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From Offshoring to Reshoring: A Conceptual Framework for Manufacturing Location Decisions in a Slow-Steam World

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FROM OFFSHORING TO RESHORING: A CONCEPTUAL FRAMEWORK FOR MANUFACTURING LOCATION DECISIONS IN A SLOW-STEAM WORLD

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ABSTRACT

FROM OFFSHORING TO RESHORING: A CONCEPTUAL FRAMEWORK FOR MANUFACTURING LOCATION DECISIONS IN A SLOW-STEAM WORLD
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Reshoring, the act of moving manufacturing operations from an offshore location to the nation of the parent company, is rapidly becoming one of the most researched topics in business. Reshoring describes the reversal of a previous offshoring decision, whereby a firm either relocated its own manufacturing operations overseas or outsourced a significant portion of production to offshore suppliers. With looming uncertainty in global consumer demand and diminishing returns in offshore markets, reshoring is gaining exposure as a viable strategy for firms experiencing a diluted competitive advantage as grounded costs approach market equilibrium.

With academic literature on reshoring only beginning to emerge, many questions remain unanswered. This study was designed to address some of those gaps by developing a conceptual framework linking the antecedents of reshoring to firm performance. Both the resource-based view of the firm and transaction cost economics were used to provide the theoretical basis for determining the direct and intervening factors contained in the conceptual model.

To empirically test the conceptual model, a longitudinal event study was conducted using archival data for 96 firms incorporated in the United States that relocated manufacturing to United States between the years 2007 and 2013. The event

study was conducted by gathering financial data for sample firms as well as closely matched firms which served as industry controls, thereby providing a to isolate the financial impact of reshoring for each sample firm. Once these abnormal returns were analyzed using Wilcoxon Signed-Rank tests, the structural model was tested using partial least squares structural equations modeling.

This dissertation contributes to the global sourcing literature in several ways. First, the event study results strongly support the theory that American firms can significantly improve performance by relocating manufacturing to the United States. Next, although strategic drivers were not supported, path modeling using PLS-SEM provides statistical support for the proposed economic drivers of reshoring. Finally, significant moderating effects were identified, offering further guidance to firms considering reshoring decisions while expanded the academic literature on reshoring.

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CHAPTER ONE: INTRODUCTION

For nearly two decades, U. S. manufacturing companies have pursued inexpensive labor in overseas markets with the belief that "global supply chains make the world go around" (Ellram, 2013, p. 3). Many companies have, however, recently come to the realization that "there's no place like home." This emerging trend of repatriating the manufacturing of goods to the U.S. is called reshoring and is rapidly becoming one of the most popular topics in business magazines and trade publications (Ellram, Tate, & Petersen, 2013). Reshoring is fundamentally a manufacturing location decision that focuses on reversing a previous decision to locate manufacturing facilities overseas (Gray, Skowronski, Esenduran, & Rungtusanatham, 2013). Proponents of reshoring suggest the resulting shorter supply chains should provide superior performance by increasing corporate flexibility and customer responsiveness (Arlbjørn & Lüthje, 2012; Harrington, 2011; Moser, 2011; Tate, 2014). With looming uncertainty in global consumer demand and diminishing returns in offshore markets, reshoring is gaining exposure as a viable strategy for firms experiencing a diluted competitive advantage as grounded costs approach market equilibrium (Wu & Zhang, 2014).

Many skeptics, however, question the ability of a traditional high-price market to sustain the function of low-cost provider (Pisano & Shih, 2012; Shih, 2014). Firms still experiencing success in offshore markets state that decreasing returns are systematic and will therefore readjust as the market improves (Fratocchi, Di Mauro, Barbieri, Nassimbeni, & Zanoni, 2014). Many firms never realized success with overseas production (Handley & W. C., Benton, 2013). This suggests, therefore, that the ability to manage an efficient network, rather than location, drives supply chain success (Fine, 2013). For firms who experienced intellectual property infringements, strategic concerns outweigh the possible cost benefits as cultural and physical distances increase (Song, Platts, & Bance, 2007). With nearly half of global partnerships failing in the first five years, it becomes evident that there is no “one size fits all” solution to global sourcing (Handley & Benton, 2009; Sanders, Locke, Moore, & Autry, 2007).

Despite the sudden emergence of reshoring in the popular press, academic literature has been slower to respond (Martínez-Mora & Merino, 2014). With better information needed to address these issues, the reshoring phenomenon has created the need for more mid-range sourcing theory and instilled a renewed interest in manufacturing locations and global sourcing decisions (Casson, 2013; Ellram, Tate, & Petersen, 2013; Gray et al., 2013; Schmeisser, 2013).

Manufacturing location is one of the most important decisions faced by firm leaders due to the impact it has on firm capital allocation and supply chain performance (Bhatnagar & Sohal, 2005). In the modern hyper-competitive era, competition has changed from business against business to supply chain against supply chain (Seuring & Gold, 2013). Thus, the decisions concerning supplier selection and product country of origin affect many aspects of a firm’s ability to leverage its competencies and supply chain structure in order to serve the final customer (Autry & Griffis, 2008). To create an advantage in sourcing, many firms in high-cost labor countries have traditionally sourced manufacturing to emerging or low cost economies (McCalman & Spearot, 2013). The focus on low-cost end-to-end supply networks became increasingly evident when the

North American Free Trade Agreement created an influx of manufacturing jobs to Mexico and Honduras (Fine, 2013). The "Made in Mexico" movement was short-lived, however, due to quality issues, more liberal trade agreements, and the potential for global retail markets overseas (Schoenherr, Rao Tummala, & Harrison, 2008).

Nearly twenty years ago, the international search for low-cost labor moved from Central America to Asia (Tate, Ellram, Schoenherr, & Petersen, 2014). Companies started moving manufacturing operations to China and India seeking lower production costs resulting from inexpensive labor, favorable exchange rates, and fewer environmental restrictions (Arlbjørn & Lüthje, 2012). Offshoring soon became the prevalent method of manufacturing. In 2003, nearly 25% of all countries in North America sourced some manufacturing in China (Wu & Zhang, 2014). By 2008, 50% of all companies had relied on China for all or most manufacturing (Minter, 2009). In 2010, China surpassed the United States to become the world's largest producer of consumer goods (Rein & Roy, 2012). By this time, U.S. firms had shifted nearly 7.5 million total jobs overseas, while the U.S. manufacturing sector accounted for only 9% of all non-agricultural employment (McMeekin & McMackin, 2012).

More recently, though, companies have been reevaluating the decision to manufacture products overseas (Rein & Roy, 2012). A Boston Consulting Group survey finds that 38% of industrial firms believe that a direct competitor is reshoring, and 14% of those surveyed currently have plans to reshore (Gray et al., 2013). Other research indicates that in 2012, more than one-third of large U.S. based companies planned to reshore production to the United States from China (Tate, 2014). As large manufacturing companies like Ford, Caterpillar and GE continue to repatriate manufacturing jobs, a

2012 survey finds that reshoring could bring up to 3 million jobs and $100 billion in output back to the U.S. by the end of 2015 (McMeekin & McMackin, 2012). Wal-Mart has announced that by 2023, it has plans to increase its sourcing within the U.S. by $50 billion (Ellram, 2013).

This reversal creates the need to reevaluate the existing literature on offshoring and global sourcing in order to understand the current phenomenon of reshoring (Gray et al., 2013). Nearly half of all outsourcing agreements failed within five years (Handley & Benton, 2009), many because firms simply failed to realize the hidden costs of offshoring (Larsen, Manning, & Pedersen, 2013). Hidden costs result from unexpected expenses such as added travel, communication, and inventory carrying costs that cause the total cost of ownership to be significantly higher than the expected grounded costs (N. Song et al., 2007).

Hidden costs can also result from failure to identify opportunism leading to strategic risk (Tate & Ellram, 2009). Many high-tech firms, such as Apple and Intel, are choosing to reshore because of recent loss of intellectual property overseas (Fishman, 2012). In addition to intellectual property, firms that outsource valuable functions run the risk of losing strategic capabilities (Sanders et al., 2007). The failed Boeing 787 provides an excellent example of tacit knowledge erosion that occurs as research and development moves further away from production (Kotha & Srikanth, 2013; Tang, Zimmerman, & Nelson, 2009).

While reshoring represents the reversal of previous offshoring decisions, not all of these reversals occur due to failed overseas relationships. Many decisions to repatriate production result from the changing global environment (Gray et al., 2013). As the economies of these low cost nations grow, so does the demand for the labor that they supply (Tate et al., 2014). More importantly, developing nations continue to drive up the demand for fuel, thus creating transportation cost instability and higher energy costs (Ellram, Tate, & Feitzinger, 2013). In response to rising fuel costs, ocean carriers have adopted a method called slow steaming (Ellram, 2013) to reduce the ship's speeds, emissions, and fuel usage (Tate et al., 2014). The practice of slow steaming significantly increases lead-time, requiring manufacturers to keep much more inventory on-hand and in-transit (Moser, 2011).

Political instability, natural disasters, and natural resource shortages all have the ability to cause supply chain disruptions and contribute to the changing global environment as well (Chen, Olhager, & Tang, 2013). As supply chains become longer, the impact of supply chain disruptions becomes more severe (Autry & Bobbitt, 2008; Bode, Wagner, Petersen, & Ellram, 2011; Ellis, Henry, & Shockley, 2010). These disruptions can occur from late shipments, lost or stolen freight, or poor supplier performance (Schoenherr et al., 2008; Tang & Musa, 2011). Larger scale disruptions occur from natural resource shortages or natural disasters like Hurricane Katrina or the constant earthquakes in Chile (Manuj & Mentzer, 2008a). Examples of synthetic catastrophes include the UPS cargo plane crash in 2013 or the explosion that caused the BP Deepwater Horizon disaster in 2010. Throughout many global regions, terrorism and political instability create the potential for supply chain disruptions (Ellram, Tate, & Petersen, 2013; Tate, 2014). For example, political unrest forced Procter and Gamble to shutter two new production facilities along with its corporate operations in Cairo, Egypt for several weeks in 2011.

Although reshoring is rapidly becoming one of the most researched topics in the popular press (Tate et al., 2014), academic research on this phenomenon is still at a nascent stage (Fratocchi et al., 2014). An examination of existing research on reshoring reveals that current understanding of the reshoring phenomenon is limited to descriptive data and potential drivers. To date, few quantitative studies exist in extant literature, most being exploratory in nature (Ellram, Tate, & Petersen, 2013; Fratocchi et al., 2014; Kinkel, 2014; Tate, 2014). Even though some exploratory research has emerged, no conceptual model exists (Ellram, Tate, & Petersen, 2013; Kinkel & Maloca, 2009). This gap in the literature creates a huge disadvantage to researchers and practitioners struggling to determine whether to remain engaged in Asian and Indonesian supply markets (Kinkel, 2014). Direct and intervening variables must be identified and empirically tested to understand the impact of these driving factors and the conditions in which they exist.

A weakening U.S. dollar along with these rising costs of overseas production could result in sourcing decisions favoring North America in the future (de Treville & Trigeorgis, 2010; Sirkin, 2011). Due to currency valuations and rising wages in overseas markets, net labor costs in China and the U.S. could converge in 2015 (McMeekin & McMackin, 2012). With limited expansion potential overseas and an extensive learning curve in the U.S., factor market rivalry suggests a first-mover advantage in reshoring (Ellram, Tate, & Feitzinger, 2013; Pisano & Shih, 2012). With no conceptual framework to guide decisions, questions remain about which firms will benefit the most from reshoring early.

Some products and companies should still benefit from offshore production, yet the academic literature has not addressed these issues (Martínez-Mora & Merino, 2014). Proximity to foreign demand, access to markets with high barriers to entry, and resource dependence all suggest that offshoring should still be beneficial if not necessary for some firms (Bhatnagar & Sohal, 2005). In this scenario, the underlying question is not "where to produce," but "what to produce where" (Baldwin & Venables, 2013; Martínez-Mora & Merino, 2014; McCalman & Spearot, 2013). A gap in the literature emerges when we consider the limited understanding of the conditions necessary for reshoring success. Because of the changing global environment, questions also remain about which factors of the manufacturing location decision affect the ability of a firm to create a sustainable competitive advantage, which ultimately increases shareholder wealth (Arlbjørn & Lüthje, 2012; Chen et al., 2013).

The purpose of this dissertation is to identify and empirically test the most salient factors influencing manufacturing location decisions of U.S. manufacturing firms in the current economic environment. In addition to factors directly influencing these decisions, the study will also consider firm-facing and market-facing characteristics that might create boundary conditions and intervening effects. The proposed research will employ an archival event study using data collected from publicly traded firms that have recently relocated manufacturing facilities from offshore or nearshore locations to the United States. This longitudinal approach will assist in isolating the effects of manufacturing location over time. Upon completion of data collection using the event study method, hierarchical moderated multiple regression will be utilized to estimate the impact of direct and intervening variables on the reshoring decision. The proposed longitudinal method and subsequent regression analysis will assist in answering the following research questions:

RQ1: What conditions allow a firm to enhance procurement proficiency and ultimately firm performance by switching to a domestic supplier?

RQ2: When considering manufacturing location decisions, which factors affect the firm's ability to create a sustainable competitive advantage?

RQ3: Concerning country of origin decisions, do market-facing or firm-facing characteristics create boundary or interaction effects that might influence the outcome of these decisions?

This study contributes to the academic literature in several ways. Grounded in transaction cost economics and the resource-based view of the firm, this research contributes to the current literature by presenting a conceptual framework that addresses both tactical and strategic factors involved in global sourcing decisions. The study also proposes to provide information concerning the company and product types most likely to benefit from reshoring. The results of this study will provide a first step towards developing workable strategies for global sourcing decisions in the modern economy.

This dissertation is organized as follows: Chapter 2 provides a theoretical foundation for the study with a review of transaction cost economics and the resource-based view of the firm. This is followed by an extensive review of global sourcing by U.S. based companies. Next, constructs are defined and relationships in the conceptual model are posited. Chapter 3 presents an overview of the research design, and then discusses the data collection method and the analytical techniques used to empirically test the hypotheses. Chapter 4 provides a discussion of the results. Chapter 5 concludes with a discussion of ways to link the theoretical findings with the practice of strategic sourcing.

CHAPTER TWO: LITERATURE REVIEW

Chapter 2 provides a review of the literature on global sourcing and presents the theoretical lens for the study. The literature review updates the audience on the current economic environment, and defines all relative factors in the changing global market. The primary purpose of this chapter is to propose a conceptual framework, grounded in theory, which provides answers to the research questions presented in the introduction.

This chapter contains four sections, organized as follows: The first section defines reshoring and provides a review of the existing literature on global sourcing. Next, a theoretical foundation for the study is developed by providing a literature review of transaction cost economics and the resource-based view of the firm. In the third section, the conceptual model is explained and construct definitions are provided. Finally, the theoretical linkages between the constructs are examined and hypotheses are developed to test the conceptual framework.

2.1 Overview of Reshoring

2.1.1 Defining Reshoring

Reshoring describes the relocation of manufacturing operations from an overseas location to the country of the parent company (Ellram, 2013). Backshoring is a common term used to describe the reshoring phenomenon in Europe (Fratocchi et al., 2014; Kinkel, 2014). Authors have commonly used other terms, such as homeshoring and onshoring when discussing reshoring (Tate, 2014). Any of these terms may be used synonymously with reshoring; however, reshoring is often incorrectly interchanged with similar sourcing terms, such as insourcing or nearshoring (Ellram, 2013; Gray et al., 2013; Kinkel & Maloca, 2009). For semantic clarity, it is therefore necessary to differentiate reshoring from other sourcing options (Kinkel & Maloca, 2009).

Global firm boundary decisions fall into two dimensions: ownership and location (Gray et al., 2013; Kinkel & Maloca, 2009). In terms of ownership, internalization is a more stringent form of organizational governance in which the production of goods occurs through vertically integrated hierarchies (Williamson, 1975). Conversely, outsourcing involves the use of specialists to provide competence, technologies, and resources to manufacture products or provide necessary components (Harland, Brenchley, & Walker, 2003). Relational contracting creates additional intermediary options, such as joint ventures and strategic alliances, in which firm boundaries are often blurred and not clearly defined (Williamson, 1991).

The second dimension, location, provides three sourcing options: offshoring, nearshoring, and reshoring. Offshoring concerns the production of any product or component in locations abroad (Kinkel & Maloca, 2009). Offshore production may occur within firm boundaries or through open exchanges. Offshore outsourcing is the term used to describe production via contracted manufacturers (Gray et al., 2013). Often firms internalize overseas production through foreign direct investment, although the level of control that firm ownership provides locally is contingent upon the laws and culture of the host country (Fahy & Smithee, 1999; Teece, 1986). To circumvent the geographical and cultural challenges of offshore manufacturing, nearshoring is emerging as a viable low-cost option (McIvor, 2013). Nearshoring occurs when firms locate manufacturing in low-cost countries within close proximity to the domicile location

(Ellram, Tate, & Petersen, 2013). Canada and Mexico are nearshore options for U.S. manufacturers, although Canada is not a clear low-cost option for labor (Moser, 2011).

Reshoring is simply the reversal of a previous decision to locate manufacturing overseas (Gray et al., 2013). Reshoring requires the interlinking of at least two sequentially adjacent relocation decisions, therefore only concerns previous offshoring decision. (Kinkel & Maloca, 2009) This definition requires that the product must have been produced offshore, but does not imply that the reshored product was previously produced domestically (Gray et al., 2013). For example, many companies in recent years adopted a sourcing strategy of designing products locally then producing overseas because the decision to offshore was inherent in the product design, and reshoring would occur if domestic production began (Casson, 2013). This is common for the "born global" startups and firms with little resource slack (Cavusgil & Cavusgil, 2012).

2.1.2 Summary of Academic Literature on Reshoring

Given the recency of the phenomenon, academic literature on reshoring is only beginning to emerge. Most of the current literature serves to define the reshoring phenomenon (Gray et al., 2013), establish the need for empirical analysis (Ellram, 2013), or provide theoretical grounding and conceptualization for future research (Casson, 2013; Fratocchi et al., 2014; Gray et al., 2013; McIvor, 2013). Much of the current quantitative data on reshoring originates from private research firms. For instance, Boston Consulting Group gathered survey data from U.S. manufacturing companies which determined the extent of current reshoring activity along with the propensity of firms to relocate production in the near future (Gray et al., 2013).

While empirical evidence about reshoring is limited, some quantitative research does exist. For instance, Kinkel and Maloca (2009) provide some of the earliest research on reshoring based upon secondary data from 1663 German companies. Their study establishes reshoring as a quantifiable phenomenon identifies product quality and loss of flexibility as primary drivers of reshoring for European firms (Kinkel & Maloca, 2009). Tate et al. (2014) examine the effects of factor market rivalry on manufacturing location using survey results from 319 companies. The most rigorous research to date comes from Ellram et al. (2013), who use multiple regression to determine the impact that perceived locational risk has on the propensity to repatriate manufacturing.

