financial distress plays a significant role in inventory management and that a firm’s power relative to its buyers and suppliers will impact the magnitude of this distress-inventory effect. Specifically, the hypotheses set forth in this essay contend that

- financially distressed firms hold less inventory than healthier firms (*Hypothesis 8*),
- more powerful firms hold less inventory than less powerful firms (*Hypothesis 9*),
- greater power relative to suppliers results in lower inventory holdings (*Hypothesis 10*),
- greater power relative to buyers results in lower inventory holdings (*Hypothesis 11*),
- the effect of financial distress on inventories increases with the firm's power (*Hypothesis 12*),
- greater power relative to suppliers increases the magnitude of the distress-inventory effect (*Hypothesis 13*),
- greater power relative to buyers increases the magnitude of the distress-inventory effect (*Hypothesis 14*).

The results of the empirical analyses of total, raw materials and finished goods inventories are summarized in *Table 32* and *Table 33*. *Table 32* shows the hypothesis testing results obtained from the analyses of both distressed and non-distressed firms. *Table 33*, in turn, focuses on the results for distressed firms only.

Hypothesis	Testing variable(s)	Expectation	Data Part I (1998-2004)			Data Part II (1997)		
			T	R	F	T	R	F
8	*DistressDummy*	–	–	–	0	–	–	0
9	*IndSalesNet*	–	–	–	–	+	+	+
9	*IndCR4*	–				–	–	0
10	*SupplyCR4*	+				0	+	0
11	*BuyCR4*	+				+	+	0

T = Total inventory, R = Raw materials inventory, F = Finished goods inventory
0 = statistically insignificant result

Table 32: Summary of results for entire data set

Focusing on the results for the entire data sets (both Part I and Part II, see *Table 32*) first, it is evident that there is strong support for the contention that distressed firms, on average, hold less inventory than financially healthy firms (*Hypothesis 8*). This finding, however, is not confirmed for finished goods inventories. This is not surprising since raw materials inventories can easily be reduced by consuming extant stock without reordering further supplies.

The hypothesis that greater levels of power should be associated with lower inventory levels (*Hypothesis 9*) also finds some empirical support. As shown in *Table 32*, the *IndSalesNet* variable carries the expected negative coefficients in the analysis of the panel data set (Part I), thus indicating that inventories decrease as firm power (as measured by the *IndSalesNet* variable) increases. The analysis of 1997 data (Part II), in turn, consistently yields (unexpected) positive coefficients for the *IndSalesNet* variable. At the same time, however, the industry concentration variable (*IndCR4*), carries negative coefficients (for total and raw materials inventories). While this latter finding is consistent with *Hypothesis 9*, the positive coefficients of the *IndSalesNet* variable are not consistent with *Hypothesis 9*. The multicollinearity between the power variables (*IndSalesNet*, *IndCR4*, *SupplyCR4*, *BuyCR4*) may partly explain this contradictory result.

Hypothesis 10 and *Hypothesis 11* suggest that greater levels of power over suppliers and buyers, respectively, should result in lower inventory holdings. *Table 32* shows positive coefficients for *SupplyCR4* (raw materials inventory only) and *BuyCR4* (total and raw materials inventory). These results imply that greater supplying and buying industry concentration levels—i.e. lower focal firm power when focal industry concentration levels are held constant—equate to greater firm inventory holdings. This is, to the best of the author's knowledge, the first study to present empirical evidence for the contention that inter-firm power balances in the supply chain affect the location and ownership of inventories in supply chains. The results also indicate that power levels affect raw materials inventories to a much greater extent than finished goods inventories which do not appear to be impacted by supply chain power.

The results of the analysis of distressed firms only are summarized in *Table 33*. The negative coefficients of the *Distress* variable further support *Hypothesis 8*. This result suggests that the magnitude of financial distress impacts the magnitude of the distressed firm's inventory reductions.

Hypothesis	Testing variable(s)	Expectation	Data Part I (1998-2004)			Data Part II (1997)		
			T	R	F	T	R	F
8	*Distress*	–	–	–	–	–	0	0
9	*IndSalesNet*	–	–	–	–	+	0	0
9	*IndCR4*	–				0	–	0
10	*SupplyCR4*	+				0	0	0
11	*BuyCR4*	+				–	+	0
12	*Distress*IndSalesNet*	–	0	–	0	0	0	0
12	*Distress*IndCR4*	–				–	–	0
13	*Distress*SupplyCR4*	+				0	0	0
14	*Distress*BuyCR4*	+				0	0	0

T = Total inventory, R = Raw materials inventory, F = Finished goods inventory
0 = statistically insignificant result

Table 33: Summary of results for distressed firms

The results for the power-inventory hypothesis (*Hypothesis 9*) are mixed. In the analysis of the panel data set (Part I), the *IndSalesNet* variable carries negative coefficients as expected, suggesting that more powerful distressed firms tend to hold less inventory. As seen in *Table 32*, however, the analysis of the second data set yields unexpected (or insignificant) coefficient estimates for the *IndSalesNet* variable. The four-firm concentration ratio (*IndCR4*), an alternative proxy for power, is shown to significantly impact distressed firms' inventory holdings only in the case of raw materials inventories. Specifically, distressed firms in more concentrated industries are found to hold less raw materials inventory, all else equal.

The supplying and buying industry concentration variables (*SupplyCR4* and *BuyCR4*) mostly carry insignificant or unexpected coefficients. Only the *BuyCR4* variable has a positive and significant coefficient in the raw materials inventory regression. This result suggests that distressed firms facing more powerful buyers may be forced to hold greater raw materials inventories and provides some support for *Hypothesis 11*.

There is, finally, only scant evidence that distressed firms reduce inventories to a greater extent when they are more powerful. Only in three instances did the interaction effects between *Distress* and the power variables have the expected negative coefficient estimates. In the first part of the data analysis (Part I), the effect of financial distress on raw materials inventories is shown to increase with the firm's power (*IndSalesNet*). The same result is obtained in the second part of the data analysis (Part II) when power is approximated with the industry concentration ratio (*IndCR4*). These findings provide some evidence in support of *Hypothesis 12*. There is, however, no support for the contention that the distress-inventory effect depends on the levels of supplying and buying industry power (*Hypothesis 13* and *Hypothesis 14*).

In summary, many of the hypotheses set forth in this study are empirically supported. It is shown that a firm's financial condition significantly impacts a firm's inventory decisions. Moreover, it is shown that power balances in supply chains may impact the distribution of inventory ownership in supply chains. At the same time, the data provide only limited evidence for the contention that power moderates the distress-inventory relationship.

This research contributes to the extant literature on multiple accounts: Different theoretical perspectives are synthesized to investigate the financial distress-inventory relationship. Specifically, insights from inventory theory and supply chain management research are used to improve upon the specification of empirical estimation models presented in prior economics research. Novel proxies for variables such as order and holding costs are proposed to overcome measurement problems that have previously hindered empirical inventory research.

The analyses presented in this essay not only refine the extant knowledge of the distress-inventory relationship but also provide new insights on inventory management issues in a supply chain context. Specifically, this is, to the best of the author's knowledge, the first study to empirically explore the role of inter-firm power in inventory management. In addition, the moderating role of power in the financial distress-inventory relationship is investigated.