To date, no research exists broadly linking reshoring to firm performance, although case studies addressing certain aspects of location decisions are beginning to emerge. A qualitative multi-case study on the Spanish footwear industry suggests that reshoring is a response to macro-economic changes and the need for customer responsiveness (Martínez-Mora & Merino, 2014). The same factors emerge from a single-case study on bicycle manufacturing in Europe. In this study the authors also identified difficulty in transferring knowledge and processes as a driving factor in the relocation (Gylling, Heikkilä, Jussila, & Saarinen, 2015). Both studies suggest that firms may improve performance by reshoring (Gylling et al., 2015; Martínez-Mora & Merino, 2014). Many of the examples of reshoring by U.S. firms have been anecdotal, and no studies link reshoring to long-term firm performance. Research on American firms is limited to an archival study examining the effect of U.S. tax codes on reshoring activity, with sample data taken between the years 1987 and 2003 (Hanlon, Lester, & Verdi, 2015).

Table 1 summarizes the existing academic literature concerning reshoring. Of the 18 articles currently available, only one appeared before 2013 (Kinkel & Maloca, 2009). Four of these studies were identified within the past year (Ancarani, Di Mauro, Fratocchi, Orzes, & Sartor, 2015; Grappi, Romani, & Bagozzi, 2015; Gylling et al., 2015; Hanlon et al., 2015). Six articles appeared in a special issue of the Journal of Supply Chain Management (Casson, 2013; Ellram, 2013; Ellram, Tate, & Petersen, 2013; Fine, 2013; Gray et al., 2013; McIvor, 2013). Another four articles emerged from a special issue of Journal of Purchasing and Supply Management (Fratocchi et al., 2014; Kinkel, 2014; Martínez-Mora & Merino, 2014; Tate, 2014). Many of the articles that appeared in special issues are conceptual articles designed to spur future research. This serves to highlight the recency of the reshoring phenomenon as well as the urgency of the need for empirical research concerning reshoring.

Table 1: Academic Articles about Reshoring

Article	Focus	Theory	Variables	Contribution
(Ancarani et al., 2015)	Reshoring	Eclectic Theory (OLI Model)	Efficiency Seeking; Market Seeking; Resource Seeking; Strategic Asset Seeking; Duration of Offshore Activity	This study uses secondary data to analyze 249 cases of reshoring in the U.S. and Europe based on previously identified drivers of reshoring. Results indicate that highly technical products and automotive products are more likely to reshore within a shorter period.
(Casson, 2013)*	Global supply chains	Internalization Theory	Conceptual	Author uses internalization theory to provide a macro-level approach to manufacturing location decisions.
(Ellram, 2013)*	Reshoring		Editorial	Intro to Special Issue of JSCM
(Ellram, Tate, & Petersen, 2013)*	Nearshoring, Reshoring	Transaction Cost Economics, Internalization Theory, Eclectic Theory (OLI Model)	Drivers of location decisions, global attractiveness of region	Empirical article uses quantitative survey data and exploratory factor analysis to identify the drivers of manufacturing location movement in and out of many global regions in the past and future 3 years. Provides 3 research propositions concerning reshoring.

(Fine, 2013)*	Manufacturing location		Conceptual	Firms should consider intelli-sourcing rather than reshoring. The smarter network, rather than the better partnership or location sees superior performance.
(Fratocchi et al., 2014)**	Backshoring (Reshoring); De-internationalization		Conceptual	Article provides a brief literature review and definition of backshoring. The authors provide insights into strategy and future research on backshoring.
(Grappi et al., 2015)	Reshoring; Offshoring; Consumer Sentiment		Gratitude; Righteous Anger; Happiness; Sadness; Animosity; Perceived Risk	Study conducts experiments to determine consumer response to reshoring. In general, consumer sentiment changed from righteous anger to gratitude if they felt the firm had genuine motives.
(Gray et al., 2013)*	Reshoring Internalization Theory; Eclectic Theory (OLI model)		Conceptual	Essay article offers a definition of reshoring, an explanation to the onset of the reshoring phenomenon, and a list of the future implications of reshoring.
(Gylling et al., 2015)	Offshore Outsourcing; Backshoring (Reshoring)	Time-Driven Activity Based Costing	Case Study	Case study analyzes cost structure of a Finnish bicycle company that outsourced production to Taiwan. The study finds that a 25% cost reduction eroded due to the changing economy, currency valuation, and productivity, thereby making backshoring the more attractive option.
(Hanlon et al., 2015)	Repatriation tax rates	Agency Theory	Repatriation Tax; Foreign Cash; Foreign Cash Controls; Abnormal Return; Sales Growth; Week Cap; PE Ratio; Size; Foreign Sales; Domestic Sales	Empirical longitudinal study analyzes secondary data to examine the effects of the U.S. repatriation tax rate on domestic and foreign investments. The authors find higher repatriation tax rates encourage offshore investment, thereby discouraging reshoring.
(Kinkel, 2014)**	Backshoring (Reshoring)		Conceptual	Paper provides some descriptive data about offshoring and backshoring activities in Germany over the past 15 years. Paper offers insights on motivations for backshoring decisions.
(Kinkel & Maloca, 2009)	Backshoring (Reshoring)	Internalization Theory; Eclectic Theory (OLI Model)	Flexibility; Quality; Coordination Costs; Infrastructure Availability of Qualified Personnel	Based on German manufacturing, the study uses probit analysis to determine the drivers of backshoring. The study finds between 15% and 25% of German offshoring practices are reversed within 4 years, and poor quality is the driving factor.
(Martínez-Mora & Merino, 2014)**	Offshoring; Backshoring (Reshoring)	Transaction Cost Economics; International Business Theory	Qualitative Multiple-Case Study	Study investigates reshoring in the Spanish footwear industry. The study uses semi-structured interviews to determine that the changing environment and the need for greater responsiveness are two primary drivers of backshoring.

(McCalman & Spearot, 2013)	Offshoring; Inshoring; Trade Agreements		Plant Capacity; Production Costs; Product Specialization; Age of Model	Study uses secondary data from trucks manufactured in Mexico and the U.S. in the NAFTA era to help explain which types of products might be outsourced and which products are manufactured at home.
(McIvor, 2013)*	Manufacturing Location	Transaction Cost Economics, Resource-Based View	Conceptual	Essay article suggesting the benefits of using transaction cost economics and resource-based view in tandem to guide manufacturing location decisions.
(Tate, 2014)**	Reshoring; Right-shoring		Conceptual	Study provides insights into the possible directions and challenges of research regarding reshoring based on survey data.
(Tate et al., 2014)	Manufacturing Location; Reshoring; Nearshoring	Resource-Based View - Factor Market Rivalry	Labor costs, labor availability, energy, exchange rate, tax rate,	Empirical article is one of the first to use quantitative data to identify factors and trends affecting reshoring decisions of U.S. companies.
(Wu & Zhang, 2014)	Backshoring (Reshoring); Sourcing equilibrium	Bayesian Nash Equilibrium (game theory)	Efficiency; Responsiveness; Sourcing Equilibrium	Paper uses mathematical modeling to simulate a sourcing game. Examines strategic sourcing from a macro-level concerning efficiency and responsiveness.

*Journal of Supply Chain Management special issue on reshoring
**Journal of Purchasing and Supply Management special issue on reshoring

2.2 Theoretical Lens

This dissertation employs the resource-based view (RBV) of the firm along with transaction cost economics (TCE) to provide a multi-tiered theoretical lens for examining the reshoring phenomenon. Transaction cost economics and the resource-based view of the firm have traditionally been two of the most influential theories used to examine organizational boundaries (McIvor, 2009). Organizational boundaries are fundamental to business policy because they define the level of vertical and horizontal integration that a firm employs as a competitive strategy (G. Walker & Weber, 1984). The manufacturing location decision is central to business strategy and of crucial concern for most manufacturing firms (Tate, 2014). As organizations consider offshore, nearshore, and domestic sourcing options, organizational boundary decisions must incorporate location as well as ownership (McIvor, 2013). Offshoring, or subsequent reshoring decisions are key aspects of strategic enterprise positioning due to the long-term impact on the competitiveness of the company (Kinkel & Maloca, 2009).

Although the RBV and TCE are two of the most commonly used theories for interim relationships, they have traditionally represented competing theories of the firm (Conner, 1991). Transaction cost economics is a governance-based theory that uses transaction costs to explain why firms exist, while RBV is a performance-based theory that uses resources and capabilities to examine how firms compete (McIvor, 2009). Resource-based view theorists argue that the resource-based view is a creator of positives, while transaction cost economics is an avoider of negatives (Conner, 1991). Table 2 provides a comparison of transaction cost economics and resource-based theory.

In the past few years, scholars have insisted that transaction cost economics and resource-based theory should be viewed as complementary, rather than conflicting theories (Holcomb & Hitt, 2007; McIvor, 2009; Neves, Hamacher, & Scavarda, 2014). This is primarily because neither theory alone can fully explain the complex global environment (Poppo & Zenger, 1998). Transaction cost economics specifies when conditions are suitable for outsourcing, while RBV helps to identify which functions to source and which to keep in house (Shook, Adams, Ketchen Jr, & Craighead, 2009). Using both TCE and RBV allows firms to examine outsourcing activities at both the strategic and operational levels (McIvor, 2013).

Table 2: Comparison of TCE and RBV

	Transaction Cost Economics	Resource-Based View
Purpose	Why firms exist	How firms compete
Unit of Analysis	Transactions	Firm Resources
Firm Definition	Transaction cost economics describes the firm as “an efficiency-inducing administrative instrument that facilitates exchange between economic actors (Leiblein, 2003, p. 939).”	Resource-based theory views the firm as a bundle of assets and resources that, if employed in distinctive ways, can create competitive advantage (Barney, 1991; Penrose, 1959).
Assumptions	Market efficiency, bounded rationality, opportunism	Heterogeneity, imperfect mobility, bounded rationality
Basic Premise	Markets and hierarchies are alternative modes of governance for economic transactions; the choice of governance should be made with a transaction cost economizing purpose (Coase, 1937; Williamson, 1975).	Firm boundaries define the possession and composition of the valuable, difficult-to-imitate resources that could ultimately create a sustainable competitive advantage (Barney, 1991; Peteraf, 1993).
Central Tenet	Economic organization is an effort to "align transactions, which differ in their attributes, with governance structures, which differ in their costs and competencies, in a discriminating (mainly, transaction cost economizing) way (Williamson, 1991, p. 79).”	Resources and capabilities must be simultaneously valuable, rare, inimitable, and organizationally accessible to drive sustainable competitive advantage (Barney, 1991; Peteraf, 1993).

2.2.1 Resource-Based View

The resource-based view is a performance-based theory of the firm that uses resources and capabilities to determine how firms achieve competitive advantages and sustain those advantages over time (Eisenhardt & Martin, 2000). The resource-based view of the firm is an internally based theory designed to explain differences in firm behaviors and performance (Wernerfelt, 1984). Resource-based theory proposes that firms have different resource endowments, and that the manner in which firms acquire, develop, maintain, bundle, and apply these resources leads to the development of competitive advantage and superior performance (Shook et al., 2009). The tenets of resource-based theory posit that resources and capabilities must be simultaneously valuable, rare, inimitable, and organizationally accessible to drive sustainable competitive advantage (Barney, 1991; Peteraf, 1993).

Resources are the tangible and intangible assets that a firm may use to conceive of and implement its strategies (Hunt & Morgan, 1995). Superior resources provide firms with higher production performance or lower average costs than other firms (Barney, 1991). Capabilities are subsets of resources, which enhance the performance or improve the value of the other resources possessed by the firm (Makadok, 2001). Collectively, resources and capabilities represent bundles of tangible and intangible assets that include a firm's management skills, its organizational processes and routines, and the information and tacit knowledge that it uses to implement strategies (Kozlenkova, Samaha, & Palmatier, 2014). Resource-based theory suggests that superior resources and capabilities lead to core competencies, which are those attributes that are difficult or costly to imitate as the source of economic rents to drive firm performance and provide a competitive advantage (Conner, 1991).

Resource-based logic relies on the assumptions that strategic resources are heterogeneously distributed across firms within an industry and that those differences are stable over time (Barney, 1991). Resource heterogeneity occurs because competing firms have differing resources, therefore each firm has an assortment of resources and capabilities that is at least in some ways unique (Hunt & Morgan, 1995). Imperfect resource mobility implies that superior resources are not readily bought, sold, or traded within the marketplace (Hunt & Morgan, 1996). These underlying assumptions suggest that superior resources are limited in supply and quasi-fixed so that supply cannot be expanded rapidly within industries (Peteraf, 1993). Firms without access to superior resources must substitute resources of lesser quality (Hunt & Morgan, 1995); therefore, some firms are more skilled in accomplishing certain activities because they possess unique resources and capabilities of superior quality (Kozlenkova et al., 2014).

Resource-based theory states that for a resource or capability to provide a sustainable competitive advantage, it must be simultaneously valuable, rare, imperfectly imitable, and organized in a way that makes it exploitable by the firm (Barney, 1991; Peteraf, 1993). First, valuable resources are those that enable a firm to exploit opportunities or neutralize threats in the competitive environment (Barney, 1991). Second, rare resources are those accessible to only a small number of firms within the same industry (Peteraf, 1993). Next, a resource is imperfectly imitable when it is costly to obtain and difficult to imitate by competing firms (Reed & DeFillippi, 1990). To pass this test, a resource must be imperfectly mobile as well as non-substitutable (Hunt & Morgan, 1995). Finally, to create a sustainable competitive advantage, the firm must be organized to exploit the competitive potential of the resource (Kozlenkova et al., 2014).

Resource-based theory considers outsourcing from a strategic perspective, which involves employing outsourcing not only to reduce costs, but also to allow an organization to develop a range of capabilities and leverage the specialist capabilities of suppliers (Teece, Pisano, & Shuen, 1997). The ability of a firm's strategies to generate suitable returns depends upon the attributes of its resources and capabilities (Barney, 2014). Resource-based theory states that activities in which firms achieve superior performance relative to competitors should be performed internally (Wernerfelt, 2014), while collaboration with external sources may provide a firm access to complementary resources, which could provide a comparative advantage (Hunt & Morgan, 1995).

2.2.2 Transaction Cost Economics

Transaction cost economics examines whether a transaction is more efficiently performed within firm boundaries or across independent entities (Steenkamp & Geyskens, 2012). According to TCE, global sourcing decisions involve a comparison of the production costs incurred from producing a product internally with the transaction costs associated in purchasing a product from an external source (Williamson, 1975). Unlike production costs, transaction costs are difficult to measure because they represent the potential consequences of alternative decisions (Klein, Frazier, & Roth, 1990). The TCE framework provides a rational view for evaluating make-or-buy decisions by allowing the properties of the transaction determine the most efficient governance structure – market, hierarchy, or alliance (Geyskens, Steenkamp, & Kumar, 2006; Geyskens et al., 2006; McIvor, 2009).

Transaction cost logic depends upon two foundational behavioral assumptions: bounded rationality and opportunism (Williamson, 1985). Bounded rationality states that while decision makers intend to act rationally, they are limited by their own information processing and communication ability (Tate & Ellram, 2009). Opportunism is defined as "self-interest seeking with guile" (Williamson, 1975, p. 6), which may involve "incomplete or distorted disclosure of information, especially to calculated efforts to mislead, distort, disguise, obfuscate, or otherwise confuse" (Williamson, 1985, p. 17). While not all economic agents behave opportunistically, transaction cost logic universally assumes opportunism because it is very costly to distinguish opportunistic agents from sincere suppliers (Williamson, 1981).

The potential for opportunistic behavior in market-based exchanges generates transaction costs, making vertical integration more efficient than market governance (Geyskens et al., 2006; Williamson, 1975, 1985). Transaction cost economics states that economic organization is an adaptation to transactional hazards emerging from opportunistic behavior (Williamson, 1981, 2008). Thus, the need for internal governance arises because all agents within an exchange are subject to bounded rationality, and at least some display opportunistic behavior when given the chance (Geyskens et al., 2006). Transaction cost economics focuses on the costs associated with exchange governance by identifying governance mechanisms that are most appropriate for the exchange conditions surrounding a given transaction (Williamson, 1991).

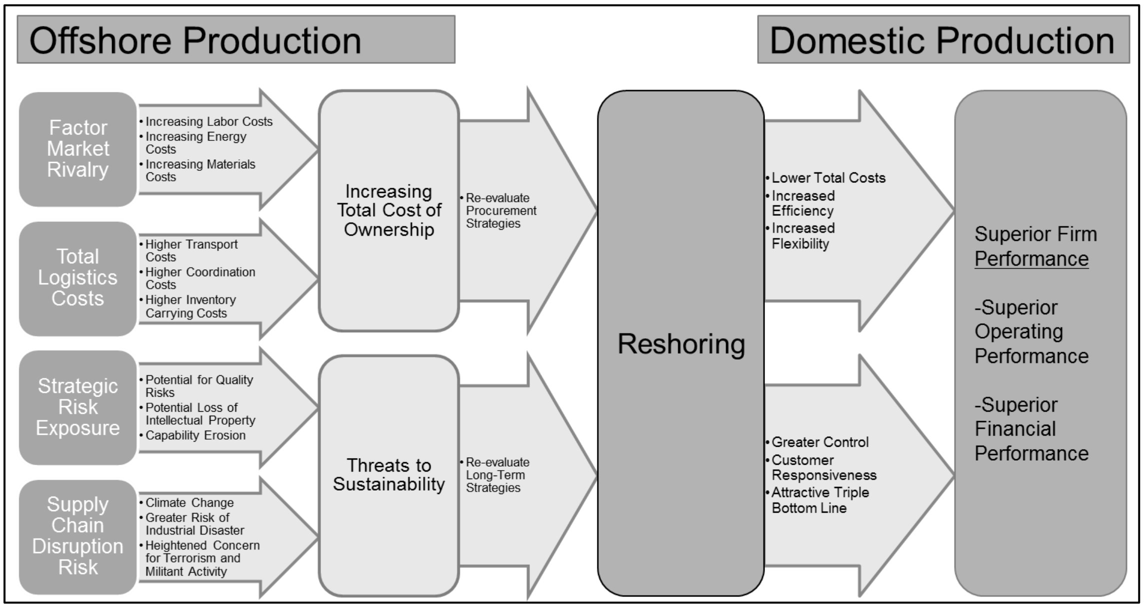
The basic premise of TCE views markets and hierarchies as alternative forms of governance, in which market regulation results from the price mechanism and hierarchies govern internal exchanges by means of legitimate authority (Coase, 1937; Williamson, 1985). Drawing on the benefits of competition and scale economies, the transaction cost framework makes the a priori assumption that market governance is more efficient than vertical integration (Geyskens et al., 2006). Under the TCE framework, asset specificity and uncertainty are the principal transactional dimensions in which opportunistic behavior may generate transaction costs (G. Walker & Weber, 1984). The level of specialized assets required to support the exchange along with the uncertainty surrounding the exchange increase the complexity of transactions, thereby making external market-based exchanges inefficient (Klein et al., 1990).

2.3 Conceptual Development and Construct Definitions

This dissertation uses a multi-step theoretical lens to determine the antecedents of reshoring that ultimately affect to firm performance (Neves et al., 2014). Using both RBV and TCE allows the focal firm to identify the hidden costs that plague global sourcing and to evaluate its ability sustain resource positions amidst a changing global environment (Fahy & Smithee, 1999). Figure 1 conceptualizes the antecedents and outcomes of reshoring.

At the exchange level, hazards generate transaction costs, which reduce the efficiency of market-based exchanges (Williamson, 1985). These economic drivers of reshoring occur as a result of factor market rivalry and increasing logistics costs. Factor market rivalry creates higher production costs , while total logistics costs provides a measure of all costs incurred when coordinating a global supply chain (Zeng & Rossetti, 2003). At the firm level, transaction hazards induce risks, which threaten the effectiveness of strategic resources and capabilities (Miller, 1992). Strategic risk exposure represents the threat to economic sustainability due to the erosion of strategic assets used in offshore production (Handley & Benton, 2009). Supply chain disruption risk indicates the potential threats to long-term firm performance created by the potential inability to obtain products and materials necessary for production (Chopra, Reinhardt, & Mohan, 2007).

Figure 1: Conceptualization of the Reshoring Phenomenon



In addition to the direct factors driving reshoring decisions, potential intervening variables are also addressed. Since no "one size fits all" strategy exists for strategic sourcing decisions, the benefits of reshoring will likely differ across industries and even across different firms within the same industries (Sanders et al., 2007). To learn more about how reshoring might affect firms differently, it is necessary to examine the firm-facing and market-facing situations that might affect the relationships (Esper, Ellinger, Stank, Flint, & Moon, 2010). These contingent or situational constructs serve as moderating variables in the conceptual model. Product innovativeness provides an indication of the industry dynamics and market turbulence that might lead to reshoring (Hult, Hurley, & Knight, 2004). Likewise, the ability to create offshore relationship value is a supply-chain facing capability which allows some firms to create a competitive advantage in offshore markets (Ritter & Walter, 2012). Both product innovativeness and offshore relationship value are expected to affect the relationship between the antecedents an outcomes of reshoring. Table 3 provides definitions and roles for all constructs in the conceptual model. The remainder of this section provides additional descriptions for each of the variables in the conceptual model.

2.3.1 Economic Drivers of Reshoring

2.3.1.1 Factor market rivalry. Factor market rivalry happens when firms must compete over the resources required to implement strategy (Barney, 1986). Factors, also called inputs, are resources necessary for firms to manufacture products or provide services (Barney, 1986). These resources are presumed to be vital, mobile, and scarce (Markman et al., 2009). As scarcity increases for any necessary resource, competition emerges (Sanders et al., 2007). Therefore, factor market rivalry, in its simplest form, happens when firms compete in upstream, rather than downstream markets (Ellram, Tate, & Feitzinger, 2013). Factor market rivalry, like any competition, significantly reduces profitability (Barney, 1991; Porter, 2008).

Markman (2009, p. 423) defines factor-market rivalry as "the competition over resource positions that occurs when two or more firms compete over necessary inputs." Although a strong factor position may potentially create a sustainable competitive advantage in product markets, factor market rivalry does not imply that the competition involves valuable, rare, inimitable, and non-substitutable resources (Barney, 1986). Factor market rivalry may be derived from competition over raw materials, natural resources, real estate location, human resources, or even outsourced services (Ellram, Tate, & Feitzinger, 2013). Often, firms overly focused on resources that contribute to a sustainable competitive advantage in product markets must face unanticipated competition in factor markets (Ellram, Tate, & Feitzinger, 2013).

Table 3: Proposed Construct Definitions

Construct	Definition	Role
Factor Market Rivalry	Factor market rivalry represents the competition over resource positions that occurs when two or more firms compete over necessary inputs. While these resources are presumed to be vital, mobile, and scarce, they need not be simultaneously valuable, rare, inimitable, and non-substitutable (Markman, Gianiodis, & Buchholtz, 2009).	Independent Variable
Total Logistics Cost	Total logistics costs consider the whole range of costs associated with logistics, which includes transport and warehousing costs, but also inventory carrying, administration, and order processing costs (Zeng & Rossetti, 2003).	Independent Variable
Strategic Risk Exposure	Strategic risk exposure defines the sensitivity to attributes in the global environment that might diminish the strategic resources and core competencies that a firm employs to create value for its customers (Harland et al., 2003; Miller, 1992).	Independent Variable
Supply Chain Disruption Risk	An individual's perception of the total potential loss associated with the disruption of supplies, inventories, and finished products within a supply chain (Ellis et al., 2010).	Independent Variable
Offshore Relationship Value	"The trade-off between the multiple benefits and sacrifices of a supplier's core offering, as perceived by key decision makers in the customer's organization, and taking into consideration the available alternative suppliers' offerings in a specific-use situation (Ulaga & Chacour, 2001, p. 530)."	Moderator
Product Innovativeness	Product innovativeness is the degree to which a product possesses new and unique attributes and features, as compared to other products in the same market (Fu, Jones, & Bolander, 2008).	Moderator
Superior Operating Performance	Superior operating performance represents the increase in efficiency of reshoring firms in comparison to those who do not reshore (Hunt & Morgan, 1995, 1996).	Ultimate Outcome
Superior Financial Performance	Superior financial performance represents the increase in profitability of firms that reshore compared to those that do not (Hunt & Morgan, 1995, 1996).	Ultimate Outcome

Competitive blind spots emerge when firms must compete over resources that are not strategically important, or when firms must compete with unexpected rivals (Markman et al., 2009). Many times unexpected competition occurs when companies must compete with adjacent or unrelated firms with overlapping needs (Barney, 1986).

This type rivalry often occurs when unrelated firms compete over limited logistics capacity or semi-skilled labor (Ellram, Tate, & Feitzinger, 2013). Moreover, the competition can come from unexpected and even unrelated firms , because factor market rivalry does not require that firms compete in the same product markets (Markman et al., 2009). For instance, Chrysler met unexpected competition when a company that manufactured kitty litter began buying the clay that it needed for prototypes and molds (Ellram, Tate, & Feitzinger, 2013).

2.3.1.2 Total logistics costs. Logistics is the costly tactical function charged with getting the right thing to the right place at the right time (Mallik, 2010). However, the logistical aspects of an exchange are substantially broader than loading, storage, and transport (Chen & Paulraj, 2004). Logistics enables supply chains to oversee the flows of, materials, information, and cash in an effort to provide customer service (Zeng & Rossetti, 2003). The Council of Logistics Management defines logistics management as "that part of the supply chain process that plans, implements, and controls the efficient flow and storage of goods, services, and information from the point of origin to the point of consumption in order to meet customers' requirements" (Mentzer et al., 2001, p. 16). Thus, total logistics costs represent a substantial portion of total supply chain costs and serve as an important indicator of supply chain efficiency (Zeng & Rossetti, 2003).

Total logistics costs include all direct and indirect costs incurred due to the transport, storage, and distribution of the product or supply part (Fawcett, Calantone, & Smith, 1996). Total transportation expenditures comprise the largest component of all logistics costs, usually more than half (Gunasekaran, Patel, & Tirtiroglu, 2001). Direct logistics costs include all transport and warehousing costs associated with the production and distribution of a product or supply part (Bhatnagar & Sohal, 2005). These costs include the tariffs, duties, handling and inspection costs incurred due to the import or export of a product to a foreign market (Baldwin & Venables, 2013).

Firms also incur indirect logistics costs: coordination, inventory carrying costs, unplanned shutdowns, quality issues, reverse logistics, cash-to-cash cycle time (Bhatnagar & Sohal, 2005; Tate et al., 2014). Since logistics crosses functional areas, many of the total costs of logistics are overlooked (Gunasekaran et al., 2001). These costs are considered hidden costs, because they are often not realized until after the transaction is completed (Larsen et al., 2013). Indirect costs may come from the demand market as well as the supply market. Firms must also consider consumer resentment resulting from loss of responsiveness, stock-outs, or product failure (Ajzen, 1991; Fine, 2013; Fishbein, 1979).

Total logistics costs consider the whole range of costs associated with logistics, which includes not only transportation and warehousing costs, but also inventory carrying costs, administration expenses, and order processing costs (Zeng & Rossetti, 2003). To minimize total costs, a firms must be able to identify and measure all logistics costs. Uncovering hidden costs requires supply chain personnel to understand the general way in which the costs are affected by the decisions at hand (Waller & Fawcett, 2012). The total cost concept has been the cornerstone of logistics, and the ability to analyze the total costs of a supply chain is the key function of efficient supply chain management (Ellram & Maltz, 1995; Stock & Lambert, 2001; Waller & Fawcett, 2012). Total cost analysis seeks to examine the aggregate costs for all logistics activities rather than focusing on each activity in isolation (Waller & Fawcett, 2012).

While the goal of total logistics analysis is to identify and minimize the entire costs throughout the supply chain, this goal must be to eliminate costs without damaging firm performance (Bygballe, Bø, & Grønland, 2012; Gunasekaran et al., 2001). Supply chain managers consider the logistics relative to other marketing objectives to reduce total logistics costs without endangering customer service (Bygballe et al., 2012). Stock and Lambert (2001) present the logistics and marketing functions as a set of trade-offs that must be made to connect supply chains with demand markets. Therefore, extant research has noted that supply chain strategy should not be based on cost alone, but rather on the issues of quality, flexibility, innovation, speed, time, and dependability (Chen & Paulraj, 2004; Fugate, Mentzer, & Stank, 2010).

2.3.2 Reshoring and Firm Sustainability

2.3.2.1 Strategic risk exposure. To increase efficiency, many organizations focus on developing a few core competencies internally and outsourcing all non-core activities (Hunt & Morgan, 1996). This strategic focus can potentially liberate resources for subsequent investment in areas that are expected to yield competitive advantage (Handley & Benton, 2009). However, many outsourcing decisions can have unintended consequences which expose the firm to substantial risks (Christopher, Mena, Khan, & Yurt, 2011). As firms relinquish more control to suppliers, they assume more risk (Sanders et al., 2007). Thus, when making outsourcing decisions, firms should consider the effect that the task might have on firm strategy (Spekman & Davis, 2004).

Strategic decisions are in essence the aggregation of a sequence of tactical decisions leading to some common planned or emergent pattern (Ritchie & Brindley, 2007), and strategic risks are those that affect a firm's ability to implement this strategy

(Harland et al., 2003). Risk expresses the probability that a given adverse event occurs during a specific time activity (Harland et al., 2003), while exposure refers to the sensitivity of a firm to changes in any of a number of interrelated uncertain variables (Miller, 1992). As such, organizational strategic choices determine a firm's exposure to uncertain environmental and organizational components that affect firm performance (Sanders et al., 2007). Hence, strategic risk exposure characterizes the sensitivity to attributes in the global environment that might diminish the strategic resources and core competencies that a firm might employ to create value for its customers.

Strategic risk describes any current or future threats to the strategic resources and core competencies that give the firm a sustained competitive advantage (Handley & Benton, 2009). According to the resource based-view, a sustained competitive advantage is achieved when a firm adopts a strategy that is “not simultaneously being implemented by any current or potential competitors and when these other firms are unable to duplicate the benefits of this strategy” (Barney, 1991, p. 102). Resources are likely to lead to a sustained competitive advantage when they are socially complex, causally ambiguous, or lacking clearly defined property rights (Reed & DeFillippi, 1990). However, the mere possession of strategic resources will not provide a competitive advantage; firms create value through bundling these resources which lead to capabilities (Fahy & Smithee, 1999). Capabilities are higher-order complex resources that allow firms to organize and exploit resources to create value for customers (Hunt & Morgan, 1996; Teece et al., 1997).

Core capabilities are the primary drivers of sustainable competitive advantage, and a key function of strategic management involves identifying core capabilities and understanding how those capabilities help the business create value (Sanders et al., 2007). Firms must consider the functional interdependencies between core competencies and other related activities that provide no direct competitive advantage (Slepniov, Wæhrens, & Johansen, 2014). For instance, many firms with core competencies in research and development often choose to outsource production to a contract manufacturer at arm's length without considering the relationship between manufacturing and innovation (Denning, 2013b). If the supplier provides poor quality or leaks proprietary information, the value of the firm's tacit knowledge may be diminished (Min, LaTour, & Williams, 1994). Thus, it is in the self-interest of firms to keep many resources and capabilities in-house to reduce the threat of imitation (Barney, 2014). when deciding whether to outsource a particular activity, firms must thoroughly understand and consider their core competencies relative to achieving broader strategic goals (Handley & Benton, 2009; Harland et al., 2003; Sanders et al., 2007; Slepniov et al., 2014).

Strategic risk assessment describes "the degree to which the outsourcing team evaluated the multitude of strategic risks associated with outsourcing the business activity" (Handley & Benton, 2009, p. 346). Risk assessment must involve the exposure to and triggers of risk, while taking into account the potential tangible implications along with any intangible, non-regulated consequences and losses (Harland et al., 2003). As markets evolve, capabilities that are expendable today may become valuable in the future; therefore, the strategic evaluation must also consider any resources or capabilities that might be critical to creating a competitive advantage in the future (Handley & Benton, 2009).

2.3.2.2 Supply chain disruption risk. Supply chain disruption risk characterizes the total potential loss resulting from a disruption of supplies, inventories, or finished products within a supply chain (Ellis et al., 2010). Supply chain disruptions are events which create a breakdown or stoppage in the expected flow of supplies, inventories, or finished products within a supply chain (Bode et al., 2011; Ellis et al., 2010). Supply chain disruptions may occur due to by terrorism, natural disasters, or even poor infrastructure (Christopher et al., 2011).

Existing literature distinguishes supply chain disruptions from operational and logistics delays (Chopra et al., 2007; Revilla & Sáenz, 2014; Talluri, Kull, Yildiz, & Yoon, 2013). Delays and distortions are recurrent transactional hazards that increase total logistics costs (Chopra et al., 2007), while disruptions are unplanned and unanticipated situations with large-scale consequences (Revilla & Sáenz, 2014). Delays describe deviations from the prompt delivery schedules, often resulting from (Chopra & Sodhi, 2004), while distortions describe discrepancies with the accuracy or expected quantity of an order (Talluri et al., 2013). Distortions may result from minor quality issues, miss-pulls, or freight damages. While recurrent interruptions may create unscheduled downtime or expedite costs, they may also be buffered with additional inventory (Chopra et al., 2007; Chopra & Sodhi, 2004; Revilla & Sáenz, 2014). In contrast, supply chain disruptions occur "when the supply chain is radically and unexpectedly transformed through non-availability of certain production, warehousing, distribution, or transportation options" (Talluri et al., 2013, p. 254).

Supply chain disruption risk is a measure of the probability of a disruption and the impact of a disruption (Bode et al., 2011). Any firm that depends upon one or more firms to supply products or materials faces the risk that a disruption in the supply chain could damage or alter the integrity of the business (Chopra & Sodhi, 2004); however, the probability of a supply chain disruption is much greater for global supply chains (Manuj & Mentzer, 2008a). Supply chain disruptions are more likely to occur as supply chains become longer and more complex, thus global supply chains face much more risk of disruption due to increased geographical, cultural, and temporal distance (Christopher et al., 2011). The risk of a supply chain disruption is further exacerbated by the increase in terrorism caused by the changing geo-political arena as well as the effects of severe weather due to climate change (Min et al., 1994; Wagner & Bode, 2006).

The potential impact or magnitude of a supply chain disruption has a stronger influence on overall perceived risk than does disruption probability (Ellis et al., 2010). Supply chain disruption impact is the potential damage that a firm could incur due to a breakdown or stoppage in the production or distribution of materials within a supply chain or network (Wagner & Bode, 2006). Supply chain disruptions negatively affect firm performance in several ways: lost revenues due to stock outs, loss of productivity due to plant shutdowns, loss of goodwill from customers, added freight costs due to expediting, and possible penalties from industrial customers (Bode et al., 2011). Supply chain disruptions have also been found to have long term negative consequences related to market share and stock price (Ellis et al., 2010). While supply chain disruptions create enormous operational costs, research finds that the long-term effects to brand image and financial performance are far more disastrous (Song et al., 2007; Wagner & Bode, 2006).

2.3.3 Outcome

2.3.3.1 Superior firm performance. Superior performance implies that the firm's resources surpass competitors in terms of relative costs, relative value, or both (Davis & Golicic, 2010). Relative firm performance indicates the efficiency and effectiveness of firm resources when compared to another firm, or other configuration of resources or firm boundaries (Hunt & Morgan, 1995). In this study, superior operating performance represents the increase in operating efficiency of firms that reshore compared to those that do not, where efficiency is measured by return on investment (Hunt & Morgan, 1995). Likewise, superior financial performance represents the increase in profitability for firms that reshore compared to those that do not (Hunt & Morgan, 1995). Firm valuations and net income margins are indicators of profitability (Sharma, 2005).

2.3.4 Contingent Factors Influencing Reshoring Decisions

2.3.4.1 Product innovativeness. Product innovativeness describes the degree to which a product possesses new and unique attributes and features, relative to other products in the same market (Fu et al., 2008). Product innovativeness indicates "the potential discontinuity a product can generate in the marketing process" (Garcia & Calantone, 2002, p. 113). Innovative products may be new to the developing firm, new to the market, or both (Danneels & Kleinschmidtb, 2001). For intended consumers, product uniqueness may create discontinuity when new product offerings provide a superior product advantage over existing offerings (Danneels & Kleinschmidtb, 2001). By offering new functions that cannot be duplicated quickly, firms may gain first-mover advantages resulting in significant market share (Lau, Tang, & Yam, 2010). Significant innovations allow firms to establish dominant market positions, and provide newcomer firms an opportunity to gain a foothold in competitive markets (Danneels & Kleinschmidtb, 2001). Innovation also creates opportunities to differentiate existing products with technological product advantages (Lau et al., 2010).

Distinctions among innovations occur along a continuum consisting of radical, incremental, and minor innovations (X. M. Song & Parry, 1999). Existing typologies define six types of new products: new-to-the-world, new product lines, additions to existing product lines, revisions to existing products, repositioning, and cost reduction (Danneels & Kleinschmidtb, 2001; Garcia & Calantone, 2002; Lau et al., 2010; X. M. Song & Parry, 1999). Highly innovative products are new to the world and new to the firm (Garcia & Calantone, 2002, p. 113). These include radical innovations and breakthrough products that bring new value to the marketplace (X. M. Song & Parry, 1999). Moderately innovative products result from additions or improvements to existing product lines; these products offer technical novelty or newness to the firm and may be somewhat new to the marketplace (Danneels & Kleinschmidtb, 2001). Moderate innovations also describe product lines which are new to the firm, but not new to the market (Garcia & Calantone, 2002, p. 113). Finally, low innovation describes repositioning existing products to new markets and modifying products for cost reductions (Garcia & Calantone, 2002, p. 113). Cost reduction products provide similar performance as existing products, but at a lower cost (Danneels & Kleinschmidtb, 2001).

The capacity to introduce new processes, products, or ideas in the organization serves as a key component in the success of industrial firms (Hult et al., 2004). New product development is the most obvious way to enhance firm performance (Lau et al., 2010). Innovative products present opportunities for growth and expansion into new areas (Danneels & Kleinschmidtb, 2001). Many innovative products provide as much as 30% of firm revenues from sales and as much as 40% market share within the industry (Lau et al., 2010). Successful innovations may provide more than 90% return on investment with payback periods of less than two years (Lau et al., 2010).