Understanding the effect of a firm's financial condition on its inventory decisions may also have important managerial implications in terms of supplier selection, for example. Managers should be aware of how a supply chain partner's distress and power may affect inventory ownership in the supply chain. While this research does not evaluate how financial distress and power imbalances in supply chains affect overall supply chain performance, it is conceivable that the shifting of inventory ownership from the distressed firm to suppliers and buyers may reduce a supply chain's effectiveness in terms of, for example, service levels and responsiveness. The investigation of these questions is left for future research.

This research investigates if and how financial distress affects firm inventories and it is shown that distressed firms tend to reduce inventory holdings. Future research may also investigate if and when cutting inventories is a viable turnaround strategy.

As noted previously, this study adds to the small, emerging body of empirical inventory research. While efforts have been made to overcome the difficulties of data collection and variable measurement that are associated with doing research in this field, the work presented here must be considered exploratory. Secondary accounting data from public firms only were used for the empirical analyses. The generalizability of the results to the entire population of manufacturing firms, both public and private, can not be ascertained.

In addition, buyer and supplier power levels could only be approximated using rather crude measures such as buying industry and supplying industry concentration ratios. The computation of these ratios relies on the Input-Output Tables and industry concentration data published by the Bureau of Economic Analysis. As noted previously, the omission of international firms in the construction of these data may lead to a misrepresentation of inter-industry power constellations. Moreover, these industry power levels are only rough approximations of firm power levels. Future research may use qualitative methods and different data collection techniques, such as dyadic surveys, for example, to further investigate how power affects supply chain inventories and how it moderates the distress-inventory relationship.

4. Firm decision making under financial distress: Summary and outlook

The structure-conduct-performance (SCP) paradigm is a theoretical framework that is widely used in the industrial organization and strategic management literatures. The basic tenet of the SCP paradigm is that the structure of markets influences firms' conduct, and the latter then is a determinant of firm and market performance. In addition, it is also recognized that feedback mechanisms may exist within this framework (Waldman and Jensen 2001, see also Figure 1). The performance observed in a market, for example, may attract new entrants, thus changing the market structure. Similarly, firms may change their conduct in the light of poor past performance. This dissertation is concerned with this particular feedback mechanism: How does a firm's financial distress affect its conduct in terms of sales prices and inventories. While the potential existence of such relationships has been recognized previously, the author is unaware of any study that has systematically investigated the nature of these causal links. This dissertation addresses this gap in the literature by investigating the following two research questions:

- Does financial distress have an impact on prices and inventories, after controlling for other relevant parameters?
- If so, how can these effects be characterized, i.e. what factors influence the magnitude of the distress-price and distress-inventory relationships?

These questions are investigated through analyses of prices in the U.S. airline industry and inventories in U.S. manufacturing industries. Upon reviewing the literature, two sets of hypotheses relating financial distress to prices and inventories, respectively, are formulated. These hypotheses reconcile the conflicts revolving around prior conceptualizations of the distress-price, and distress-inventory links. More precisely, it is suggested that firm-specific and structural contingencies moderate these relationships. As a consequence, it is implied that financial distress may have a strong influence on prices and inventories in some instances, but not in others.

Large-scale empirical analyses are conducted to test the hypotheses set forth in this research. Data from the U.S. airline industry are used to investigate how financial distress affects prices. The results present substantial evidence in support of the hypotheses. Financial distress is found to be negatively related to air fares, with the magnitude of this relationship depending on the distressed firm's operating costs, market shares, and size. In addition, the degree of market concentration and the competitors' financial situations are shown to impact the distress-price relationship.

As to the effect of financial distress on inventories, data from the U.S. manufacturing industry are used for the empirical tests. It is shown that greater degrees of financial distress will result in lower inventory levels, *ceteris paribus*. In some instances, this effect is found to be stronger the greater the distressed firm's power over its buyers and suppliers.

Both the price and inventory studies thus suggest the following:

- Firm financial distress is an important determinant of a firm's actions.

- The nature of the distress-conduct relationship is further impacted by market structural and firm characteristics. Specifically such factors impact the occurrence and magnitude of the effect of distress on firm conduct parameters.

This research thus helps refine and enhance researchers' understanding of the relationship between structure, conduct and performance. While only one particular feedback mechanism within the structure-conduct-performance paradigm—the effect of distress on firm conduct—is investigated here, it is expected that there exist further, previously unexplored links between structural, conduct, and performance parameters. The analyses of such relationships are suggested for future research.

Managers may benefit from this work through an enhanced understanding of how firms' financial conditions may impact (competing) firms' behavior. Competitors of distressed firms, for example, may be able to better anticipate distressed firms' competitive moves, and as a consequence, may be in a better position to implement preemptive measures or respond to distressed firms' actions. Moreover, the findings of this work may be of interest to cooperation partners of distressed firms. Specifically, managers may want to understand how a distressed firm's actions may ultimately impact the cooperating firm, in terms of service levels, costs, or required inventory holdings, for example. While the findings presented here do not provide direct evidence for the implications of a firm's distress on its cooperation partners, there are some indications that a distressed firm's supply chain partners will be affected by the changes in the distressed firm's conduct. It is suggested that future research further explore these issues.

This dissertation research, thus, enhances researchers' and managers' understanding of how firm financial distress affects prices and inventories. Following these descriptive causal analyses, a normative approach to the research question at hand is suggested for future research. Specifically, the following questions could be addressed:

- Is the cutting of prices or the reduction of inventories a viable turnaround strategy, i.e. do distressed firms that lower prices or reduce inventories exhibit greater turnaround performance?
- In what specific instances is price or inventory cutting advisable? Are there certain organizational or situational characteristics that influence the extent to which lower prices or inventories result in distressed firms' performance improvements?
- How does distress affect firm and supply chain operating performance? Are there any effects in customer service levels or purchasing lead times, for example?

These and more questions may be of great interest to both the academic and practitioner communities. While these issues are not within the scope of this dissertation, the work presented here provides a solid basis for further investigations of the managerial implications and consequences of firm financial distress.

This dissertation empirically investigates the relationship between financial distress and select firm conduct parameters using secondary data from the U.S. airline and manufacturing industries. The use of secondary data is desirable in that advanced statistical methods can be utilized to analyze large data sets and obtain robust and generalizable estimation results. At the same time, however, the use of secondary data often requires researchers to approximate variables for which no direct measures are available or to omit explanatory factors from empirical models altogether should data not be available. In this dissertation, variables such as order costs and sourcing lead times, for example, could not be measured directly but could only be approximated. In addition, some data sources present inherent deficiencies and limitations. The data from the Input-Output tables, which are used to construct industrial supply chains for the analyses of the distress-inventory relationship, for example, do not include information on trade flows involving foreign buyers and suppliers. While a research design based on the analysis of secondary data is deemed suitable for an initial study of the distress-conduct link, future research could employ qualitative methods such as case studies, for example, to gain an in-depth understanding of the managerial decision processes that are triggered by the deterioration of a firm's financial condition. At the same time, insights could be gained into when and why specific turnaround strategies and actions result in performance improvements.