While highly innovative products can be more profitable than incremental ones, they also carry significant risks (X. M. Song & Parry, 1999). Successful new product development depends on the characteristics of the competitive environment in which the industrial firm operates (Hult et al., 2004). Research states that innovative products utilize more firm resources and require a different development approach (Danneels & Kleinschmidtb, 2001). Breakthrough products encounter difficulties because the firm's experience base is often less relevant to product development than to product improvement or extension (X. M. Song & Parry, 1999). Highly innovative product markets are also characterized as turbulent and volatile (van Hoek, 2001). Market turbulence reflects rapidly changing buyer preferences across a wide range of needs and wants. As buyers continuously enter and exit the marketplace, firms in turbulent markets must place a constant emphasis on offering new products (Hult et al., 2004). Accordingly, product life cycles shorten, product variety increases, and customer demands escalate (van Hoek, 2001). Finally, additional risks arise from the threat of quick imitation. This occurs when competitors attempt to economize on engineering and marketing costs by building on the investments and consumer sentiment of an innovative firm (X. M. Song & Parry, 1999).

2.3.4.2 Offshore relationship value. Offshore relationship value represents an evaluation of the benefits that the firm gains by maintaining the relationship and producing offshore relative to any costs or sacrifices that the firm must make to continue the offshore relationship. Ulaga and Chacour (2001, p. 530) define perceived relationship value as:

> *"the trade-off between the multiple benefits and sacrifices of a supplier's core offering, as perceived by key decision makers in the customer's organization, and taking into consideration the available alternative suppliers' offerings in a specific-use situation"*

Other definitions include specific items, like terms of the agreement:

> *"Customer-perceived value can, therefore, be defined as the difference between benefits and the sacrifices (e.g. the total costs, both monetary and non-monetary) perceived by the customers in terms of their expectations, i.e. needs and wants." (Lapierre, 2000, p. 123)*

A common theme among all definitions is that firms engaged in alliances or supply relationships are willing to sacrifice some expense and risk if the relationship provides benefits that exceed those available elsewhere (Scheer, Miao, & Garrett, 2010; Ulaga & Eggert, 2006).

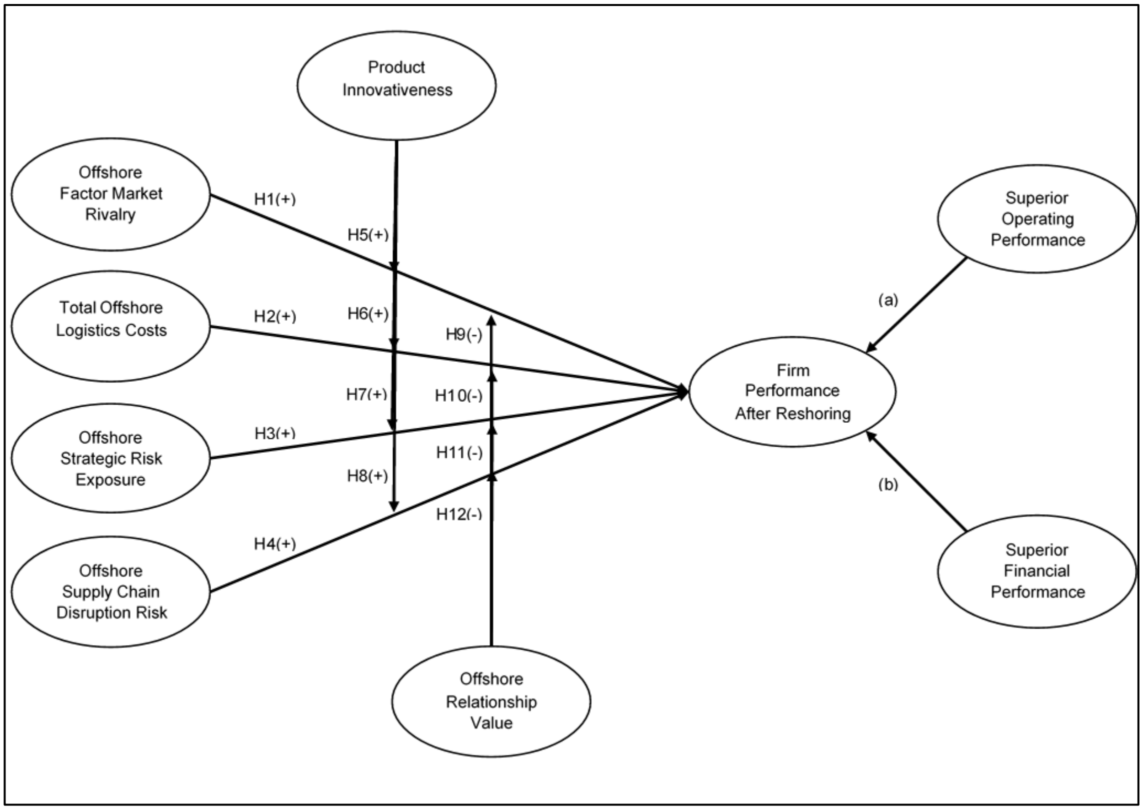
Sourcing literature finds that cost reduction is the primary reason for manufacturing in emerging countries (Ellram, 1993; Song et al., 2007). Other companies engage in foreign relationships for strategic reasons, such as extending global reach in growing consumer segments (Harland et al., 2003). Many firms outsource offshore to gain access to supplier capabilities or materials, while others simply lack manufacturing capacity locally (Ulaga & Chacour, 2001). In these situations, firms gain benefits from offshore relationships or through partnerships that outweigh the benefits of producing domestically (Cheng & Sheu, 2012). For instance, partnership with offshore suppliers is often necessary in order to enter the consumer market in that region (N. Song et al., 2007).

Some studies have shown, however, that *where* to source major components is less important than *how* to source them (Kotabe & Murray, 2004). Resource-based theory states that the economic rents provided by an attractive product market position cannot be evaluated independent of the kinds of resources and capabilities a firm used to create this position (Barney, 2014). Extant literature presents relationship value as a second-order construct consisting of both costs and benefits (Ulaga & Eggert, 2005). The ability to create valuable, mutually beneficial relationships in global markets represents a higher order capability that only certain firms possess (Hunt & Morgan, 1996). Relational resources provide a resource barrier position in the supply chain which may be critical to developing a competitive advantage (Scheer et al., 2010).

2.4 Development of Hypotheses

The final section of this chapter examines the linkages among the variables in the conceptual model. Hypotheses are then developed to explain the conditions in which reshoring provides superior performance and creates a sustainable competitive advantage. The full conceptual model with hypothesized relationships appears in Figure 2.

Figure 2: Conceptual Model with Hypothesized Relationships



2.4.1 Linking Reshoring to Firm Performance

2.4.1.1 Factor market rivalry and firm performance. Factor market rivalry creates a growing concern for firms seeking cost-based advantages in emerging markets (Tate et al., 2014). Research indicates that cost reduction is the primary reason firms pursue offshore markets (Gray et al., 2013). While emerging markets offer location-specific advantages stemming from factor endowments and low wages (Arlbjørn & Lüthje, 2012), competition over resource positions emerges when attractive resources are homogeneously distributed and mobile (Hunt & Morgan, 1995). Resource-based logic states that "privileged positions in attractive industries will not produce economic rents if the full values of these positions were anticipated in the factor markets where the resources and capabilities needed to build up these positions were acquired" (Barney, 1986). Thus, cost advantages based on resource positions in global factor markets are sustainable only if the tacit knowledge involved in building a strong resource position is ambiguous or socially complex (Barney, 2014).

Factor market rivalry creates scarcity and competition over inputs that were once freely available (Barney, 1986). The resulting competition introduces macroeconomic uncertainty, whereby cost advantages in the short term may decrease and finally disappear over time (Arlbjørn & Lüthje, 2012). Location-specific cost advantages are contingent upon the current economic conditions along with any potential future economic development within that particular location (Arlbjørn & Lüthje, 2012). Since many emerging countries have limited natural resources, firms risk supply chain interruptions if they do not ensure a plentiful supply of water, fuel, and raw materials (Ellram, Tate, & Petersen, 2013). Global industrial activity raises the demand for finite natural resources while simultaneously reducing their availability (Tate, Ellram, & Kirchoff, 2010). Access to semi-skilled labor, fuel, and natural resources are each critical to the success of offshore production. As competition grows, the prices for these inputs rise (Ellram, Tate, & Feitzinger, 2013).

As more companies pursue low-cost production locations, competition increases for the labor that these countries supply (Tate et al., 2014). Labor costs may rise unexpectedly as demand increases for the labor in a particular market. When other companies begin to source manufacturing in the same area, demand for the qualified labor pool exceeds supply (Ellram, Tate, & Feitzinger, 2013; Tate, 2014). Due to the recession and the mass exodus of manufacturing jobs, U.S. wages have remained stagnant over the past several years while unemployment rates have risen (Tate, 2014).

Meanwhile, Chinese wages continue to grow at a rate of 15% to 20% per year (Harrington, 2011). In some areas of China, wages have more than doubled since the turn of the century. From a total cost perspective, China is nearly even with Mexico, India, Russia, and even some low wage regions of the United States (Tate, 2014).

Recruiting from nearby areas is not an option for most emerging markets. Due to poor infrastructure, inland factories are only good if the area lies in close proximity to a strong demand market (Schmeisser, 2013). For instance, hinterland transportation in Southeast Asia often costs more than shipping from China to most ports in Europe. Nearby countries usually lack the skills and training to compete in the market, so labor costs rise and the foreign currency strengthens (Liu, Li, Tao, & Wang, 2008).

As traditionally low-cost economies strengthen, macroeconomic uncertainty creates less predictable exchange rates, which alters purchasing power (Manuj & Mentzer, 2008b; Miller, 1992). While the currency in China strengthens, the U.S. currency continues to weaken (Ellram, Tate, & Petersen, 2013). When the U.S currency is weak relative to other countries, producing overseas is less attractive because the goods cost more in relative terms due to the exchange rate (Tate, 2014). More importantly, as developing nations strengthen, they continue to drive the demand for fuel higher. China is very dependent on imports for energy, and its costs have continued to rise due to shortages in energy supplies (Tate et al., 2014).

As the balance of labor shifts, the U.S. continues to improve its level of manufacturing productivity (Ellram, Tate, & Petersen, 2013). Due to the decreasing price of robotics, many formerly labor-intensive jobs are becoming automated (Tate et al., 2014). Productivity in the U.S. is as much as six times higher than that of developing nations (Moser, 2011). Factoring in the currency valuation, and improved production rates in the U.S., net labor costs should converge by 2015 (Moser, 2012). Because wage rates account for less than 30% of a product's total cost, products manufactured in China will be only 15% lower than United States products before inventory and shipping costs are considered (Harrington, 2011).

The price of energy and the push for green supply chains should both serve to make American production more attractive. Energy represents a significant portion of manufacturing costs, and U.S. energy costs are lower than in many other parts of the world (Tate et al., 2014). The U.S. has the lowest energy prices per megawatt in the world, along with the second lowest cost of natural gas and diesel fuel comparatively speaking (Tate, 2014). Environmental concerns and the push for social corporate responsibility have ended the era of producing oversees to avoid regulations (Gray et al., 2013). New approaches to corporate social responsibility are emerging in response to stakeholder demands, more government regulations, and increasing competitive pressure (Cavusgil & Cavusgil, 2012). Companies are aware of the strong link between corporate social responsibilities and consumer preferences, and consumers are demanding that companies use manufacturing processes that are less harmful to the environment and to communities (Tate et al., 2010).

Factor market rivalry, like any competition, significantly reduces profitability (Barney, 1991; Porter, 2008). Increasing demand leads to tighter supply markets and correspondingly higher prices, reducing the attractiveness of a given supply market (Tate et al., 2014). Amid rising prices in Asian factor markets and uncertainty concerning global financial markets, offshore factor market rivalry is expected to create cost advantages for firms that repatriate manufacturing to the United States.

H1: As factor market rivalry increases in offshore markets, firms that reshore will achieve (a) superior operating efficiency and (b) superior firm performance compared to firms that continue to produce overseas.

2.4.1.2 Total logistics costs and firm performance. Global supply chains create additional challenges with the efficient and timely distribution of goods that flow across supply chains (Gereffi & Lee, 2012). Many of these challenges result from the increased geographical and cultural distance involved with global sourcing (Handley & W. C., Benton, 2013). The greater physical distance along with the cultural differences also serve to extend the lead-times, thereby introducing more uncertainty to global networks (Min et al., 1994). Cost reduction is one of the main reasons that companies produce offshore, yet the additional complexity and uncertainty involved in extended supply chains creates hidden costs (Min et al., 1994; Song et al., 2007). The further the distance between the host country and the outsourcer, the more uncertainties and risk are present (Gray, Roth, & Leiblein, 2011). The resulting unexpected costs along with the increase in transportation costs could offset any gains derived from cheaper labor (Song et al., 2007).

First, the increased geographical distance increases the direct transport costs involved in shipping products across the world (Bygballe et al., 2012). Longer shipping routes also create more opportunities for freight to be lost or damaged, thereby increasing scrap and rework costs (Zeng & Rossetti, 2003). Firms also tend to underestimate the travel expenses involved in foreign production (N. Song et al., 2007). As more firms produce offshore, additional transportations costs arise from the resulting trade imbalance. From 2005 to 2008, 60% of all containers on Pacific routes from Asia to North America, and 41% of all European containers returned to Asia empty (Fransoo & Lee, 2013). Buyers absorb these additional transport costs through increased rates on heavy lanes for one-way trips or return mileage for empty containers on dedicated voyages (D. P. Song & Dong, 2013).

Cultural distance is a second factor driving hidden costs in global supply chains. These costs arise from the additional inventory necessary to buffer changes in demand, unexpected coordination costs of managing an international supply chain, quality concerns, and unexpected costs incurred with process changes (Platts & Song, 2010). Costs of coordination and governance increase drastically for global supply chains (Handley & W. C., Benton, 2013). Communication difficulties create operational concerns because of language barriers and limitations in telecommunications capabilities (Kotabe & Murray, 2004). These costs are exacerbated when the supply chain is interdependent (Baldwin & Venables, 2013). Interpretive uncertainty also creates problems when cultural differences create unintentional performance issues or misalignment of goals (Weber & Mayer, 2014). Differences in payment terms may also generate unexpected financial costs by negatively affecting the firm’s cash-to-cash cycle time (Spekman & Davis, 2004). Many Asian firms, for example, require a significant payment before production with final payment terms as little as 5-15 days (N. Song et al., 2007).

The temporal distance involved in global sourcing is possibly the greatest source of hidden costs. Longer supply chains create less responsive firms, because firms must keep more inventory on hand to buffer the extended lead time (Tate et al., 2014). Deliveries with longer lead-times must work with extended planning times and use forecast data further into the future (Brandon-Jones, Squire, Autry, & Petersen, 2014). As the distance between production and demand lengthens, the ability to pursue a pull strategy erodes (Kannan & Tan, 2005). This limits the ability of forecasters to hedge purchasing and manufacturing decisions and places the firm at risk due to demand uncertainty (Christopher et al., 2011). For example, a sudden drop in demand resulting from the dot-com bubble forced Cisco to write off over $2.5 billion in inventory in 2001 (Manuj, Esper, & Stank, 2014; Spekman & Davis, 2004). Firms must also consider the financial costs of inventory, especially with purchase agreements that extend all the way to raw materials (Gunasekaran et al., 2001). Hummels (2007) estimates average inventory carrying costs for ocean freight to be 0.8% per day, which is equivalent to an additional 16% tariff rate (Nordås, Pinali, & Grosso, 2006).

These hidden costs became more evident with the onset of stow steam carriers in 2009, because ships now take 20% to 30% longer to reach port for a normal trip (Tate, 2014). Slow steaming reduces the ship's average speeds from between 23-25 knots to as low as 20 knots (Fransoo & Lee, 2013). For longer routes, carriers may engage in extra slow steaming at 17 knots to further reduce emissions and fuel usage (Lee, Lee, & Zhang, 2015). New ships are currently being built to optimize performance at slow-steaming speeds; therefore, this method will likely continue regardless of fuel prices because cargo ships take many years to build (Tate, 2014). While carriers originally introduced slow steaming practices as a way to reduce fuel costs, early empirical research shows that fuel surcharges imposed on shipping customers have largely remained unchanged (Notteboom

& Cariou, 2013). Since each additional nautical mile per hour changes the ship's capacity by over 6%, carriers also use slow steaming to inflate shipping demand artificially (Knowler, 2014). Thus, the practice of slow steaming significantly increases lead-time and requires manufacturers to keep much more inventory both on-hand and in-transit (Tate, 2014). To provide perspective, ocean carriers consistently hold more inventory between China and its next export location than all major U.S. retailers combined use in an entire year (Fransoo & Lee, 2013).

In addition to delivery speed, delivery dependability also plays an important role in determining the costs of an extended supply chain (Luo, Fan, & Liu, 2009). Many shippers suggest that the variance in shipping times is far more costly that the extended lead times (Bygballe et al., 2012). While transport time is relatively consistent once the cargo is seaborne, differences in port efficiency leads to considerable time variation among countries with similar shipping distances (Nordås et al., 2006). Poor infrastructure in many countries creates added concerns over transportation stability and availability, thereby creating additional costs for already strained logistics budgets (Clarke, 1997). As ships and ports become more crowded, the variation in processing and sail times increases, especially in emerging countries with poor infrastructure (Kannan & Tan, 2005). In some countries, the customs clearance time alone is lengthy enough to preclude a contract with any lean manufacturing customer (Nordås et al., 2006). Many foreign nations create a small portion of the added value of a product (Gereffi & Lee, 2012; Nordås et al., 2006). Thus, costs and variance increase exponentially for each part or sub-assembly that must clear customs more than once in these countries (Baldwin & Venables, 2013).

As these costs and uncertainty continue to rise, the benefits of offshore manufacturing steadily decline (Bode et al., 2011). Proponents of reshoring proclaim that the resulting shorter supply chains should provide superior performance by increasing corporate flexibility and customer responsiveness (Arlbjørn & Lüthje, 2012; Harrington, 2011; Moser, 2011; Tate, 2014). The ability to reduce lead-time enables a firm to control costs while enacting firm strategies that provide customer value (van Hoek, 2001). Reshoring eliminates many of the costs and delays of global sourcing. As the physical distance shortens, many of the hidden costs are eliminated along with some of the direct costs (Min et al., 1994). Eliminating cultural differences also reduces inefficiencies resulting from the challenges of monitoring global supply chains (Handley & W. C., Benton, 2013). The resulting reduction in temporal distance, in turn, decreases additional inventory carrying costs (Bygballe et al., 2012). A reduction in lead-time also reduces the supply chain response time, which directly influences customer satisfaction, increases responsiveness, and makes the firm more flexible (Gunasekaran et al., 2001). Therefore, the total logistics costs involved in offshore manufacturing should encourage reshoring and lead to superior firm performance.

H2: Firms that relocate manufacturing to the U.S. will reduce total logistics costs, thereby leading to (a) superior operating efficiency and (b) superior firm profitability when compared to firms that continue to produce overseas.