Appendix 1

Table 34 below presents the residuals of the regression of airlines' operating expenses per available seat-mile (ASM) on average stage length. This regression was performed to evaluate U.S. carriers' operating costs after controlling for differences in the airlines' average stage length. Negative residuals indicate relative cost advantages, while positive residuals suggest relative cost disadvantages. Based on the results displayed in *Table 34*, twelve carriers were identified as low-cost carriers (LCC). While the cut-off between low-cost and high-cost carriers (HCC) is arbitrary, it is noted that there is a sizeable difference in the magnitude of the residuals between the highest-cost LCC (Valujet Airlines: -0.142), and the lowest-cost HCC (Carnival Airlines: -0.105). In the empirical analyses, the top twelve airlines in *Table 34* are, therefore, identified as LCCs.

Carrier code	Carrier name	Ranked residuals	LCC indicator
WN	Southwest Airlines, Co.	-0.371	1
QQ	Reno Air, Inc.	-0.303	1
SY	Sun Country Airlines	-0.268	1
NK	Spirit Air Lines	-0.237	1
B6	Jetblue Airways	-0.231	1
W7	Western Pacific Airlines	-0.223	1
FL	Airtran Airways Corporation	-0.216	1
TZ	American Trans Air, Inc.	-0.214	1
BE	Braniff Int'l Airlines, Inc	-0.172	1
HP	America West Airlines, Inc.	-0.157	1
F9	Frontier Airlines, Inc.	-0.142	1
J7	Valujet Airlines, Inc.	-0.142	1
KW	Carnival Air Lines, Inc.	-0.105	0
AS	Alaska Airlines, Inc.	-0.099	0
NJ	Vanguard Airlines, Inc.	-0.081	0
KP	Kiwi International	-0.073	0
N7	National Airlines	-0.051	0
TW	Trans World Airlines, Inc.	-0.039	0
XJ	Mesaba Airlines	-0.036	0
NW	Northwest Airlines, Inc.	-0.022	0
BF	Markair, Inc.	-0.010	0
WV	Air South, Inc.	-0.002	0
HQ	Business Express	-0.001	0
DL	Delta Air Lines, Inc.	0.012	0
CO	Continental Air Lines, Inc.	0.018	0
EV	Atlantic Southeast Airlines	0.031	0
JI	Midway Airlines, Inc.	0.086	0
YV	Mesa Airlines, Inc.	0.090	0
ZN	Key Airlines, Inc.	0.090	0
OE	Westair Airlines	0.093	0
AQ	Aloha Airlines, Inc.	0.112	0
RU	Continental Express Airline	0.125	0
FF	Tower Air, Inc.	0.132	0
AA	American Airlines, Inc.	0.140	0
ZW	Air Wisconsin Airlines Corp	0.166	0
UA	United Air Lines, Inc.	0.170	0
US	US Airways, Inc.	0.171	0
YX	Midwest Express Airlines	0.179	0
HA	Hawaiian Airlines, Inc.	0.195	0
TB	USAir Shuttle	0.263	0
PA	Pan American World Airways	1.243	0

Table 34: Ranked residuals of regression of OpEx/ASM on avg. stage length (n=41)

Appendix 2

Table 35 presents the OLS regression estimates of the empirical model presented in Chapter 2 of this dissertation. These basic regression results are used solely to investigate the presence of heteroskedasticity. This is done by means of the Breusch-Pagan/Cook-Weisberg Lagrange multiplier test (Breusch and Pagan 1979, Cook and Weisberg 1983). The test result suggests the presence of heteroskedasticity and motivates the choice of a generalized least squares procedure for the empirical analyses.

Source	SS	df	MS
Model	3522.49	20	176.12
Residual	1471.77	23018	0.06
Total	4994.26	23038	0.22

Number of obs	23039
F(21, 23017)	2754.5
Prob > F	0.000
R-squared	0.705
Adj R-squared	0.705
Root MSE	0.253

Fare	**Coefficient**	**Std. error**	**P>|t|**
Constant	1.473	0.171	0.000
AirlinePass	-0.048	0.002	0.000
Distance	0.713	0.048	0.000
DistanceSquared	-0.023	0.004	0.000
SlotRoute	0.134	0.005	0.000
RouteHHI	-0.005	0.006	0.416
MaxAirportHHI	0.107	0.005	0.000
RouteShare	0.001	0.000	0.000
MaxAirportShare	0.004	0.000	0.000
LCCCompForHCC	-0.148	0.004	0.000
LCCCompForLCC	-0.103	0.008	0.000
AltRouteLCC1M	-0.016	0.004	0.000
Circuity	-0.162	0.024	0.000
Distress	0.005	0.001	0.000
Loadfactor	-0.004	0.000	0.000
AirlineCost	0.462	0.013	0.000
Size	0.034	0.002	0.000
Quarter 2	-0.086	0.005	0.000
Quarter 3	-0.120	0.006	0.000
Quarter 4	-0.060	0.005	0.000
2002	-0.260	0.006	0.000

Table 35: OLS regression estimates (n = 23,039)

Appendix 3

The regression results shown in *Table 36* and *Table 37* are used to evaluate the benefit of adding fixed effects to the regression model. This benefit is measured by means of an F statistic as proposed by (Greene 2003). The test returns a statistically significant F value, suggesting that a fixed effects model should be used for the empirical analyses.

Source	SS	df	MS
Model	1878.66	16	117.42
Residual	3115.60	23022	0.14
Total	4994.26	23038	0.22

Number of obs	23039
F(17, 23021)	1582.87
Prob > F	0.000
R-squared	**0.3762**
Adj R-squared	0.3757
Root MSE	0.3679

Fare	**Coefficient**	**Std. error**	**P>|t|**
AirlinePass (fitted)	0.272	0.012	0.000
Distance	-0.033	0.074	0.654
DistanceSquared	0.043	0.006	0.000
SlotRoute	0.051	0.008	0.000
RouteHHI	0.031	0.008	0.000
MaxAirportHHI	0.254	0.008	0.000
RouteShare	-0.006	0.000	0.000
MaxAirportShare	0.000	0.000	0.103
LCCCompForHCC	-0.223	0.006	0.000
LCCCompForLCC	-0.158	0.011	0.000
AltRouteLCC1M	-0.136	0.007	0.000
Circuity	1.136	0.057	0.000
Distress	-0.001	0.001	0.277
Loadfactor	-0.022	0.001	0.000
AirlineCost	0.960	0.016	0.000
Size	0.030	0.003	0.000
Constant	2.536	0.242	0.000

Table 36: 2SLS regression estimates without fixed effects (n = 23,039)

The Tables in Appendix 4 and Appendix 5 provide further details of the empirical estimation results.

Table 37 (Appendix 4) presents the second-stage estimation results of the regression of air fares on the set of independent variables as specified in Sections 2.3.2.2 and 2.3.2.3. In addition, air carrier fixed effects are included in this regression to evaluate the contribution of these fixed firm effects to the explanatory power of the model. This analysis is needed to determine the appropriate econometric estimation technique as discussed in Section 2.3.4.

Table 38 (Appendix 5) presents the first-stage estimation results for all five empirical models. This table, thus, is an extension of the baseline first-stage estimation results shown in *Table 3*. It is noted that the estimation results are generally consistent across all five models such that the discussion of the baseline first-stage results (see Section 2.4.1) also apply to the results shown in *Table 38*.