2.4.1.3 Strategic risk exposure and firm performance. In addition to operational costs, firms must also consider the long-term implications of increased exposure to strategic risks due to global manufacturing (McIvor, 2009). Offshore production often exposes strategic resources to unexpected risks arising from cultural, procedural, and behavioral uncertainty (Manuj & Mentzer, 2008a). As firms face increasing levels of opportunism, they risk erosion of the strategic resources and capabilities that allow them to compete (Handley & Benton, 2009). In particular, brand image and brand position represent firm-specific resources that may not be easily duplicated or obtained in open markets (Barney, 2014; Fahy & Smithee, 1999; Gatignon & Anderson, 1988). The complexity of global production, along with the potential for opportunism, could reduce the effectiveness of these rent-producing assets (Ritter & Walter, 2012).

A brand image is a socially complex resource that could provide a sustained competitive advantage (Fahy & Smithee, 1999). A brand name represents a relationship between a firm and its customers (Barney, 2014). Although brand image cannot be easily duplicated, the value of any intangible asset is subject to erosion over time (Gatignon & Anderson, 1988). Research shows that poor product quality from offshore manufacturing locations significantly reduces consumer perceptions about the ability of a firm to provide customer value (Kinkel & Maloca, 2009).

Quality risk is the likelihood that a product shipped from a given establishment will not perform as intended due to manufacturing-related issues (Gray et al., 2011). Poor quality results from upstream supply uncertainty, which is much more common in global sourcing due to the complexity which results from the extended geographic and cultural distance (Handley & W. C., Benton, 2013). Cultural distance creates communication problems, which might impede supplier selection and training (Min et al., 1994). Often, quality issues emerge if the focal firm has difficulty codifying production processes or quality control programs (Ansari, Fiss, & Zajac, 2010). American and

European firms have been practicing quality control procedures for years, so there will be a substantial learning curve in foreign lands (Song et al., 2007).

Gray et al. (2011) find that even when knowledge is codified and clearly communicated, quality concerns increase as the geographic distance increases. They determine that this is partly due to a loss of familiarity with personnel from the focal firm and partly due to the decreased visibility (Gray et al., 2011). Many firms in emerging countries might not have the qualified personnel necessary for zero-defect manufacturing philosophies (Tate et al., 2014). The lack of visibility may also create information impactednesss, which allows foreign firms to exaggerate capabilities during negotiations (Brandon-Jones et al., 2014). Firms may be able to create a prototype, yet lack the capabilities necessary to mass produce (Song et al., 2007). The inability to measure performance in complex exchanges increases the risk of shirking by opportunistic suppliers (G. Walker & Weber, 1987). This introduces behavioral uncertainty and allows quality issues to arise from opportunism (Williamson, 1985).

Opportunistic suppliers may create liability risks which lead to recalls, warranty claims, and bad publicity (Spekman & Davis, 2004). Liability uncertainties are associated with harmful effects resulting from the production or consumption of a company's product (Miller, 1992). Product liability uncertainty relates to unanticipated negative effects associated with the use of a product that can result in legal actions against the producer (Harland et al., 2003). For example, Mattel Inc. was forced to recall over 9 million Chinese-made toys from the market because they contained high levels of lead-based paint on the surface (Christopher et al., 2011). Firms may also be held legally responsible for certain external effects such as emissions of contaminants into the environment, even if suppliers are to blame (Miller, 1992). Evidence of this is seen with the BP Deepwater Horizon oil spill (Anon, 2013). Although BP only acknowledged partial responsibility, the disaster will likely cost the firm over $46 billion in damages and reparations (Barrett, 2014). This also holds true for serious quality situations, such as Ford's quality issues with Firestone Tires, in which people were seriously injured or killed (Zsidisin, Ellram, Carter, & Cavinato, 2004).

Foreign production creates other risks, as well. For firms that are capable of codifying and transferring strategic knowledge, the issue of appropriability arises (Fahy & Smithee, 1999). Appropriability refers to the extent to which an innovating firm is able to capture economic rents or value associated with innovation before competitors can overcome their initial competitive disadvantage (Kotabe, 1990). Outsourcing production facilitates the transfer of knowledge and technical capabilities (Shook et al., 2009). Since legal redress is often very weak in overseas locations, the inability to protect intellectual property can threaten the rarity and inimitability of these resources (Kotabe & Murray, 2004).

When firms choose suppliers with overlapping, rather than complementary capabilities, they risk creating potential competitors through the transfer of proprietary knowledge (Shook et al., 2009). Ellram and Maltz (1995) provide as an example the history of Intel and Advanced Micro Devices (AMD). In the late 1980's, Intel outsourced much of its microprocessor technology to AMD, yet failed to establish contractual governance to prevent intellectual property loss. AMD soon began selling computer chips built with Intel technology, thus acting as a direct competitor to Intel (Ellram & Maltz, 1995). A more recent example involves the legal battle between Apple and Samsung (Brutti, 2015). Because of the increased risk involved with global sourcing, instances like these are much harder to detect and avoid overseas.

Other forms of opportunistic behavior also pose threats to sustainable competitive advantage when operating offshore. Counterfeit products, gray marketing attempts, and product dumping are often more difficult to detect in offshore locations (Bertrand & Mol, 2013; Min et al., 1994; Poppo & Zenger, 1998). Increasing reports of intellectual property infringement in offshore markets suggest that risks to strategic assets might be growing (Ellram, Tate, & Petersen, 2013). Outsourcing to offshore markets eventually creates specialization within industries whereby competitors must use the same suppliers (Sanders et al., 2007). In this situation, competitors may be able to derive certain cues, which may diminish causal ambiguity, thereby exposing tacit capabilities (Ritter & Walter, 2012).

An over-reliance on global sourcing may create erosion of the focal firm's core capabilities (Spekman & Davis, 2004). When firms purchase strategic inputs through arm's length relationships, they face the risk becoming dependent on independent suppliers (Kotabe & Murray, 2004). As firms become more dependent on offshore suppliers, host firms and corporations gain more bargaining power (Handley & Benton, 2009). The resulting higher switching costs in offshore locations may expose firms to government corruption as well as opportunistic suppliers (Klein et al., 1990). In many cases, foreign governments may even dictate which suppliers may or may not be used (N. Song et al., 2007). As direct involvement in the production process decreases, the tacit knowledge and capabilities needed to protect a competitive advantage vanishes. The erosion of these resources could threaten the firm's strategic position and longevity (Ritter & Walter, 2012).

This could create the danger of capability erosion, which over time could limit the absorptive capacity, and ultimately diminish the firm's customer responsiveness (Kotabe & Murray, 2004). As much as 70% of a firm's market value may be derived from the intangible resources and capabilities that global production places at risk (Kozlenkova et al., 2014). It is therefore expected that as firms face higher levels of strategic risk, they will be more likely to repatriate manufacturing.

H3: As the risk to strategic resources in offshore markets increases, the likelihood that firms who relocate production to the U.S. will achieve (a) superior operating efficiency and (b) superior firm profitability over those that do not increases.

2.4.1.4 Supply chain disruption risk and firm performance. Supply chain disruptions and related issues represent one of the most pressing concerns facing firms competing in today's global marketplace (Revilla & Sáenz, 2014). Yet, despite the increased focus on supply chain risk management, supply chains have become more vulnerable while the severity and frequency of supply chain disruptions continues to increase (Brandon-Jones et al., 2014). The increased likelihood of disruptions may partially result form more occurrences of natural disasters beyond managerial control, however, the greater impact of disruptions is due to more complex supply chain designs (Wagner & Bode, 2006). While tighter coupling, reduced inventory levels, and faster throughput have reduced costs in supply chains, the greater geographic dispersion and increased complexities have made created greater vulnerabilities (Bode et al., 2011).

Since accidents become recurrent in rapid, tightly coupled technological systems, research indicates that supply chain disruptions are much more common in complex global supply chains (Revilla & Sáenz, 2014).

Supply chain disruptions may be caused by result from may occur as a result of natural disasters, resource shortages, or large-scale industrial accidents (Christopher et al., 2011). Disruptions may also have socio-economic origins, like relational hazards or geopolitical uncertainty (Revilla & Sáenz, 2014). As supply chains become longer and more complex, they are also more exposed to different and higher risk levels (Van den Bossche, 2014). When supply chains expand overseas, different tiers and sub-tiers may be exposed to different types of disruption risks simultaneously (Revilla & Sáenz, 2014). Thus, it is necessary to assess the probability and potential impact for each type of disruption by country, because both natural and man-made disasters cause immense financial and reputational damage to global supply chains (Van den Bossche, 2014).

Natural disruptions often follow large-scale natural disasters such as hurricanes, earthquakes, or severe floods (Christopher & Peck, 2004). As global networks are more closely intertwined, major disasters have the capability to halt production completely across the globe, as seen by the earthquake and subsequent tsunami that crippled Japan in 2011 (Brandon-Jones et al., 2014). Because Japan is a global leader in automotive technology, most automakers across the globe were forced to halt production for several days following the event (Revilla & Sáenz, 2014). Low inventory levels left Toyota particularly vulnerable as the tsunami simultaneously disrupted its offshore and diminished nearly half of its domestic capacity (Canis, 2011). The disaster allowed

General Motors to regain enough market share to surpass Toyota as the world's largest automotive company.

Natural disasters may create disruptions without directly striking a factory or supplier. In 2010, a volcanic eruption in Iceland shutdown air traffic between Northern Europe and the North America (Revilla & Sáenz, 2014). With increased globalization, disruptions may also result from biological and physiological epidemics as well as weather-related disasters. For example, the onset of Foot and Mouth disease in 2001 created economic turmoil for the British agricultural sector, although medical pandemics usually occur in less advanced countries (Christopher & Peck, 2004). The SARS virus served to limit travel to Asian countries in 2002, just months after China's entry into the World Trade Organization (Manuj & Mentzer, 2008a). More recently, the Ebola virus has limited efforts to build a sustainable economic infrastructure in African countries.

Other natural occurrences are less dramatic, although equally as disruptive. World population growth and increased consumption are depleting a number of natural resources such as oil, coal, and precious metals on a global scale (Bell, Autry, Mollenkopf, & Thornton, 2012). The rapid depletion of necessary resources along with droughts and other severe weather created by climate change may create disruption risks in both emerging and current economies (Bell et al., 2012). This is particularly true for many agricultural and chemical operations. For instance, 23 U.S. chemical plants issued force majeure in 2014, many of which were due to disruptions in utilities and feedstock supplies (Kelley, 2014a, 2014b). LyondellBasell issued 14 of 23 total force majeures, and the company estimates that disruptions in the first quarter of 2014 alone cost the company $300 million (Kelley, 2014b). Many issues leading to these disruptions resulted from weather-related phenomena affecting raw material costs and availability (Kelley, 2014a). The impact of such shortages has been even greater in Europe, where chemical plants have issued over 40 force majeures in the first four months of 2015 ("40 Force Majeure cases," 2015). This is partly because the aging factories and equipment in Europe are inefficient and more prone to breakdowns, but the main reason for the unprecedented number of European shutdowns concerns prices and availability of feedstocks (Weddle, 2015).

As global consumption continues to grow, firms must consider resource availability when choosing manufacturing locations (L. Chen et al., 2013). In addition to oil and precious metals, water supplies and food sources are also growing scarce (Bell et al., 2012). Wasteful usage and accelerates the depletion of existing natural resources, while unnecessary pollution contributes to climate change and increases the likelihood of future natural disasters (Hassini, Surti, & Searcy, 2012). China is often criticized for prioritizing economic development while ignoring social responsibility issues (Thornton, Autry, Gligor, & Brik, 2013). Hence, Southern Asia shows the highest probability for geological and weather-related supply chain disruptions (Revilla & Sáenz, 2014).

In addition to disruptions with natural causes, firms must assess the possibility of man-made disasters (Macdonald & Corsi, 2013). Many disruptions result from large-scale industrial accidents (Revilla & Sáenz, 2014). Such accidents may be caused by faulty equipment or human error. The lack of government oversight and building standards in emerging economies may serve to increase the risk of a disaster (Seuring & Müller, 2008). For instance, a fire in at a textile factory in Bangladesh caused the building to collapse, killing over 100 workers. It was later discovered that the building had faulty wiring and inadequate fire escapes (H. Walker, Huq, Stevenson, & Zorzini, 2014). Another example involves a significant number of suicide attempts at a Taiwanese factory that supplies semiconductors to Apple, Dell, and Hewlett Packard (Thornton et al., 2013). The high number of industrial accidents in Asian countries highlights the need to consider corporate social responsibility when selecting suppliers (H. Walker et al., 2014).

Supply chain disruptions may also stem from socio-economic causes such as relational hazards, financial risks, and geopolitical threats (Revilla & Sáenz, 2014). Financial and relational hazards are additional types of business risks, which come from within the supply chain (Zsidisin, Panelli, & Upton, 2000). One type of relational hazard is contention risk, which addresses the limitations of suppliers concerning volume and process changes (Sanders et al., 2007). Business risk is often created by economic uncertainty (Zsidisin et al., 2000).

Firms must therefore consider the financial stability of potential suppliers and host governments, especially in emerging countries (Bode, Hübner, & Wagner, 2014). Financial distress is becoming more common amid uncertain global markets (Sheffi & Rice Jr, 2005). Even traditional powerhouses like Visteon have had trouble securing funds to increase or complete projects (Bode et al., 2014). For instance, Land Rover faced an immediate disruption due to the insolvency of its primary chassis supplier, UPF-Thompson (Christopher & Peck, 2004). Because Thompson had not notified Land Rover of financial distress, creditors appeared without notice and demanded immediate payment from Land Rover of $40 million (Christopher & Peck, 2004). Land Rover was able to obtain a temporary injunction to avoid the holdup hazard and locate another supplier;

however, the incident nearly caused over1400 workers to be laid off (Sheffi & Rice Jr, 2005).

Supply chain disruptions may also be derivative of planned events, triggered by changes in the geopolitical environment (Macdonald & Corsi, 2013). Geopolitical uncertainty often results from major changes in political regimes, which may create political instability or social unrest (Spekman & Davis, 2004). Political instability may result in war, revolution, or coup d'état (Miller, 1992). This type political turmoil has plagued the Middle East in recent years. In 2011, many companies were forced to shutter factories or evacuate during Arab Spring, which orchestrated the overthrow of political leaders in many countries including Libya, Yemen, Egypt, and Palestine (Elzarka, 2013). Terrorism and political instability is most likely to occur in emerging economies, and extant literature suggests that Sub-Saharan Africa has the highest probability of disruption due to political instability (Ellram, Tate, & Petersen, 2013; Revilla & Sáenz, 2014). This may be wholly due to constant terrorist acts committed by pirates off the coast of Somalia (Tummala & Schoenherr, 2011). Militant behavior is not limited to the host country, however. For instance, the bombing of the World Trade Center and U.S. Pentagon in 2001 was a terrorist act that stopped all U.S. air traffic for several days costing over $33 billion and 3000 lives (Autry & Bobbitt, 2008).

Democratic changes in governments or heads of state may create political uncertainty regarding laws and government policies that impact the business community (Miller, 1992). Policies concerning natural or human resources may reduce production output or disrupt the throughput of feedstock supplies (Harland et al., 2003). For example, in 2011 the Chinese government restricted the export of rare earth metals needed to build electronic components. Since China refines 90% of the global supply of these elements, many firms were left searching for other supply sources (Ramzy, 2013). Other types of government policy uncertainties are price controls, changes in trade barriers, threats of nationalization, and changes in government regulation (Fahy & Smithee, 1999; Miller, 1992; Teece, 1986).

Multinational firms may also face government policy uncertainties in their home country as well as in host countries (Miller, 1992). For instance, public companies in the U.S. must now comply with the Securities and Exchange Commission's Conflict Minerals filing requirements for products containing tantalum, tin, tungsten, or gold (Harris, de Carbonnel, & Bauman, 2014). These four so-called "conflict minerals" are primary sources of funding for armed groups involved in human rights violations in many African locations (Gianopoulos, 2015). However, these materials are essential to the production of countless products: electronics, plastics, glass, jewelry, zippers, buttons, drill bits, and even and golf clubs (Harris et al., 2014). To provide transparency into corporate practices, Section 1502 of the Dodd-Frank Act now requires firms to disclose the source and chain of custody for any of these minerals. While the requirement has only been in effect for one year, many firms are finding that tracing the origin of these minerals is extremely costly, if not impossible (Gianopoulos, 2015).

The physical and cultural distance involved with global supply chains magnifies the impact as well as the probability of supply chain disruptions (Christopher & Peck, 2004). Global supply chains create complexity and uncertainty, which reduces the ability of firms to restart production following a disruption (Bode et al., 2011). The longer physical distance also extends the timeframe required to recover from a disruption

(Zsidisin & Ellram, 2003). Existing empirical studies show that supply chain disruptions reduce market share and operating performance (Hendricks & Singhal, 2003, 2005a, 2005b). Hendricks and Singhal (2005b) find that in the year following a supply chain disruption, firms experience industry-adjusted changes in operating income, return on sales, and return on assets are -107%, -114%, and -92%, respectively. Their study also finds that these firms experienced a 6.92% decline in sales, while costs and inventories both increased by 10.66% and 13.88%, respectively (Hendricks & Singhal, 2005b). However, disruptions cost firms much more than lost revenue and market share (Hendricks & Singhal, 2003). Research indicates that investors view lengthy disruptions as an indication of inefficiency and poor management, which has a significant negative impact on shareholder value (Wagner & Bode, 2006). For example, in the year following a disruption, average shareholder wealth decreased by 10% (Hendricks & Singhal, 2003), while the two year abnormal stock return rate decreased by 40% (Hendricks & Singhal, 2005a).

As these risks continue to increase, many firms strive to mitigate the threats of disruptions by creating agile supply chains that are resilient and robust (Brandon-Jones et al., 2014). Resilience describes the ability of a supply chain to recover fully within an acceptable period of time following a disturbance (Christopher & Peck, 2004). Robustness concerns the ability of a firm to continue operations without disrupting production despite the occurrence of a disaster or threat (Brandon-Jones et al., 2014). Supply chain agility requires increased flexibility and visibility; thus, local networks with shorter lead times tend to be more robust and resilient to failure (Brandon-Jones et al., 2014). Since supply chain disruptions create operational costs and long-term strategic and financial risks, firms with higher supply chain disruption risk should be more likely to repatriate manufacturing to the U.S. (Ellram, Tate, & Petersen, 2013).

H4: As the risk of a supply chain disruption in offshore markets increases, firms who relocate production to the U.S. will achieve (a) superior operating efficiency and (b) superior firm profitability compared to firms that continue to manufacture products overseas.

2.4.2 Assessing the Impact of Downstream Markets on Reshoring Success

2.4.2.1 Product innovativeness and factor market rivalry. As labor becomes scarce in emerging economies, foreign governments have less incentive to invest in operations with high asset specificity and increased quality demands (Gatignon & Anderson, 1988). Host countries also have no incentive to invest in the human resource training and skilled labor necessary to create customized products when the demand for semi-skilled labor is high (Shelanski & Klein, 1995). To boost other aspects of foreign economies, governments often institute counter-trade agreements in exchange for the investments in education and job training required for highly technical production (Min et al., 1994). These agreements require the supplier to purchase a certain percentage of goods from local suppliers, thereby limiting the purchasing power of the multi-national enterprise while strengthening the foreign economy (Min et al., 1994; N. Song et al., 2007; Teece, 1986).

In addition to the direct labor problems arising from the shortage of skilled workers and quality management, firms also incur additional costs from indirect labor relations (Gatignon & Anderson, 1988; Sydow & Frenkel, 2013). These costs arise from additional negotiations and regulations imposed by workers organizations, trade unions, and other non-government organizations (Schoenherr et al., 2008; Sydow & Frenkel, 2013). Along with the political uncertainty of potential government intervention, both the process uncertainty arising from potential labor disputes and the macro-uncertainty caused by unstable foreign exchange rates can nullify any price advantages offered by a foreign supplier (Min et al., 1994).

Factor market rivalry creates thin markets, which reduces the incentives for foreign suppliers to invest in the specialized equipment and changing technology required to produce innovative products (Teece, 1986). When firms must make these investments themselves, they leave themselves subject to expropriation risks (Joskow, 1988). The rapid rate of change for innovative product markets leaves manufacturers at an even greater risk of ex-post price increases, especially when customized tools and machinery are required (G. Walker & Weber, 1984). For instance, in automobile manufacturing, dies and other special tools have low salvage value, yet provide a quasi-rent stream that is highly dependent on the machinery and the skilled labor required for production (G. Walker & Weber, 1987). Here, the greater the research and development expense for the product, the higher the expropriation risk from hold-up hazards (Joskow, 1988). The resulting switching costs introduce behavioral uncertainty and the potential for opportunism (Mooi & Ghosh, 2010).

Investment in non-fungible assets leads to small numbers bargaining and hold-up hazards (Williamson, 1985). Without sufficient safeguards, either party could attempt to capitalize on the fact that the other cannot exit the arrangement without incurring great cost (Williamson, 1991). The dynamism present in innovative markets precludes the ability of the focal firm to develop specific, binding contracts (Huang & Chu, 2010).

Likewise, the rate of change in innovative markets introduces technical uncertainty, which limits the ability of firms to implement effective safeguards due to the potential lock-in hazard (Klein et al., 1990). These transaction hazards may be costly in terms of possible delays and disruptions due to shirking, labor shortage, and opportunistic behavior (G. Walker & Weber, 1987). The potential for market competition to safeguard buyers and sellers is limited to the extent that efficient production requires specialized or dedicated assets (Williamson, 1981). Thus, markets competition cannot effectively govern transactions subject to a high degree of uncertainty and consisting of long-term exchanges of complex and heterogeneous products between a comparatively small number of traders (Teece, 1986).

Internalization can only neutralize these threats when host governments offer the same protections and incentives to both local and foreign investors (Gatignon & Anderson, 1988; Klein, 1989; Klein et al., 1990). Thus, foreign direct investment, whether it is vertical or horizontal, replaces some of the disadvantages encountered in foreign markets with a direct interface between the subsidiary and the host government (Teece, 1986). If host governments treat multinational enterprises differently from indigenous entities, the foreign firm may have circumvented one hold-up hazard through direct investment only to encounter another from nationalization (Gatignon & Anderson, 1988; Teece, 1986). Thus, location rather than ownership should be the best strategy to protecting assets in tight markets with innovative product (Peng, 2001). Hence, for firms in highly innovative product markets, the increasing competition in offshore factor markets should heighten the operational and financial incentives to reshore production.

H5: As product innovativeness increases (decreases), the effect that factor market rivalry has on (a) superior operating efficiency and (b) superior firm profitability increases (decreases).

2.4.2.2 Product innovativeness and total logistics costs. Product market characteristics may significantly increase logistics expenditures as well as factor market costs (Ancarani et al., 2015). When determining manufacturing locations, firms must consider the impact that the expected product life cycle has on total logistics costs (Mol, Pauwels, Matthyssens, & Quintens, 2004). Innovative product markets are characterized as volatile and dynamic, thus the expected life cycle for innovative products is usually short (Mol, van Tulder, & Beije, 2005). Market dynamism defines the rate of change in customer preferences and competitor actions (Homburg, Fürst, & Kuehnl, 2012), whereas volatility describes the extent to which the environment changes rapidly without notice (Klein et al., 1990). This type of market turbulence introduces technical uncertainty and process uncertainty in upstream markets as well as demand uncertainty from downstream markets (Zsidisin et al., 2000). This level of uncertainty coupled with the specificity of highly technical products increases production costs, total landed costs, and inventory carrying costs for innovative products produced abroad (Platts & Song, 2010).

First, the rate of technological change within an industry often dictates the level of process uncertainty, which consequently raises production costs (Bertrand & Mol, 2013). Task complexity arises because highly innovative production targets emerging or potential markets in which product requirements are unarticulated and no dominant design exists (X. M. Song & Parry, 1999). This also increases quality related costs of additional scrap and rework due to the constant learning curve involved (Smith, 1999).

Many times engineers must remain onsite for additional inspection because the rapid technological change creates quality issues due to the constant learning curve involved (Mol et al., 2004). Excessive product modification and proliferation reduces production efficiency, thereby creating additional manufacturing costs (Kotabe & Murray, 2004). Innovative products often require additional oversight from the focal firm due to the frequent retooling and changeover costs (Bhatnagar & Sohal, 2005). Expatriation costs of long-term engineering visits are also substantial and typically unexpected (Platts & Song, 2010). Moreover, due to the novelty of innovative projects, firms typically lacks relevant experience to simplify the task and process complexity (X. M. Song & Parry, 1999).

The level of product innovation also increases the total grounded costs for globally sourced products (Boute & Van Mieghem, 2015). The longer geographic distance increases the transport costs required (Smith, 1999). Increased task complexity inhibits coordination and communication, which increases the likelihood of expediting costs (Baldwin & Venables, 2013). A high rate of technical change requires idiosyncratic technical assets while the products often require inputs that are more expensive (Platts & Song, 2010). Thus, the financial costs of inventory is much greater in highly innovative markets, thereby increasing the impact of longer cash-to-cash cycle times (Gunasekaran et al., 2001). The higher demand for innovative products leads to higher retail pricing, which increases the impact of in-transit damages and shrinkage; therefore, firms must carry additional transportation insurance at a higher rate (Min et al., 1994). The difference in product price may also affect the tariff rate for imported materials and parts along with any tariffs due upon arrival to the product market (N. Song et al., 2007).

Thus, product innovativeness should drastically increase inventory carrying costs, tariffs and duties, as well as insurance costs for overseas transport (Smith, 1999).

Innovative products also incur additional downstream costs due to greater demand uncertainty, higher product values, and shorter product life cycles (Mol et al., 2005). Innovative firms suffer higher inventory carrying costs due to reinvention and subsequent obsolescence (Kotabe & Murray, 2004). Companies in high clock-speed industries are less likely to recoup losses by refurbishing or reselling product returns. Additionally, breakthrough projects target latent consumer needs, which limit the ability to forecast accurately (X. M. Song & Parry, 1999). For instance, Nintendo lost valuable market share to PlayStation and other competitors in 2007 when it underestimated seasonal demand for its Wii gaming console creating Christmas shortages. The planned obsolescence inherent to electronics and other highly technical products involves constant redesign to provide wider arrays of customer offerings and customizations (van Hoek, 2001). As industry competition strengthens, customer demands escalate and product variety increases (Homburg et al., 2012).

This continuous redesign creates volatile markets as heightened industry demand changes rapidly and becomes less predictable (Mol et al., 2005). The resultant shorter life cycles reduce the window of opportunity for successful new product development. For profitable growth through new products, firms need to move these products to market faster because of shrinking product life cycles and the rapid obsolescence of established products on the market (Wagner, 2010). However, as windows of opportunity become smaller, research indicates that product timing may be even more important than product cycle time. Launch timing is increasingly important in dynamic markets because product launch delays may lead to lost sales revenue and lower market share (Calantone & Di Benedetto, 2012). Conversely, faster cycle times may allow firms to adopt a pioneer role within the industry providing first mover advantages (Wagner, 2010). Shorter supply chains allow more time for market sensing before investing in production, finished goods inventory (van Hoek, 2001). For maximum returns from the product, the order-to-completion cycle time should be as short as possible (Bygballe et al., 2012). Considering the additional operational costs globalization creates for innovative products, the level of product innovativeness should strengthen the effect of total logistics costs on reshoring.

> *H6: As product innovativeness increases (decreases), the effect that total logistics costs has on (a) superior operating efficiency and (b) superior firm profitability increases (decreases).*

2.4.2.3 Product innovativeness and strategic risk exposure. Globalization exposes innovative companies to greater strategic risks as the reduced visibility in dynamic industries creates quality concerns and increases the potential for capability erosion. First, quality risk is greater for innovative products due to novelty of the product and the rapid rate of change inherent to dynamic markets (Paladino, 2007). The continuous redesign increases both product and task complexity, which thereby induces process uncertainty (Handley & W. C., Benton, 2013). Radical innovations are also highly technical, requiring ongoing research and development (R&D) support (Platts & Song, 2010). The use of external R&D to manage ongoing changes reduces visibility for the focal firm and may be disruptive to the success of new product development (Bertrand & Mol, 2013). For instance, Boeing's effort to speed the development cycle time for its 787 Dreamliner resulted in a series of production problems that delayed the product launch over two years, cost billions of dollars in lost sales, and created post-launch problems that remain to this day (C. S. Tang et al., 2009).

Successful global sourcing strategies require close coordination among R&D, manufacturing, and marketing activities across national boundaries (Kotabe & Murray, 2004). Close relationships between buyers and suppliers enhance the success of new product launches (Prior, 2012). Collaboration increases trust, information transparency, and cooperation with strategic partners and suppliers, thereby facilitating the development of new products while mitigating potential risks (Christopher et al., 2011). Frequent interaction also increases the probability that relevant processes and systems are integrated between buyers and suppliers (Chang, Cheng, & Wu, 2012). However, partnerships are extremely resource-intensive, and a buyer can only be highly involved with a limited number of offshore suppliers. Thus, global sourcing is often managed at arm's length despite the increased risk (Pereira, Sellitto, Borchardt, & Geiger, 2011).

Along with the potential losses resulting from a failed product launch, an over-reliance on outsourced manufacturing can also lead to an unintended loss of operational-level knowledge and capabilities (Sanders et al., 2007). To free up valuable resources and focus on core capabilities, many companies design products domestically and manufacture them offshore (Kotabe, 1990). While global sourcing reduces the required investment in manufacturing facilities and lowers the breakeven point for new developments, the separation causes the design team to lose direct contact with manufacturing on a daily basis (Kotabe & Murray, 2004). As firms adopt this designer role in manufacturing, they eventually lose an inherent understanding of how production operations work (Denning, 2013b). With no direct involvement in manufacturing, R&D

departments struggle to keep abreast of changes in machinery and technology (Kotabe, 1990). Over time, these designer firms risk losing the ability to determine the how best to manufacture the products they conceive (Denning, 2013a).

Past research shows that when manufacturing operations are sent overseas, some innovative ability is lost in the long run (Denning, 2013a, 2013b). Innovative capability represents the ability of a firm relative to its competitors to develop new approaches, techniques and ideas to solve identified problems and to put these into practice (Prior, 2012). This loss of absorptive capacity reduces strategic capabilities by limiting a firm's market sensing capabilities and likely creates other downstream risks, as well (Bertrand & Mol, 2013). As firms depend more heavily on independent suppliers at an arm's-length basis, they also lose sight of how to incorporate emerging technologies and expertise into the development of new products (Kotabe & Murray, 2004). The loss of production and innovation capabilities also reduces the firm's ability to provide technical support to customers when problems arise (Brandon-Jones et al., 2014). Thus, an overdependence on foreign production may induce a long-term loss of manufacturing capabilities, and consequently, a loss of global competitiveness (Kotabe, 1990).

Global sourcing adds considerable risk to manufacturing, whether outsourced or internalized, because firms must manage not only the supplying partner, but also its supply chain or supporting network (Kotabe & Murray, 2004). Extant literature suggests that most firms producing overseas lack visibility past their second tier suppliers, thereby negating the ability to develop the close relationships necessary for innovative production (Brandon-Jones et al., 2014). Since innovative products are highly technical and require a greater amount of strategic assets to produce, the risk of asset erosion is greater than for commoditized products (Danneels & Kleinschmidtb, 2001; Song & Parry, 1999). The greater the distance between design and production, the greater the likelihood that focal firms will lose valuable manufacturing capabilities (Kotabe & Murray, 2004). Thus, companies that compete in innovative markets should be more susceptible to strategic risks and more likely to repatriate production (Smith, 1999).

> *H7: As product innovativeness increases (decreases), the effect that strategic risk has on (a) superior operating efficiency and (b) superior firm profitability increases (decreases).*

2.4.2.4 Product innovativeness and supply chain disruption risk. Several factors increase the impact of a supply chain disruption for innovative markets. First, the highly customized product offerings create thin factor markets, which reduce the robustness of global supply chains (Wagner & Bode, 2006). Item customization refers to the level of specificity involved in the manufacturing process or the level of customization involved in the final product (Duray, Ward, Milligan, & Berry, 2000). Customized products require greater asset specificity and often carry higher prices, therefore more risk is involved (Geyskens et al., 2006). The level of specialization involved in innovative design requires highly technical skills, which create switching costs. The high changeover and retooling costs involved in innovative production further limits the number of alternative suppliers available for the particular component or product (Bertrand & Mol, 2013). Fewer potential suppliers bring more risk because companies cannot fulfill demand elsewhere in the event of a disruption (Ellis et al., 2010). Thin upstream market conditions negatively affect the robustness in a global supply chain, which increases the total supply chain disruption risk (Brandon-Jones et al., 2014).

The item importance and cost structure of breakthrough products serve to reduce the firm resilience in the aftermath of a supply chain disruption. Item importance represents the level of importance that the particular good or component has on the buyer's entire portfolio (Ellis et al., 2010). Breakthrough products may represent up to 30% of a firm's sales revenue and may account for up to 90% of a firm's total return on investments, and as much as 40% of the industry market share (Lau et al., 2010). Supply chain disruptions are very costly for firms in innovative markets because most new products have a limited shelf life coupled with high R&D costs (van Hoek, 2001; Wagner, 2010). With shorter life cycles planned, manufacturers have a limited number of days to sell the product (Wagner, 2010). Since innovative markets are volatile and extremely competitive, disruptions create the potential for much larger loss of market share due leading to negative long-term outcomes (Hendricks & Singhal, 2005a; Hult et al., 2004). Supply chain disruptions in innovative products also lead to revenue loss for accessories and possibly future product upgrades (Foss & Foss, 2005). Product innovativeness should therefore strengthen the relationship between supply chain disruption risk and reshoring success.

H8: As product innovativeness increases (decreases), the effect that supplies chain disruption risk has on (a) superior operating efficiency and (b) superior firm profitability increases (decreases).

2.4.3 Moderating Effects of Offshore Networks on Reshoring Success

2.4.3.1 Offshore relationship value and factor market rivalry. Firms with valuable relationships in offshore markets may be able to minimize or eliminate the ability of factor market rivalry to weaken resource positions (Fine, 2013). Relational sourcing competence provides sustainability because relationship value differs from product value (Prior, 2012). Relationship value includes the additional potential benefits and sacrifices arising from interactions between customers and suppliers (Ritter & Walter, 2012). These value-based relationships develop trust between firms, which creates socially complex resources that are difficult to imitate (Barney, 2014).

One way suppliers actively benefit customers is by establishing contacts with potential exchange partners or influential people. These contacts can be with potential buyers or with other vendors (Scheer et al., 2010). Greater supplier access reduces switching costs and prevents thin markets (G. Walker & Weber, 1987). Strategic outsourcing also allows firms to decrease production costs, improve quality, enhance new product development, and reduce time to market (Huang & Chu, 2010). Thus, widening the provider base improves quality and reduces costs, while providing a safeguard against expropriation risks associated with factor market rivalry (Pereira et al., 2011).

The perceived relationship value resulting from this access function depends on the value of the new relationships (Walter, Müller, Helfert, & Ritter, 2003). The allocation of a larger purchase volume to selected suppliers allows customers to influence suppliers, to ensure the consistency of their supplies, and to reduce communication costs (Ritter & Walter, 2012). This purchasing power may act as a resource position barrier to deter upstream competition (Wernerfelt, 1984). For instance, Japanese auto manufacturers, whether domestic or abroad, will not allow first or second tier suppliers to produce parts for other auto manufacturers within the same plants. The resulting ability of certain firms to create socially complex relational value, while limiting the entry of other firms into a given factor market should limit the effect of offshore factor market rivalry on firm performance.

H9: As offshore relational value increases (decreases), the effect that offshore factor market rivalry has on (a) superior operating efficiency and (b) superior firm profitability decreases (increases).

2.4.3.2 Offshore relationship value and total logistics costs. While the primary reason for offshore manufacturing is cost-reduction, many firms use foreign production to implement global expansion strategies (Hult, 2012). Global reach defines a firm's presence on the international scale. As firms increase global market share and strengthen global brand image, they develop strategic advantages (Cavusgil & Cavusgil, 2012). Global reach increases strategic and logistical flexibility, which should alleviate many of the hidden costs incurred with offshore production (Fawcett et al., 1996). Successful implementation of globalization strategies requires the capability to build valuable offshore relationships and global networks (Elg, Deligonul, Ghauri, Danis, & Tarnovskaya, 2012).

Global reach describes a firm's ability to identify and penetrate profitable global markets (Fawcett et al., 1996). The expansion of manufacturing in emerging economies led to a rise in disposable domestic income in these areas, thereby creating attractive emerging markets (Cavusgil & Cavusgil, 2012). For example, consumer expenditures have more than doubled in India and portions of China since the turn of the century, and China is now the third largest consumer market (Feng, Sun, & Zhang, 2010). Expansion into these emerging markets carries risks, and market entry is insufficient for a sustainable competitive advantage (Homburg et al., 2012). Valuable offshore networks are vital to overcome the liability of foreignness that firms face a when operating or competing in foreign markets (Cavusgil & Cavusgil, 2012). Consumers prefer products that are local or produced in culturally similar locations (Rugman, Oh, & Lim, 2012). Partnerships with local suppliers and retailers are often useful in creating a local or global brand image (Nath, Nachiappan, & Ramanathan, 2010).

The liability of foreignness extends beyond retail sales, however (Teece, 1986). Foreign firms incur higher operating costs, which prevent them from conducting business activities as effectively as local firms (Cavusgil & Cavusgil, 2012). Familiarity with local customs, market trends, supplier capabilities, and business reputations provides local business a distinct advantage in both upstream and downstream markets (Barney, Wright, & Ketchen, 2001). Many of the hidden costs of offshore manufacturing occur as pre-transaction costs: prospecting, screening, negotiating, and establishing business relationships with potential suppliers (Ellram, 1993). Firms may also use valuable offshore relationships to reduce or eliminate many of the hidden costs and strategic risks incurred in offshore production(Pagano, 2009). Suppliers may provide an access function by helping firms establish new relationships with potential exchange customers, other suppliers, or government entities (Ritter & Walter, 2012; Walter et al., 2003). For instance, U.S. firms benefit by creating purchasing centers in Taiwan because Taiwanese suppliers provide valuable roles as intermediaries to bridge the cultural distance between China and western nations (Chang et al., 2012). Taiwan also provides a strategic locational advantage for importing and exporting supplies and finished goods throughout Asia and Europe.