Appendix 4

Source	SS	df	MS
Model	2558.23	50	51.16
Residual	2436.04	22988	0.11
Total	4994.26	23038	0.22

Number of obs	23039
F(51, 22987)	715.34
Prob > F	0.000
R-squared	**0.5122**
Adj R-squared	0.5112
Root MSE	0.3255

Fare	**Coefficient**	**Std. error**	**P>|t|**
AirlinePass (fitted)	0.247	0.011	0.000
Distance	-0.033	0.066	0.618
DistanceSquared	0.040	0.005	0.000
SlotRoute	0.034	0.007	0.000
RouteHHI	0.069	0.008	0.000
MaxAirportHHI	0.192	0.007	0.000
RouteShare	-0.006	0.000	0.000
MaxAirportShare	0.000	0.000	0.353
LCCCompForHCC	-0.194	0.006	0.000
LCCCompForLCC	-0.106	0.010	0.000
AltRouteLCC1M	-0.118	0.006	0.000
Circuity	0.960	0.050	0.000
Distress	-0.040	0.003	0.000
Loadfactor	-0.022	0.001	0.000
AirlineCost	0.300	0.041	0.000
Size	0.090	0.017	0.000
Constant	0.527	0.376	0.161
Quarter2	-0.045	0.007	0.000
Quarter3	-0.048	0.009	0.000
Quarter4	-0.048	0.006	0.000
2002	-0.301	0.020	0.000
aq	0.097	0.143	0.499
as	0.002	0.050	0.961
b6	0.217	0.074	0.003
be	0.414	0.131	0.002
co	0.243	0.024	0.000
dl	0.060	0.010	0.000
f9	0.007	0.084	0.929
ff	0.190	0.182	0.295
fl	0.048	0.075	0.525
hp	0.172	0.050	0.001
hq	0.006	0.136	0.965
ji	0.794	0.121	0.000
kp	-0.074	0.206	0.721
kw	0.656	0.165	0.000
n7	0.629	0.104	0.000
nj	1.345	0.116	0.000
nk	0.098	0.094	0.295
nw	0.133	0.015	0.000
oe	0.287	0.133	0.030
qq	0.287	0.146	0.048
sy	-0.012	0.152	0.935
tb	-0.479	0.140	0.001
tw	0.300	0.032	0.000
tz	0.162	0.068	0.017
ua	0.184	0.009	0.000
us	0.074	0.019	0.000
wn	-0.393	0.037	0.000
yx	0.400	0.091	0.000
zn	3.164	0.374	0.000
zw	0.191	0.163	0.242

Table 37: 2SLS regression estimates with fixed effects (n = 23,039)

Appendix 5

First-stage G2SLS regression		*Number of obs.*	*23039*	*Obs. per group:*	*min.*	*1*
(fixed effects)		*Number of groups*	*4508*		*avg.*	*5.1*
					max.	*8*

		1		2		3		4		5	
Dependent variable: **AirlinePass**		**Coefficient**	**P>|t|**	**Coefficient**	**P>|t|**	**Coefficient**	**P>|t|**	**Coefficient**	**P>|t|**	**Coefficient**	**P>|t|**
Constant		444.458	0.000	440.911	0.000	446.816	0.000	454.492	0.000	477.332	0.000
Distance		-136.296	0.000	-134.880	0.000	-136.560	0.000	-139.647	0.000	-145.605	0.000
DistanceSquared		10.181	0.000	10.067	0.000	10.186	0.000	10.444	0.000	10.821	0.000
SlotRoute		0.099	0.001	0.101	0.001	0.103	0.000	0.104	0.000	0.085	0.004
RouteHHI		-0.412	0.000	-0.411	0.000	-0.411	0.000	-0.420	0.000	-0.421	0.000
MaxAirportHHI		-0.367	0.000	-0.373	0.000	-0.375	0.000	-0.366	0.000	-0.375	0.000
RouteShare		0.027	0.000	0.027	0.000	0.027	0.000	0.027	0.000	0.027	0.000
MaxAirportShare		0.001	0.007	0.001	0.005	0.001	0.010	0.001	0.004	0.001	0.013
LCCCompForHCC		0.227	0.000	0.229	0.000	0.229	0.000	0.223	0.000	0.221	0.000
LCCCompForLCC		0.238	0.000	0.226	0.000	0.224	0.000	0.236	0.000	0.249	0.000
AltRouteLCC1M		-0.022	0.061	-0.021	0.068	-0.021	0.065	-0.022	0.055	-0.019	0.094
Circuity		-2.326	0.000	-2.327	0.000	-2.326	0.000	-2.344	0.000	-2.335	0.000
Distress		0.005	0.190					-0.138	0.038		
Chpt11Ops				-0.015	0.141						
DistressDiff										0.018	0.000
Pre4Chpt11						0.018	0.107				
Post4Chpt11						-0.046	0.001				
Loadfactor		0.016	0.000	0.015	0.000	0.015	0.000	0.015	0.000	0.017	0.000
AirlineCost		-0.095	0.023	-0.097	0.021	-0.089	0.034	-0.083	0.053	-0.091	0.029
Size		0.028	0.150	0.008	0.666	0.015	0.370	0.042	0.059	0.065	0.000
Quarter 2		0.048	0.000	0.051	0.000	0.053	0.000	0.051	0.000	0.044	0.000
Quarter 3		0.074	0.000	0.079	0.000	0.079	0.000	0.076	0.000	0.062	0.000
Quarter 4		0.047	0.000	0.051	0.000	0.053	0.000	0.049	0.000	0.044	0.000
2002		-0.055	0.315	-0.036	0.509	-0.038	0.485	-0.057	0.306	-0.108	0.046
Population		0.579	0.000	0.567	0.000	0.568	0.000	0.588	0.000	0.577	0.000
Income		-0.034	0.785	-0.035	0.780	-0.048	0.702	-0.033	0.791	-0.014	0.912
AirlineCost*Distress								-0.025	0.020		
Size*Distress								-0.002	0.458		
RouteShare*Distress								0.000	0.185		
RouteHHI*Distress								0.013	0.033		
F			1038.3		1038.3		992.3		873.7		1051.3
Prob > F			0.000		0.000		0.000		0.000		0.000
R-squared:	*within*		0.541		0.541		0.541		0.541		0.544
	between		0.006		0.007		0.008		0.005		0.009
	overall		0.006		0.007		0.007		0.004		0.010

Table 38: First-stage G2SLS regression estimates (n = 23,039)

Appendix 6

Table 39 presents the means of select variables for those firms that are included in the statistical analyses and those firms for which data are available in the Compustat database but which have been deleted from the data sample due to missing data on one or more variables. As discussed in Sections 3.4.5.1 and 3.4.5.2, the sampled firms, on average, tend to be smaller than those firms firms that are not included in the data sample. A Hotelling T-squared test confirms that the two groups are statistically significantly different in both time periods studied (1997 and 1998-2004).

	1997		**1998-2004**	
Variable	Sample mean	Compustat	Sample mean	Compustat
Total Inventory (million $)	110.9	190.5	103.9	186.2
Sales (million $)	835.2	1698.7	835.6	1788.2
COGS (million $)	626.0	1162.5	537.4	1217.0
Total Debt (million $)	148.0	488.4	158.1	574.9
Total Assets (million $)	760.1	1792.9	733.8	2023.6

Table 39: Mean comparisons between sampled firms and Compustat population

Bibliography

Abdel-Malek, Layek L, and Roberto Montanari. "On the Multi-Product Newsboy Problem with Two Constraints." *Computers & Operations Research* 32, no. 8 (2005): 2095.

Aiken, Leona S, and Stephen G West. *Multiple Regression: Testing and Interpreting Interactions*. Newbury Park, CA: Sage Publications, 1991.

Alstrom, Poul. "Numerical Computation of Inventory Policies, Based on the Eoq/Ox Value for Order-Point Systems." *International Journal of Production Economics* 71, no. 1-3 (2001): 235.

Altman, Edward. *Bankruptcy, Credit Risk, and High Yield Junk Bonds*. Malden, MA: Blackwell Publishers, 2002.

Altman, Edward I. "Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy." *The Journal of Finance* 23, no. 4 (1968): 589-609.

———. "A Further Empirical Investigation of the Bankruptcy Cost Question." *The Journal of Finance* 39, no. 4 (1984): 1067.

Amihud, Yakov, and Haim Mendelson. "Inventory Behaviour and Market Power: An Empirical Investigation." *International Journal of Industrial Organization* 7, no. 2 (1989): 269.

Anonymous. "American Bankruptcy: The Uses and Abuses of Chapter 11." *The Economist* 310, no. 7594 (1989): 72.

———. "America's Airlines, Flying on Empty." *Economist.com / Global Agenda* (2005): 1.

Arogyaswamy, Kamala, Vincent L III Barker, and Masoud Yasai-Ardekani. "Firm Turnarounds: An Integrative Two-Stage Model." *The Journal of Management Studies* 32, no. 4 (1995): 493.

Bain, Joe S. *Barriers to New Competition*. Cambridge, MA: Harvard University Press, 1956.

Baker, Samuel A. "Risk, Leverage and Profitability - an Industry Analysis." *The Review of Economics and Statistics* 55, no. 4 (1973): 503.

Ballou, Ronald H. "Estimating and Auditing Aggregate Inventory Levels at Multiple Stocking Points." *Journal of Operations Management* 1, no. 3 (1981): 143.

Barla, Philippe, and Bonchun Koo. "Bankruptcy Protection and Pricing Strategies in the Us Airline Industry." *Transportation Research. Part E, Logistics & Transportation Review* 35 (1999): 101.

Betker, Brian L. "The Administrative Costs of Debt Restructurings: Some Recent Evidence." *Financial Management* 26, no. 4 (1997): 56.

Blazenko, George W, and Kirk Vandezande. "Corporate Holding of Finished Goods Inventories." *Journal of Economics and Business* 55, no. 3 (2003): 255.

Borenstein, Severin. "Hubs and High Fares: Dominance and Market Power in the U.S." *The Rand Journal of Economics* 20, no. 3 (1989): 344.

Borenstein, Severin, and Nancy L Rose. "Bankruptcy and Pricing Behavior in U.S. Airline Markets." *The American Economic Review* 85, no. 2 (1995): 397.

Bowman, Edward H. "Risk Seeking by Troubled Firms." *Sloan Management Review (pre-1986)* 23, no. 4 (1982): 33.

Bradbury, Michael E, and Suzanne Lloyd. "An Estimate of the Direct Costs of Bankruptcy in New Zealand." *Asia Pacific Journal of Management* 11, no. 1 (1994): 103.

Branch, Ben. "The Costs of Bankruptcy: A Review." *International Review of Financial Analysis* 11, no. 1 (2002): 39.

Brander, James A., and Tracy R. Lewis. "Oligopoly and Financial Structure: The Limited Liability Effect." *The American Economic Review* 76, no. 5 (1986): 956.

Breusch, T S, and A R Pagan. "A Simple Test for Heteroskedasticity and Random Coefficient Variation." *Econometrica* 47, no. 5 (1979): 1287.

Busse, Maghan. "Firm Financial Condition and Airline Price Wars." *The Rand Journal of Economics* 33, no. 2 (2002): 298.

Buxbaum, Peter A. "A Case of Corporate Turnaround." *Distribution* 94, no. 1 (1995): 30.

Buzacott, John A, and Rachel Q Zhang. "Inventory Management with Asset-Based Financing." *Management Science* 50, no. 9 (2004): 1274.

Cachon, Gerard P. "Stock Wars: Inventory Competition in a Two-Echelon Supply Chain with Multiple Retailers." *Operations Research* 49, no. 5 (2001): 658.

Campbell, Steven V. "Predicting Bankruptcy Reorganization for Closely Held Firms." *Accounting Horizons* 10, no. 3 (1996): 12.

Carey, Susan, and Melanie Trottman. "Airlines, Battered by Losses, Look Set for Rebound; Falling Costs, Fewer Seats May Be Ticket to Recovery for Some Major Carriers." *Wall Street Journal*, Nov 26 2005, A.1.

Carpenter, Robert E, Steven M Fazzari, and Bruce C Petersen. "Financing Constraints and Inventory Investment: A Comparative Study with High-Frequency Panel Data." *The Review of Economics and Statistics* 80, no. 4 (1998): 513.

Carpenter, Robert E, Steven M Fazzari, Bruce C Petersen, Benjamin M Friedman, and Anil K Kashyap. "Inventory Investment, Internal-Finance Fluctuations, and the Business Cycle; Comments and Discussion." *Brookings Papers on Economic Activity*, no. 2 (1994): 75.

Caves, R. E., and M. E. Porter. "Market Structure, Oligopoly, and Stability of Market Shares." *The Journal of Industrial Economics* 26, no. 4 (1978): 289.

Caves, Richard E., and Pankaj Ghemawat. "Identifying Mobility Barriers." *Strategic Management Journal* 13, no. 1 (1992): 1.

Chakravarthy, Balaji S. "Measuring Strategic Performance." *Strategic Management Journal* 7, no. 5 (1986): 437.

Chand, Suresh, and James Ward. "A Note on "Economic Order Quantity" under Conditions of Permissible Delay in Payments"." *Journal of the Operational Research Society* 38, no. 1 (1987): 83-84.

Chang, Chun-Tao, and Jinn-Tsair Teng. "Retailer's Optimal Ordering Policy under Supplier Credits." *Mathematical Methods of Operations Research* 60, no. 3 (2004): 471.

Chapman, C. B., S. C. Ward, Dale F. Cooper, and M. J. Page. "Credit Policy and Inventory Control." *The Journal of the Operational Research Society* 35, no. 12 (1984): 1055.

Chattopadhyay, Prithviraj, William H Glick, and George P Huber. "Organizational Actions in Response to Threats and Opportunities." *Academy of Management Journal* 44, no. 5 (2001): 937.

Chen, Ming-Jer. "Competitor Analysis and Interfirm Rivalry: Toward a Theoretical Integration." *Academy of Management. The Academy of Management Review* 21, no. 1 (1996): 100.