Other benefits of global reach stem from increased market share and access to supplier capabilities (Ulaga & Eggert, 2005). Often host firms may be assist in lowering logistics costs by providing valuable marketing capabilities and insights in to local consumer customs and preferences, which in turn improves demand forecasting. As firms extend their global reach, the increased geographic dispersion creates complexity, requiring firms to manage many dissimilar consumer trends and demands across a variety of environments (Klein et al., 1990). Global partners with extensive marketing capabilities may be able to simplify much of the complexity and reduce many of the hidden costs of globalization (Homburg et al., 2012). Focal firms may also benefit from access to existing distribution channels. Host suppliers have valuable experience within their respective country or region, and independent channel members within the foreign market are often more efficient than heterogeneous multi-national corporations (Klein et al., 1990). Because these suppliers serve other customers within the same industries, they may also be able to provide information about local markets and downstream trends in global markets (Ritter & Walter, 2012).

Closer relationships allow greater visibility and coordination. This may allow firms to adjust production rates more seamlessly, thus minimizing the need for much of the safety stock that drives hidden costs (Bygballe et al., 2012). As firms expand globally, the larger market share marginalizes forecasting errors and allows for longer production runs, therefore production efficiency increases with global market share due to economies of scale (Cavusgil & Cavusgil, 2012). This proximity to foreign demand would serve to hedge the increase in transportation costs domestic logistics costs by decreasing the average aggregate (Bhatnagar & Sohal, 2005; Bygballe et al., 2012).

Thus, the impact of total logistics costs on reshoring should be less for firms with valuable offshore relationships.

H10: As offshore relational value increases (decreases), the effect that total logistics cost has on (a) superior operating efficiency and (b) superior firm profitability decreases (increases).

2.4.3.3 Offshore relationship value and strategic risk exposure. Other aspects of globalization may serve to reduce many of the strategic risks encountered in foreign production. As firms extend global reach, the larger global market share provides greater purchasing power (Sichtmann & Diamantopoulos, 2013). Larger purchase volumes from fewer strategic suppliers shorten the learning curve, thereby reducing some of the potential product quality risks (Eggert & Ulaga, 2010). The increased frequency of interaction should also improve communication (Andersen & Christensen, 2005). The increased purchasing power may also reduce the potential for opportunism or shirking, while allowing focal firms to dictate quality standards, purchasing terms, or delivery schedules (Liu, Su, Li, & Liu, 2010).

Also, innovative capacity increases with entry into foreign markets because collaboration with suppliers often increases market sensing capabilities (Li, Wei, & Liu, 2010). Suppliers can serve as a gateway to technical, exchange, or market-related information (Walter et al., 2003). Specialization allows suppliers to develop highly technical knowledge and process capabilities, which focal firms may not possess (Scheer et al., 2010). Suppliers may also contribute to new product development by providing innovative ideas, supplying innovative components and production facilities, or engaging in collaborative development projects (Ritter & Walter, 2012). Access to supplier resources can speed development times and free up resources to invest into other innovations or global markets (Wagner, 2010).

Firms with valuable offshore relationships may gain access to critical information faster than the competition and may eventually be able to decrease market research costs (Ritter & Walter, 2012). They may also provide insights into competitor intentions since they supply other firms in the same markets (Sanders et al., 2007). Global production also allows for faster diffusion of information, products, and ideas into emerging markets (Li et al., 2010; Liu et al., 2010). The creation of connections between customers and suppliers and their respective activities and resources creates socially complex interdependent relationships that are difficult to imitate (Bygballe et al., 2012). The bilateral dependency created by these relationships also serves to reduce the potential for opportunism (Williamson, 1991). Since few firms possess the capability to create a valuable offshore network, firms with valuable offshore supplier relationships should be less susceptible to strategic risk in global markets.

H11: As offshore relational value increases (decreases), the effect that strategic risk has on (a) superior operating efficiency and (b) superior firm profitability decreases (increases).

2.4.3.4 Offshore relationship value and supply chain disruption risk. Higher offshore relationship value should also reduce supply chain disruption risk. Often, offshore relational exchanges serve as a mode of entry into global consumer markets (Fawcett et al., 1996). When offshore suppliers fulfill this access function, entry into foreign consumer markets creates proximity to demand for offshore production (Bygballe et al., 2012). This effectively reduces the overall supply chain length, thereby reducing risk of disruption and recovery time in case of disruption (Ellis et al., 2010; Wagner & Bode, 2006). The shorter lead times for host markets serves to make the supply chain more resilient. An increase in global market share also reduces the impact of a disruption by adding diversity to the total market interests (Bode et al., 2011).

The ability to develop a network of flexible suppliers is another source of value because it allows firms to change order volumes at short notice (Ritter & Walter, 2012). The presence of such a network reduces distribution costs and inventory levels, and creates a reserve supply pool to decrease their dependency on other suppliers (Scheer et al., 2010). Suppliers fulfilling these safeguard and volume functions increase visibility, making the supply chain more resilient (Brandon-Jones et al., 2014). For example, Cisco was able to communicate with over 300 suppliers to assess the impact of the 2011 tsunami with 12 hours. This added visibility reduced uncertainty and created options which minimized downtime and avoided additional losses (Revilla & Sáenz, 2014). Thus, valuable offshore relationships should reduce the impact and subsequently the long-term operational and financial risk associated with supply chain disruptions.

H12: As offshore relational value increases (decreases), the effect that supply chain disruption risk has on (a) superior operating efficiency and (b) superior firm profitability decreases (increases).

CHAPTER THREE: RESEARCH METHODOLOGY

3.1 Research Design

This dissertation will utilize a longitudinal event study to assess the impact of reshoring on firm performance. This study will compare financial data for firms that have relocated manufacturing to the United States against data for matched portfolios, which serve as industry control groups (Hendricks & Singhal, 2005a). These industry benchmark groups will be created by using different combinations of the following matching criteria: pre-event return on assets (ROA), company size, and industry type (Barber & Lyon, 1996; Jacobs, Swink, & Linderman, 2015; Kinney & Wempe, 2002; Swink & Jacobs, 2012). The archival data for the study will be obtained using the S&P Capital IQ financial software tools. Event studies commonly include three steps: defining the parameters of the event, computing the forecast errors within those parameters, and finally, regressing cross-sectional abnormal performance on the factors assumed to influence the impact of the event (Serra, 2004). Due to the nature of this topic, this dissertation will use path model estimation to determine which factors influence abnormal returns.

The remainder of Chapter 3 is divided into four additional sections, which address the three steps presented in the previous paragraph along with a final section discussing the steps taken to reduce endogeneity. First, section 3.2 discusses the proposed sample characteristics, indicates the proposed methods for identifying the target sample, and provides the parameters imposed by the longitudinal nature of the study. Section 3.3

explains event study methodology, provides the benefits of event studies relative to other methods, defines the parameters used to calculate abnormal performance, and discusses the analytical techniques used to provide statistical support for the study. Next, Section 3.4 discusses the regression analysis used to determine significant factors driving the reshoring phenomenon. Here, the proposed statistical technique, potential measures, and software programs are presented. Finally, Section 3.5 explains the specific measures taken throughout the study to reduce endogeneity and other unobserved heterogeneity.

3.2 Sample Characteristics

The sample for this study consists of publicly traded firms currently listed on major stock exchanges. The target sample includes firms that have relocated manufacturing to the U.S. from any other country. While customer service and logistics centers comprise a substantial portion of the reshoring phenomenon, activities not directly related to manufacturing are outside the scope of this study. For matching purposes, all companies retained in the final sample have financial data available for the five years prior to reshoring as well as the two years following the event. Thus, to provide a full two-year period following the reshoring event, the sample is limited to firms that began domestic production on or before the end of the 2013 fiscal year. The matching technique is discussed further in the following section.

Several tools are used to identify firms that have reshored operations to the U.S. First, an event search was conducted using Capital IQ. The search was conducted for all events, announcements, and key developments classified as “Business Expansion,” “Business Reorganization,” and “SEC Announcements.” To further supplement the search, the ABI/Inform Trade and Industry search tool was utilized to access documented instances of reshoring in trade journals. Search terms such as “reshoring,” “homeshoring,” “onshoring,” “insourcing,”, and “nearshoring” were utilized in this search engine. Finally, government commerce data and non-government trade groups was used to identify repatriation events. For each noted event, verification had to be available that the product was previously manufactured outside the United States because the previous country of origin is necessary for regression analysis.

While the exact number of reshoring companies is not readily available, an estimation can be made based on reporting statistics from the U.S. Census Bureau, international trade associations such as OECD, and other non-government organizations. For example, using information from OECD and NSF, the Reshoring Initiative indicates that 585 companies relocated manufacturing jobs to the United States from abroad between 2011 and 2014 (“Reshoring Initiative Data Report,” 2015). Many other companies have moved work to the U.S. from countries not monitored by OECD, while many instances of reshoring occurred outside of years 2011-2014. The actual population of reshoring companies is likely between 750 and 1000 total firms, although financial information will not be readily available from all companies. The expected sample size was estimated to be 100-200 individual cases. This should provide a sample that is representative of the population.

3.3 Event Study Methodology

3.3.1 Overview

Event studies employ econometric techniques to estimate the impact of a particular event on firm performance (Serra, 2004). Events of interest may include industry-wide changes that occur at a particular time, such as new legislation or changes to existing laws (Rabinovich & Cheon, 2011). This methodology is also useful in examining performance changes following corporate events in which firms experience the same type event across industries and times (Hendricks & Singhal, 2005b). Examples of corporate events in existing event studies include changes in ownership, changes in quality control measures (Jacobs et al., 2015; Sharma, 2005; Swink & Jacobs, 2012), the introduction of new operating or logistical procedures (Kinney & Wempe, 2002), and supply chain disruptions (Hendricks & Singhal, 2003, 2005a, 2005b). The use of event studies provides researchers the ability to identify abnormalities in dependent construct measures resulting from a specific event (Rabinovich & Cheon, 2011).

The primary focus of event studies concerns the concept of abnormal returns (Serra, 2004). Abnormal performance represents the difference between performance measures for focal firms and the same performance measures for appropriate benchmarks, assuming the benchmarks control for external factors known to affect firm performance (Hendricks & Singhal, 2005a). In principle, long-term event studies are performed by first identifying a sample of firms that have experienced the same event, and then testing the null hypothesis that the ex post abnormal returns for those sample firms are equal to zero over a specified period (Rabinovich & Cheon, 2011). The underlying assumption of event study methodology is that after controlling for all known external and industry-wide factors, the remaining unexplained variance may be attributed to the focal event (Hendricks & Singhal, 2005a).

To isolate the impact of the reshoring event from the effects of normal market conditions, the proposed method is designed to analyze the abnormal performance results of reshoring firms (Jacobs et al., 2015). Using industry benchmark groups allows the changes in operating performance of reshoring firms to be compared against the estimated operating performance that the firm would have had if offshore production had continued (Barber & Lyon, 1996). Moreover, the event study methodology provides a more robust analysis than a uniform comparison between the performance variance detected in reshoring firms and global manufacturing performance measures (Hendricks & Singhal, 2005b). Thus, abnormal performance is the difference between the firm's actual performance following the event and the expected performance had the event not occurred (Swink & Jacobs, 2012). Given the subjective nature of superior performance, positive (negative) ex post abnormal returns provide the best proxy measure for superior (inferior) firm operating and financial performance resulting from an event.

3.3.2 Defining Event Parameters

The first task in conducting an event study is to define the focal event and the period over which the event occurred (Serra, 2004). Many types of events occur over extended periods of time, rather than single, discrete instances (Rabinovich & Cheon, 2011). Moreover, the impact of events is often lagged over long periods of time (Hendricks & Singhal, 2005a). Thus, effective event studies must accurately specify the occurrence of the event and provide relative parameters in order to isolate the effects of the focal event (Sharma, 2005). The chosen parameters often depend upon the characteristics of the focal event and the measures used to determine the impact. For existing event studies, the period of analysis spans from one year to 10 years (Hendricks & Singhal, 2005b). Although no standard guidelines exist for the length of time an event study should cover, most long-run studies examine a three to five year horizon (Hendricks & Singhal, 2005a).

In addition to isolating the events, the research design must also establish the dependent construct measure used to identify and determine the impact of the focal events (Rabinovich & Cheon, 2011). Event studies compare firm performance before and after an event using some form of return on investment (ROI). When measuring operating performance, long range accounting-based measures offer more statistical power than market-based measures such as earnings per share (Barber & Lyon, 1996). This is because investors are often slow to react to events affecting operations, outstanding shares are seldom held constant over time, and also because earnings radiate from all capabilities, not just operations efficiency (Barber & Lyon, 1996; Hendricks & Singhal, 2005a; Sharma, 2005).

Barber and Lyon (1996) find that lagged return on assets (ROA) is the most significant predictor of future performance. In their study on systematic and unsystematic risk, Miller and Bromiley (1990) find that lagged ROA attenuates the potential effect of omitted variable bias, and previous performance may accurately predict future performance for periods up to five years. Aaker and Jacobson (1987) find that ROI lagged even one year explains more variance in firm performance than 28 variables used in the Profit Impact of Marketing Strategies database.

This dissertation examines performance for each sample firm for five total years. This period includes the two years prior to the reshoring event, the year that domestic production began, and the two years following the reshoring year. Sharma (2005) employs a similar approach in his study of firm performance after ISO 9000 certification. This range allows the initial impact of reshoring to be realized, while also capturing some of the ongoing effects (Hendricks & Singhal, 2005b). Considering the magnitude of manufacturing location decisions, performance changes leading to reshoring likely appear many months before the event (Hendricks & Singhal, 2005b; Kinney & Wempe, 2002). Thus, the two-year pre-event period reduces selection bias by allowing preexisting trends and performance to be examined (Sharma, 2005). This reduces the possibility that ex post abnormal performance is not a continuation of prior firm performance, thereby ensuring that statistical significance is not an artifact of the event study methodology (Kinney & Wempe, 2002; Sharma, 2005).

To allow the data to pool over time, the fiscal years are transformed into event years with the fiscal year of the reshoring event designated as year 0 (Hendricks & Singhal, 2005b). The previous year is designated as year -1, while the subsequent year is designated year +1. This pattern continues for all years, with the extreme years designated as year -2 and year +2. Because year -2 is the first year of analysis, year -3 will be lag year used for benchmark matching. Identifying fiscal years in relation to the focal event allows the study to examine performance changes from year to year as well as aggregate changes over multiple years (Swink & Jacobs, 2012).

3.3.3 Industry Control Groups

Creating the model for calculating expected performance is the most important step in conducting an event study(Barber & Lyon, 1996). Selection bias may occur if the abnormal performance is simply a continuation of previous success (Sharma, 2005). Under conditions of perfect competition, the impact of a change in manufacturing operations could be measured by simply comparing the pre- and post-event performance (Shafer & Moeller, 2012). However, such a naive approach is not possible because all performance measures are subject to a myriad of market-wide and firm-specific factors unrelated to reshoring (Serra, 2004). To isolate the event, the research design must control for such external factors (Barber & Lyon, 1996). Thus, the selection of appropriate benchmarks is critical to the successful implementation of event study methodology (Serra, 2004).

Simulation results indicate that using matched portfolios as industry control groups yields test results that are well specified and statistically significant when the proper matching criteria are applied (Barber & Lyon, 1996). When establishing expected operating performance, measures should be taken to use firms as similar as possible to the sample firms (Jacobs et al., 2015). The design for this study utilizes different combinations of industry classifications, performance, and size as matching criteria to create three distinct matching groups, which will serve as industry control groups. The filters for each of these three industry control groups are adapted from existing studies that achieved statistically significant results (Jacobs et al., 2015; Swink & Jacobs, 2012).

3.3.3.1 Performance and industry (PI) matching group. The first industry-matching group, *Performance Industry Matching* (PI), controls for the effect of industry and firm performance. For each sample firm, all firms within the same two-digit SIC code, whose ROA falls within the range of 90% and 110% of the sample firm's ROA in for the fiscal year -3 are included. In a simulation study, Barber and Lyon (1996) found the 90%-110% filter yields test statistics that are well specified for samples, including those with very high or very low historical performance. Subsequent studies also indicate that this measure provides a tight grouping for all firms in the benchmark group (Jacobs et al., 2015; Swink & Jacobs, 2012).

Criterion 1: Firms must be in the same industry as designated by the first two-digits of the standardized industrial classification (SIC) code.

Criterion 2: Financial data for the matching firm must be accessible for all years from year -3 through year +2 for the sample firm.

Criterion 3: Matching firms will have an ROA in year -3 that falls within the range of 90% and 110% of the sample firm ROA in the same fiscal year.

3.3.3.2 Median performance and industry (MPI) matching group. Criteria for the second industry-matching group include an additional constraint to control for measurement error present in accounting-based performance measures (Swink & Jacobs, 2012). Financial performance data is prone to outliers due to cross sectional dependency and mean reversion (Hendricks & Singhal, 2005a). Put differently, any firm may show uncharacteristic performance in a given year due to overlapping periods and the recency of sales or purchases. However, as the data pools over time, the firm's high or low abnormal performance will revert back toward the mean under of normal operating conditions (Barber & Lyon, 1996). To reduce this type error, Kinney and Wempe (2002) define pre-event performance as the median value of performance over the three years prior to the event.

Using measures adapted from Swink and Jacobs (2012), the second industry matching group further controls for endogeneity and mean reversion by matching ROA based on the median returns over three fiscal years: -5, -4, and -3. For each sample firm, *Median Performance and Industry Matching* (MPI) consists of all firms within the same two-digit SIC code whose median ROA in years -3, -4, and -5 lies within the range of 90% and 110% of the of the median ROA for the sample firm over the same three years.

Criterion 1: Firms must be in the same industry as designated by the first two-digits of the standardized industrial classification (SIC) code.

Criterion 2: Financial data for the matching firm must be accessible for all years from year -5 through year +2 for the sample firm.

Criterion 3: The median ROA in years -3, -4, and -5 for each matching firm must be within the range of 90% and 110% of the median ROA for the sample firm in the same fiscal years.

3.3.3.3 Median performance, industry, and size (MPIS) matching group. The final and most stringent group uses the same conditions as MPI matching group with the added criterion that selected firms are also closely matched with sample firms in terms of size. While matching on the basis of performance and industry provides well-specified test statistics for all groups, simulation results indicate that this method is anticonservative for small sample firms with high performance (Barber & Lyon, 1996). Thus, matching firms on the basis of industry, performance, and size provides more statistical power if sufficient benchmark firms exist. The filter for group three is adapted from existing studies that employ performance, industry, and size matching techniques (Jacobs et al., 2015; Swink & Jacobs, 2012). *Median Performance, Industry, and Size Matching* (MPIS) matches all firms with the same two-digit SIC, whose median ROA in years -3, -4, and -5 are within 10%, and whose median total assets are within a factor of 25 of the sample firm's median total assets for that same three years.

Criterion 1: Firms must be in the same industry as designated by the first two-digits of the standardized industrial classification (SIC) code.

Criterion 2: Financial data for the matching firm must be accessible for all years from year -5 through year +2 for the sample firm.

Criterion 3: The median ROA in years -3, -4, and -5 for each matching firm must be within the range of 90% and 110% of the median ROA for the sample firm in the same fiscal years.