Chen, Ming-Jer, Ken G. Smith, and Curtis M. Grimm. "Action Characteristics as Predictors of Competitive Responses." *Management Science* 38, no. 3 (1992): 439.

Cook, R. Dennis, and Sanford Weisberg. "Diagnostics for Heteroskedasticity in Regression." *Biometrika* 70, no. 1 (1983): 1-10.

Corbett, Jenny, Donald Hay, and Helen Louri. "A Financial Portfolio Approach to Inventory Behavior: Japan and the Uk." *International Journal of Production Economics* 59, no. 1-3 (1999): 43.

Cox, Andrew. "Understanding Buyer and Supplier Power: A Framework for Procurement and Supply Competence." *Journal of Supply Chain Management* 37, no. 2 (2001): 8.

Cox, Andrew, Chris Lonsdale, Glyn Watson, and Hong Qiao. "Supplier Relationship Management: A Framework for Understanding Managerial Capacity and Constraints." *European Business Journal* 15, no. 3 (2003): 135.

Cox, Andrew, Joe Sanderson, and Glyn Watson. "Supply Chains and Power Regimes: Toward an Analytic Framework for Managing Extended Networks of Buyer and Supplier Relationships." *Journal of Supply Chain Management* 37, no. 2 (2001): 28.

Crandall, Robert. "Coffee, Tea ... Or Bankruptcy?" *Wall Street Journal*, Sep 16 2005, A.14.

Dasgupta, Sudipto, and Sheridan Titman. "Pricing Strategy and Financial Policy." *The Review of Financial Studies* 11, no. 4 (1998): 705.

Denardo, Eric V. *Dynamic Programming: Models and Applications*. first ed. Mineola, New York: Dover Publications Inc., 2003.

Derfus, Pamela J., Curtis M. Grimm, Ken G. Smith, and Patrick G. Maggitti. "The Red Queen Effect: Competitive Action and Performance." *Academy of Management Journal* (forthcoming).

Dobson, Paul W. "Exploiting Buyer Power: Lessons from the British Grocery Trade." *Antitrust Law Journal* 72, no. 2 (2005): 529.

Dresner, Martin, Jiun-Sheng Chris Lin, and Robert Windle. "The Impact of Low-Cost Carriers on Airport and Route Competition." *Journal of Transport Economics and Policy* 30, no. 3 (1996): 309.

Drukker, D.M. "Testing for Serial Correlation in Linear Panel-Data Models." *Stata Journal* 3 (2003): 168-77.

Emerson, Richard M. "Power-Dependence Relations." *American Sociological Review* 27, no. 1 (1962): 31-41.

Erlenkotter, Donald. "Ford Whitman Harris and the Economic Order Quantity Model." *Operations Research* 38, no. 6 (1990): 937.

Ferrier, Walter J. "Navigating the Competitive Landscape: The Drivers and Consequences of Competitive Aggressiveness." *Academy of Management Journal* 44, no. 4 (2001): 858.

Ferrier, Walter J, Cormac Mac Fhionnlaoich, Ken G Smith, and Curtis M Grimm. "The Impact of Performance Distress on Aggressive Competitive Behavior: A Reconciliation of Conflicting Views." *Managerial and Decision Economics* 23, no. 4,5 (2002): 301.

Finkin, Eugene F. "Company Turnaround." *The Journal of Business Strategy* 5, no. 4 (1985): 14.

Followill, Richard A., Michael Schellenger, and Patrick H. Marchand. "Economic Order Quantities, Volume Discounts, and Wealth Maximization." *The Financial Review* 25, no. 1 (1990): 143.

Fraser, Donald R., and Norman Gaither. "Estimating Financing Costs in Managing Inventory Positions at Large Corporations: Practice and Implications." *Managerial Finance* 10, no. 2 (1984): 21.

Frazier, Gray L, and Kersi D Antia. "Exchange Relationships and Interfirm Power in Channels of Distribution." *Academy of Marketing Science. Journal* 23, no. 4 (1995): 321.

French, John R. P., and Bertram Raven. *The Bases of Social Power*. Edited by Dorwin Cartwright. Ann Arbor: University of Michigan Press, 1959.

Gaski, John F. "The Theory of Power and Conflict in Channels of Distribution." *Journal of Marketing (pre-1986)* 48, no. 3 (1984): 9.

Gelman, Judith R., and Steven C. Salop. "Judo Economics: Capacity Limitation and Coupon Competition." *The Rand Journal of Economics* 14, no. 2 (1983): 315.

Gertler, Mark, and Simon Gilchrist. "Monetary Policy, Business Cycles, and the Behavior of Small Manufacturing Firms." *The Quarterly Journal of Economics* 109, no. 2 (1994): 309.

Gibbons, Robert. *Game Theory for Applied Economists*. First ed. Princeton, NJ: Princeton University Press, 1992.

Greene, William H. *Econometric Analysis*. Fifth ed. Delhi/India: Pearson Education Inc., 2003.

Grice, John Stephen, and Robert W. Ingram. "Tests of the Generalizability of Altman's Bankruptcy Prediction Model." *Journal of Business Research* 54 (2001): 53-61.

Gritta, Richard D. "Air Carrier Financial Condition: A Review of Models for Measuring the Financial Fitness of the U.S. Airline Industry." *Proceedings of the 2004 Conference of the Air Transport Research Society* (2004).

Guariglia, Alessandra. "The Effects of Financial Constraints on Inventory Investment: Evidence from a Panel of Uk Firms." *Economica* 66, no. 261 (1999): 43.

Guariglia, Alessandra, and Fabio Schiantarelli. "Production Smoothing, Firms' Heterogeneity, and Financial Constraints: Evidence from a Panel of Uk Firms." *Oxford Economic Papers* 50, no. 1 (1998): 63.

Guffey, Daryl M., and William T. Moore. "Direct Bankruptcy Costs: Evidence from the Trucking Industry." *The Financial Review* 26, no. 2 (1991): 223.

Haley, Charles W, and Robert C Higgins. "Inventory Policy and Trade Credit Financing." *Management Science (pre-1986)* 20, no. 4 (1973): 464.

Hall, M., and L. Weiss. "Firm Size and Profitability." *Review of Economics and Statistics* 49 (1967): 319-31.

Halley, Alain, and Jean Nollet. "The Supply Chain: The Weak Link for Some Preferred Suppliers?" *Journal of Supply Chain Management* 38, no. 3 (2002): 39.

Hambrick, Donald C., and Steven M. Schecter. "Turnaround Strategies for Mature Industrial-Product Business Units." *Academy of Management Journal* 26, no. 2 (1983): 231.

Harris, F.W. "How Many Parts to Make at Once." *Factory, The Magazine of Management* 10 (1913): 135-36, 52.

Hausman, J A. "Specification Tests in Econometrics." *Econometrica (pre-1986)* 46, no. 6 (1978): 1251.

Hendel, Igal. "Competition under Financial Distress." *The Journal of Industrial Economics* 44, no. 3 (1996): 309.

Hingley, M K. "Power to All Our Friends? Living with Imbalance in Supplier-Retailer Relationships." *Industrial Marketing Management* 34, no. 8 (2005): 848.

Hingley, Martin K. "Power Imbalanced Relationships: Cases from Uk Fresh Food Supply." *International Journal of Retail & Distribution Management* 33, no. 8/9 (2005): 551.

Hitt, Michael A., Brian K. Boyd, and Dan Li. "The State of Strategic Management Research and Vision of the Future." In *Research Methodology in Strategy and Management, 1*, edited by David J. Ketchen and Donald D. Bergh, 1-32: JAI Press, 2004.

Hofer, Charles W. "Toward a Contingency Theory of Business Strategy." *Academy of Management Journal (pre-1986)* 18, no. 4 (1975): 784.

Hofer, Charles W. "Turnaround Strategies." *The Journal of Business Strategy* 1, no. 1 (1980): 19.

Hofer, Christian, Martin Dresner, and Robert Windle. "Financial Distress and Us Airline Fares." *Journal of Transport Economics and Policy* 39, no. 3 (2005): 323.

Kahneman, Daniel, and Amos Tversky. "Prospect Theory: An Analysis of Decision under Risk." *Econometrica (pre-1986)* 47, no. 2 (1979): 263.

Kashyap, Anil K, Owen A Lamont, and Jeremy C Stein. "Credit Conditions and the Cyclical Behavior of Inventories." *The Quarterly Journal of Economics* 109, no. 3 (1994): 565.

Kashyap, Anil K, Jeremy C Stein, and David W Wilcox. "Monetary Policy and Credit Conditions: Evidence from the Composition of External Finance." *The American Economic Review* 83, no. 1 (1993): 78.

Kennedy, Robert E. "The Effect of Bankruptcy Filings on Rivals' Operating Performance: Evidence from 51 Large Bankruptcies." *International Journal of the Economics of Business* 7, no. 1 (2000): 5.

Kim, Yong H., and Kee H. Chung. "An Integrated Evaluation of Investment in Inventory and Credit: A Cash Flow Approach." *Journal of Business Finance & Accounting* 17, no. 3 (1990): 381.

Lant, Theresa K., Frances J. Milliken, and Bipin Batra. "The Role of Managerial Learning and Interpretation in Strategic Persistence and Reorientation: An Empirical Exploration." *Strategic Management Journal* 13, no. 8 (1992): 585.

LeBlanc, Greg. "Signalling Strength: Limit Pricing and Predatory Pricing." *The Rand Journal of Economics* 23, no. 4 (1992): 493.

Lee, Darin, and María José Luengo-Prado. "The Impact of Passenger Mix on Reported "Hub Premiums" in the U.S. Airline Industry." *Southern Economic Journal* 72, no. 2 (2005): 372.

Lieberman, Marvin B, Susan Helper, and Lieven Demeester. "The Empirical Determinants of Inventory Levels in High-Volume Manufacturing." *Production and Operations Management* 8, no. 1 (1999): 44.

Longenecker, Justin G, and Charles D Pringle. "The Illusion of Contingency Theory as a General Theory." *Academy of Management. The Academy of Management Review (pre-1986)* 3, no. 000003 (1978): 679.

Luthans, Fred, and Todd I Stewart. "A General Contingency Theory of Management." *Academy of Management. The Academy of Management Review* 2, no. 2 (1977): 181.

Mahajan, Siddharth, and Garrett van Ryzin. "Inventory Competition under Dynamic Consumer Choice." *Operations Research* 49, no. 5 (2001): 646.

Maksimovic, Vojislav, and Josef Zechner. "Debt, Agency Costs, and Industry Equilibrium." *The Journal of Finance* 46, no. 5 (1991): 1619.

Mason, Edward S. "The Current State of the Monopoly Problem in the United States." *Harvard Law Review* 62, no. June 1949 (1949): 1265-85.

———. "Price and Production Policies of Large-Scale Enterprise." *American Economic Review* 29, no. March 1939 (1939): 61-74.

Mazzeo, M.J. "Product Choice and Oligopoly Market Structure." *The Rand Journal of Economics* 33, no. 2 (2002): 221-42.

McCafferty, Joseph. "Is Bankruptcy an Unfair Advantage?" *CFO* 11, no. 6 (1995): 28.

McCracken, Jeffrey. "Auto Maker Recovery Bid Intensifies; Ford to Accelerate, Deepen Its Restructuring Efforts; Gm Cites Rosier Fiscal View." *Wall Street Journal*, Aug 10 2006, A.2.

McKinley, William. "Organizational Decline and Adaptation: Theoretical Controversies." *Organization Science* 4, no. 1 (1993): 1-9.

McLaughlin, Curtis P, Gyula Vastag, and D Clay Whybark. "Statistical Inventory Control in Theory and Practice." *International Journal of Production Economics* 35, no. 1-3 (1994): 161.

Miller, Danny, and Ming-Jer Chen. "Sources and Consequences of Competitive Inertia: A Study of the U.S. Airline Industry." *Administrative Science Quarterly* 39, no. 1 (1994): 1.

Modigliani, Franco, and Merton H. Miller. "The Cost of Capital, Corporation Finance and the Theory of Investment." *The American Economic Review* 48, no. 3 (1958): 261-97.

Mone, Mark A, William McKinley, and Vincent L Barker III. "Organizational Decline and Innovation: A Contingency Framework." *Academy of Management. The Academy of Management Review* 23, no. 1 (1998): 115.

Moon, I, and E A Silver. "The Multi-Item Newsvendor Problem with a Budget Constraint and Fixed Ordering Costs." *The Journal of the Operational Research Society* 51, no. 5 (2000): 602.

Morrison, Steven A. "Actual, Adjacent, and Potential Competition." *Journal of Transport Economics and Policy* 35, no. 2 (2001): 239.

Moses, O Douglas. "Organizational Slack and Risk-Taking Behaviour: Tests of Product Pricing Strategy." *Journal of Organizational Change Management* 5, no. 3 (1992): 38.

Moulton, Wilbur N, and Howard Thomas. "Bankruptcy as a Deliberate Strategy: Theoretical Considerations and Empirical Evidence." *Strategic Management Journal* 14, no. 2 (1993): 125.

Opler, Tim C, and Sheridan Titman. "Financial Distress and Corporate Performance." *The Journal of Finance* 49, no. 3 (1994): 1015.

Osteryoung, Jerome S., Eldon Nosari, Daniel E. McCarty, and Walter J. Reinhart. "Use of the EOQ Model for Inventory Analysis." *Production and Inventory Management* 27, no. 3 (1986): 39.

Peteraf, Margaret A. "Intra-Industry Structure and the Response toward Rivals." *Managerial and Decision Economics (1986-1998)* 14, no. 6 (1993): 519.

Porter, Michael. *Competitive Strategy*. New York, NY: Free Press, 1980.

Pryor, Frederic L. "New Trends in U.S. Industrial Concentration." *Review of Industrial Organization* 18, no. 3 (2001): 301.

Queen, Maggie, and Richard Roll. "Firm Mortality: Using Market Indicators to Predict Survival." *Financial Analysts Journal* 43, no. 3 (1987): 9.

Rabinovich, Elliot, and Philip T Evers. "Enterprise-Wide Adoption Patterns of Inventory Management Practices and Information Systems." *Transportation Research. Part E, Logistics & Transportation Review* 38E, no. 6 (2002): 389.

Rachamadugu, Ram. "Effect of Delayed Payments (Trade Credit) on Order Quantities." *Journal of the Operational Research Society* 40, no. 9 (1989): 805-13.

Ravenscraft, David J. "Structure-Profit Relationships at the Line of Business and Industry Level." *The Review of Economics and Statistics* 65, no. 1 (1983): 22.

Reuter, Vincent G. "Are We Using the Inventory Management Tools?" *Industrial Management* 20, no. 3 (1978): 26.

Rodgers, Kimberly Jo Guthrie. "Chapter 11 Reorganization Policy and the Economic Viability of Filing Firms." 3017860, Purdue University, 2000.

Rollman, Daniel P. "Flying Low: Chapter 11's Contribution to the Self-Destructive Nature of the Airline Industry Economics." *Emory Bankruptcy Developments Journal* 21, no. 1 (2004): 381.

Rose-Green, Ena, and Mark Dawkins. "Strategic Bankruptcies and Price Reactions to Bankruptcy Filings." *Journal of Business Finance & Accounting* 29, no. 9/10 (2002): 1319.

Rosenblatt, Meir J. "Multi-Item Inventory System with Budgetary Constraint: A Comparison between the Lagrangian and the Fixed Cycle Approach." *International Journal of Production Research* 19, no. 4 (1981): 331-39.

Roumiantsev, Serguei, and Serguei Netessine. "What Can Be Learned from Classical Inventory Models: A Cross-Industry Empirical Investigation." *Manufacturing & Service Operations Management* forthcoming (2007).

Rustenburg, W D, G J van Houtum, and W H M Zijm. "Spare Parts Management for Technical Systems: Resupply of Spare Parts under Limited Budgets." *IIE Transactions* 32, no. 10 (2000): 1013.

Scherer, F M. *Industrial Market Structure and Economic Performance*. Second ed. Chicago: Rand McNally College Publishing Company, 1980.

Schoonhoven, Claudia Bird. "Problems with Contingency Theory: Testing Assumptions Hidden within the Language of Contingency "Theory"." *Administrative Science Quarterly* 26, no. 3 (1981): 349.

Scott, John T. "Multimarket Contact and Economic Performance." *Review of Economics and Statistics* 64 (1982): 368-75.

Shoham, Aviv, and Avi Fiegenbaum. "Competitive Determinants of Organizational Risk-Taking Attitude: The Role of Strategic Reference Points." *Management Decision* 40, no. 1/2 (2002): 127.

Singh, Jitendra V. "Performance, Slack, and Risk Taking in Organizational Decision Making." *Academy of Management Journal* 29, no. 3 (1986): 562.

Smart, Carolyne, and Ilan Vertinsky. "Strategy and the Environment: A Study of Corporate Responses to Crises." *Strategic Management Journal* 5, no. 3 (1984): 199.

Smith, Ken G, Curtis M Grimm, Stefan Wally, and Greg Young. "Strategic Groups and Rivalrous Firm Behavior: Towards a Reconciliation." *Strategic Management Journal* 18, no. 2 (1997): 149.

Smith, Ken G., Curtis M. Grimm, Martin J. Gannon, and Ming-Jer Chen. "Organizational Information Processing, Competitive Responses, and Performance in the U.S. Domestic Airline Industry." *Academy of Management Journal* 34, no. 1 (1991): 60.

Smith, Malcolm, and Christopher Graves. "Corporate Turnaround and Financial Distress." *Managerial Auditing Journal* 20, no. 3 (2005): 304.

Spanos, Y., G. Zaralis, and S.Lioukas. "Strategy and Industry Effects on Profitability: Evidence from Greece." *Strategic Management Journal* 25, no. 2 (2004): 139-66.

Staw, Barry M., Lance E. Sandelands, and Jane E. Dutton. "Threat-Rigidity Effects in Organizational Behavior: A Multilevel Analysis." *Administrative Science Quarterly* 26, no. 4 (1981): 501.

Stundza, Tom, and Brian Milligan. "How Chrysler Will Cut Costs." *Purchasing* 130, no. 3 (2001): 30.

Sudarsanam, Sudi, and Jim Lai. "Corporate Financial Distress and Turnaround Strategies: An Empirical Analysis." *British Journal of Management* 12, no. 3 (2001): 183.

Sun, Daning, and Maurice Queyranne. "Production and Inventory Model Using Net Present Value." *Operations Research* 50, no. 3 (2002): 528.

Tersine, Richard J. *Principles of Inventory and Materials Management*. Fourth ed. Upper Saddle River, NJ: Prentice-Hall, 1994.

Timme, Stephen G. "The Real Cost of Holding Inventory." *Supply Chain Management Review* 7, no. 4 (2003): 30.

Tiras, Samuel L. "Which Firms Are Likely to Survive Chapter 11?" *Commercial Lending Review* 17, no. 6 (2002): 18.

Trottman, Melanie. "Airline Bankruptcy Filings Put Continental, American at Risk." *Wall Street Journal*, Sep 22 2005, B.4.

Waldman, Don E, and Elizabeth J Jensen. *Industrial Organization: Theory and Practice*. Second ed: Addison Wesley Longman, 2001.

Wallin, Cynthia, M. Johnny Rungtusanatham, and Elliot Rabinovich. "What Is the "Right" Inventory Management Approach for a Purchased Item?" *International Journal of Operations & Production Management* 26, no. 1 (2006): 50.

Warner, Jerold B. "Bankruptcy Costs - Some Evidence." *The Journal of Finance* 32, no. 2 (1977): 337.

White, Halbert. "A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity." *Econometrica* 48, no. 4 (1980): 817-38.

Wiersema, William H. "Financing the Unfinanceable." *Electrical Apparatus* 58, no. 5 (2005): 42.

Wiseman, Robert M, and Philip Bromiley. "Toward a Model of Risk in Declining Organizations: An Empirical Examination of Risk, Performance and Decline." *Organization Science* 7, no. 5 (1996): 524.

Wiseman, Robert M, and Luis R Gomez-Mejia. "A Behavioral Agency Model of Managerial Risk Taking." *Academy of Management. The Academy of Management Review* 23, no. 1 (1998): 133.

Wooldridge, J M. *Econometric Analysis of Cross Section and Panel Data*. Cambridge, MA: MIT Press, 2002.

Xu, Tianji, and Robert L K Tiong. "Risk Assessment on Contractors' Pricing Strategies." *Construction Management and Economics* 19, no. 1 (2001): 77.

Yaffee, Robert. "A Primer for Panel Data Analysis." New York University, NY: http://www.nyu.edu/its/pubs/connect/fall03/yaffee_primer.htm, 2003.

Yoffie, David B, and Mary Kwak. "Judo Strategy: 10 Techniques for Beating a Stronger Opponent." *Business Strategy Review* 13, no. 1 (2002): 20.

Young, Greg, Ken G Smith, and Curtis M Grimm. ""Austrian" and Industrial Organization Perspectives on Firm-Level Competitive Activity and Performance." *Organization Science* 7, no. 3 (1996): 243.

Zinn, Walter, and John M Charnes. "A Comparison of the Economic Order Quantity and Quick Response Inventory Replenishment Methods." *Journal of Business Logistics* 26, no. 2 (2005): 119.