Criterion 4: For each matching firm, the median value of Total Assets for years -3, -4, and -5 must be within a factor of 25 of the median value of Total Assets for the sample firm for the same fiscal period.

3.3.4 Analytical Techniques

Upon creating the industrial control groups, appropriate benchmarks can be established to determine the expected performance of sample firms relative to each control group. Expected performance, then estimates the performance that a sample firm would have achieved had reshoring not occurred (Swink & Jacobs, 2012). Thus, expected performance modeling allows researchers to isolate the effect of reshoring. Event study methodology assumes that the difference between a sample firm's actual ex post performance and its expected performance is an abnormality attributable to the event (Rabinovich & Cheon, 2011). Thus, if the difference is significantly different from zero, the abnormal performance for this study estimates the impact that reshoring has on firm performance.

In their simulation-based research, Barber and Lyon (1996) find that test statistics for the change in operating performance relative to an appropriate benchmark are more powerful than the relative comparison of a sample firm to a benchmark in the same period. Due to the common occurrence of extreme outliers in accounting-based performance measures, nonparametric techniques based on the median change in the benchmark firms have more predictive power than parametric tests that use the mean change (Barber & Lyon, 1996; Kinney & Wempe, 2002). Thus, the expected operating performance of a sample firm relative to each matching group is equal to the sum of the sample firm's actual operating performance in the preceding or lag period and the median change in operating performance for the respective matching group (Swink & Jacobs, 2012). For example, for each 1% change in median ROA for the industry-matching group, the sample firm is expected to have 1% change in ROA during the same period. Equation 1 presents the formula for calculating expected performance.

Equation 1: Expected Performance of Sample Firms

$$Exp(P_{it)} = P_{i,t-1} + Median\,\Delta\, PI_{it}^{j}, \qquad j=1, 3.$$

where P_{it} represents the performance of firm i in fiscal year t,
and j represents industry matching groups $1-3$.

The abnormal performance is then calculated by subtracting the sample firm's expected performance for the period from the sample firm's actual operating performance for the same period. This formula appears in Equation 2. When abnormal operating performance is calculated for each reshoring firm in all years for each group, statistical testing can be used to determine if the impact of reshoring on operating performance is significant (Swink & Jacobs, 2012).

Equation 2: Abnormal Performance of Sample Firms

$$Ab(P_{\mathrm{it}}) = \mathrm{P_{it}} - Exp(P_{\mathrm{it}}),$$

where represents the fiscal performance of firm i in year t.

Wilcoxon Signed-rank tests were used to determine if the median abnormal performance of any group is significantly different from zero (Hendricks & Singhal, 2005b). This nonparametric test determines significance based on the assumptions that both the sign and magnitude are important (Wilcoxon, 1945). Parametric tests are not well specified for abnormal returns (Barber & Lyon, 1996), since previous studies have shown that abnormal returns distributions are right-skewed (Hendricks & Singhal, 2005b). Parametric tests reject too often when testing for positive abnormal performance and too seldom when testing for negative abnormal performance (Serra, 2004). Thus, nonparametric Wilcoxon test statistics are more powerful than parametric t-statistics when analyzing abnormal returns (Barber & Lyon, 1996).

3.4 Path Model Estimation

3.4.1 Overview

To determine which variables influence the performance, partial least squares structural equations modeling (PLS-SEM) was employed to estimate the structural equations for superior operating and financial performance. The calculations of abnormal returns in the longitudinal event study are representative of superior firm performance. Thus abnormal ROA and abnormal ROS for each control group serve as the dependent variable in separate structural models. Proxy measures for the independent variables are discussed in the following section. Latent interaction variables are modeled and empirically tested to determine the significance of hypothesized moderating effects. Separate structural models are necessary to identify the determinants of superior operating performance and superior financial performance using abnormal ROA and abnormal ROS as dependent variables, respectively. The analyses were also performed for each control group to ensure reliability.

3.4.2 Measurement Items

3.4.2.1 Economic indicators. The economic drivers of reshoring are macroeconomic factors in which the primary vehicles for variance in the dependent variable are the competitiveness and global reach of previous countries of origin (Mann, 2012). To measure the impact of offshore factor market rivalry on the probability and success of reshoring events, variance in the price of inputs before the event must first be measured (Lall, 2001). Since the focus of this dissertation concerns reasons for moving manufacturing back to the United States, the measure must also be scaled so that the costs can be analyzed relative to manufacturing costs in the U.S over time.

Each year, the World Economic Forum compiles an index of data that ranks over 160 countries on the ability to compete in global commerce (Arvis, Mustra, Ojala, Shepherd, & Saslavsky, 2012). This index, called the Global Competitiveness Report, uses national wealth along with survey data to measure the macroeconomic, social, and political policies that might affect competitiveness (Porter, Delgado, Ketels, & Stern, 2008). Examples of the measures used to compile the index include national gross domestic product, purchasing parity, productivity, labor costs, education levels, technological advancements, access to medical care, and poverty rates (Schwab, 2012). Thus, as a measure for factor market rivalry, this study uses the Global Competitiveness Report country competitiveness measure of the previous country of origin at the time of reshoring (Porter et al., 2008).

Similarly, to isolate the variance in the dependent variable resulting from changes in total logistics costs due to reshoring, the measure must compare the logistics proficiency, rather than factor prices. The World Bank periodically compiles a publicly available data set that ranks countries on the basis of domestic and international infrastructure and logistical capabilities previously found to influence bilateral trade (Mann, 2012). The Logistics Performance Index, found in the World Bank Data archives, provides detailed country-level data based on the time and monetary costs of importing or exporting a twenty foot container between the nation's largest port and its most industrious city (Hausman, Lee, & Subramanian, 2013). Among the measures included are average export processing time, average import processing time, average cost to import, average cost to export, infrastructure, information technology infrastructure, and on time delivery performance (Nordås et al., 2006). Hence, the proxy measure for ex ante total logistics costs is the global Logistics Performance Index rating of the previous country of origin at the time of reshoring.

3.4.2.2 Risk measures. Strategic risk exposure and supply chain disruption risk indicate the level of unsystematic and systematic risk, respectively (Aaker & Jacobson, 1987). Strategic risk exposure is a company-specific measure derived from the amount of intangible assets that a company possesses (Christopher & Peck, 2004). While risk is a function of both probability and impact, strategic risk exposure is unsystematic and bounded by the current and future value of the strategic resources exposed to a potential threat (Ritchie & Brindley, 2007). Thus, the value of a firm's capabilities and intangible assets should correlate with the variance in reshoring performance specific to strategic risk exposure. However, capabilities and assets that are not well defined, not easily duplicated, and not readily mobile are also not easily measured (Hunt & Morgan, 1995, 1996). Falkenberg (1996) calculated the value of such non-tradable assets by using the ratio of market price to book value. This measure is a proxy for a firm's brand equity, intellectual property, and other capabilities that allow a firm to charge a price premium (Nath et al., 2010). Market to book value also indicates firm growth potential (Hendricks & Singhal, 2003, 2005a). Thus, market to book value is the measure for strategic risk exposure in this study.

Conversely, the impact of a supply chain disruption for any given product or component is the same for any location, while the probability of a disruption differs substantially across regions and nations (Christopher & Peck, 2004). Thus, country risk is the primary vehicle for variance in the dependent variable relative to supply chain disruption risk. Much like the macroeconomic drivers of reshoring, a scaled measure of risk for the previous country of origin is used to isolate the impact of supply chain disruption risk on manufacturing location decisions. Miller (1992) suggests that since firms can only transfer or share systematic risk, average insurance rates for a particular area or region provide a proxy measure for environmental risk factors.

Factory Mutual Insurance Company (FM Global) compiles a yearly assessment of supply chain risk factors for each region and for most developed countries (Elkins, Handfield, Blackhurst, & Craighead, 2005). Similar to the Logistics Performance Index, the FM Global Resilience Index uses multivariate analysis to rank 130 countries and regions by resilience to supply chain disruption (*FM Global Resilience Index*, 2015). The index uses three measures to determine the country risk level: socio-economic risk; supply chain, or business, risk; and catastrophic or environmental risk (Madalin, 2015).

Thus, the measure for supply chain disruption risk is the FM Global Resilience Index factor for the previous country of origin at the time of reshoring.

3.4.2.3 Intervening measures. Firm-specific accounting measures are also used as proxy measures for each of the moderating variables. Product innovativeness indicates the complexity and value of the products for each firm as well as the level of turbulence and the dynamic nature of the markets in which each firm competes. One of the most widely used indicators of innovativeness is R&D intensity, which is measured by dividing the amount of research and development expenditures by net profits (Kinney & Wempe, 2002). Thus, the measure for product innovativeness in this study is R&D intensity.

Offshore relationship value represents the firm-specific capabilities that allow firms to compete in offshore markets (Nath et al., 2010). Research suggests that these capabilities develop over time with increasing experience in offshore markets (Cavusgil & Cavusgil, 2012; Rugman & Verbeke, 2004; Sichtmann & Diamantopoulos, 2013). Thus, while globalization has created many multinational firms, only a small percentage of multinationals possess the capabilities to create true global reach (Rugman et al., 2012). The ultimate test to assess whether firms are truly global is the actual penetration in foreign markets, especially those outside their home triad (Rugman & Verbeke, 2004). The percentage of foreign revenue is the most commonly used measure of internationalization in extant international business literature (Marshall, 2012). Thus, this research uses the ratio of foreign revenue to total revenue as a proxy for offshore relationship value.

3.4.2.4 Control variables. Three additional measures are included to reduce the possibility of omitted variable bias (endogeneity). First, firm size may inadvertently affect operating performance (Sharma, 2005). Larger firms are more likely to have implementation resources and access to the capital necessary to relocate globally (Barber & Lyon, 1996). Conversely, smaller firms tend to be more focused and agile, making relocation less demanding. In addition, the relative impact of any event designed to improve performance is likely to be greater in small firms (Swink & Jacobs, 2012). To control for issues related to firm size, measures such as the natural log of total firm employees, the natural log of firm value, and the natural log of total firm assets are commonly used in archival studies (Barber & Lyon, 1996; Kinney & Wempe, 2002). For reshoring, market value provides a suitable measure of size, due to the fact that the number of employees and the value of tangible assets differs with the labor productivity and level of automation used across nations and cultures. Thus, the natural log of firm market value at the end of year -3 is operationalized to control for the effects of firm size (Swink & Jacobs, 2012).

The remaining two control measures address the possibility that firms with historically higher and lower than normal performance might bias the results (Swink & Jacobs, 2012). To examine the effect of past performance, the industry-adjusted ROA for each sample firm is computed as the difference between its ROA in year -3 and the median ROA in year -3 for all firms with the same three digit SIC code (Hendricks & Singhal, 2008). Thus, industry-adjusted performance is a paired difference (Shafer & Moeller, 2012). From this calculation, Swink and Jacob (2012) create two different control variables: prior positive firm performance (PFP) and prior negative firm performance (NFP). For prior positive performance (PFP), industry-adjusted ROA is used for all positive values, and all negative values are replaced with zero. For prior negative performance (NPF), the industry-adjusted performance is used for negative values, while all positive values are replaced with zero. Table 6 summarizes the proxy measures for the theoretical model and control variables.

Table 4: Proposed Measures

Variable	Role	Measure	Source
Factor Market Rivalry	Independent Variable	Global Competitive Index for Previous Country of Origin	World Economic Council Forum
Total Logistics Costs	Independent Variable	Logistics Performance Index for Previous Country of Origin	World Bank Data
Strategic Risk Exposure	Independent Variable	Control of Corruption	World Governance Indicators
Supply Chain Disruption Risk	Independent Variable	Country Risk Factor for Previous Country of Origin	FM Global Resilience Index
Product Innovativeness	Moderator	R&D Intensity	Company 10K using Capital IQ
Offshore Relationship Value	Moderator	Percentage of Revenue from Foreign Countries	Company 10K using Capital IQ
Superior Operating Value	Dependent Variable	Abnormal ROA	Section 3.3 Calculations
Superior Financial Performance	Dependent Variable	Abnormal ROS	Section 3.3 Calculations
Firm Size	Control Measure	Natural log of firm market value at year -3	Company 10K using Capital IQ
Prior Firm Performance	Control	Dummy variable designed to indicate positive or negative performance compared to the three-digit SIC code in year -3.	Capital IQ

3.4.3 Analytical Techniques

Partial Least Squares Structural Equation Modeling (PLS-SEM) is used to test hypothesized relationships among constructs using the SmartPLS 3.0 software (cite). PLS-SEM is a second generation variance-based method used to estimate structural equation models (Hair, Ringle, & Sarstedt, 2012). Often called path modeling, PLS-SEM offers several advantages over first-generation multiple linear regression techniques (Hair, Sarstedt, Pieper, & Ringle, 2012). For instance, technological advances in PLS software now provide the ability to empirically test hierarchical component models, analyze moderating effects, and examine non-linear functions for interactions between latent variables (Hair, Sarstedt, Ringle, & Mena, 2012).

PLS-SEM maximizes the explained variance in dependent variables, and provides a viable alternative to covariance-based structural equation modeling (CB-SEM) for models that violate the assumptions imposed by maximum likelihood methods (Hair, Sarstedt, Ringle, et al., 2012). Thus, PLS-SEM is well suited for analyzing predictive, complex models with a large number of variables and relationships (Hair, Hult, Ringle, & Sarstedt, 2016). The complex model in this research design uses moderation, and contains both single-item and categorical dummy variables. If alternate measures are required, some factors may use formative multiple item measures. Partial least squares path modeling produces acceptable results when using single-item, reflective, and formative measures (Hair, Ringle, & Sarstedt, 2013). It may also be used with scaled, ordinal, or categorical data. However, the ultimate endogenous variable must not be categorical data and cannot violate any of the underlying assumptions of ordinary least squares multiple regression (Hair, Sarstedt, Pieper, et al., 2012).

The PLS-SEM approach is also capable of producing robust results with both large and small sample sizes (Hair, Ringle, & Sarstedt, 2011). Considering the recency of the reshoring phenomenon, the sample size is likely to be low, while the data are expected to be non-normally distributed. While PLS-SEM can produce reliable results for sample sizes as low as 20 (Davis & Golicic, 2010), the expected sample size should be at least 10 times the maximum number of structural paths leading to a single construct (Hair et al., 2011). However, these figures are only estimates, and traditional measures of statistical power are needed to determine the necessary sample size (Cohen, 1992).

Like any statistical method, PLS-SEM relies on the assumption that the sample provides a true representation of the target population (Hair et al., 2011). Partial least squares uses nonparametric bootstrapping to obtain the standard errors for testing hypotheses, and therefore makes no assumption regarding normality (Hair, Sarstedt, Ringle, et al., 2012).

This method was also selected due to the exploratory nature of this study as well as the complexity of the structural model. Variance based path modeling is preferred in exploratory studies because it focuses on prediction rather than confirmation of structural relationships (Hair et al., 2011). In addition to bootstrapping, PLS-SEM also applies a blindfolding technique to endogenous variables to assess the predictive validity of the structural model (Hair et al., 2016). PLS-SEM also allows for the modeling and empirical assessment of latent interaction variables used in moderated multiple regression (Chin, Marcolin, & Newsted, 2003). Moderation violates maximum likelihood assumptions because covariance-based methods assume that error terms for all exogenous factors are unrelated, whereas interaction variables are created through multiplication and must have correlated error terms (Eggert & Ulaga, 2010). However, latent interactions may enhance the validity of PLS models by explaining a greater portion of the unobserved heterogeneity (Hair et al., 2011). The models used to measure the main antecedents of reshoring on superior operating performance and superior financial performance appear in Equation 4 and Equation 5, respectively.

Equation 3: Superior Operating Efficiency Regression Equation

$$\begin{aligned}
Abnormal\ ROA\ = {} & \beta_0 \\
& + \beta_1 \times Factor\ Market\ Rivalry \\
& + \beta_2 \times Total\ Logistics\ Costs \\
& + \beta_3 \times Strategic\ Risk\ Exposure \\
& + \beta_4 \times Supply\ Chain\ Disruption\ Risk \\
& + \beta_5 \times Product\ Innovativeness \\
& + \beta_6 \times Product\ Innovativeness \times Factor\ Market\ Rivalry \\
& + \beta_7 \times Product\ Innovativeness \times Total\ Logistics\ Costs \\
& + \beta_8 \times Product\ Innovativeness \times Strategic\ Risk\ Exposure \\
& + \beta_9 \times Product\ Innovativeness \times Supply\ Chain\ Disruption\ Risk \\
& + \beta_{10} \times Offshore\ Relationship\ Value \\
& + \beta_{11} \times Offshore\ Relationship\ Value \times Factor\ Market\ Rivalry \\
& + \beta_{12} \times Offshore\ Relationship\ Value \times Total\ Logistics\ Costs \\
& + \beta_{13} \times Offshore\ Relationship\ Value \times Strategic\ Risk\ Exposure \\
& + \beta_{14} \times Offshore\ Relationship\ Value \times Supply\ Disruption\ Risk \\
& + \beta_{15} \times Prior\ Positive\ Performance \\
& + \beta_{16} \times Prior\ Negative\ Performance \\
& + \beta_{17} \times Firm\ Size \\
& + \sigma_{ui} + \sigma_{eit},
\end{aligned}$$

where σ_{ui} is the firm-specific error term (unobserved heterogeneity) and σ_{eit} is the model error, with the *i* and *t* subscripts referring to the individual firms and the two measurement waves, respectively.

Equation 4: Superior Firm Profitability Regression Equation

$$
\begin{aligned}
Abnormal\ ROS = \beta_0 & \\
& + \beta_1 \times Factor\ Market\ Rivalry \\
& + \beta_2 \times Total\ Logistics\ Costs \\
& + \beta_3 \times Strategic\ Risk\ Exposure \\
& + \beta_4 \times Supply\ Chain\ Disruption\ Risk \\
& + \beta_5 \times Product\ Innovativeness \\
& + \beta_6 \times Product\ Innovativeness \times Factor\ Market\ Rivalry \\
& + \beta_7 \times Product\ Innovativeness \times Total\ Logistics\ Costs \\
& + \beta_8 \times Product\ Innovativeness \times Strategic\ Risk\ Exposure \\
& + \beta_9 \times Product\ Innovativeness \times Supply\ Chain\ Disruption\ Risk \\
& + \beta_{10} \times Offshore\ Relationship\ Value \\
& + \beta_{11} \times Offshore\ Relationship\ Value \times Factor\ Market\ Rivalry \\
& + \beta_{12} \times Offshore\ Relationship\ Value \times Total\ Logistics\ Costs \\
& + \beta_{13} \times Offshore\ Relationship\ Value \times Strategic\ Risk\ Exposure \\
& + \beta_{14} \times Offshore\ Relationship\ Value \times Supply\ Disruption\ Risk \\
& + \beta_{15} \times Prior\ Positive\ Performance \\
& + \beta_{16} \times Prior\ Negative\ Performance \\
& + \beta_{17} \times Firm\ Size \\
& + \sigma_{ui} + \sigma_{eit},
\end{aligned}
$$

where σ_{ui} is the firm-specific error term (unobserved heterogeneity) and σ_{eit} is the model error, with the i and t subscripts referring to the individual firms and the two measurement waves, respectively.

CHAPTER FOUR: QUANTITATIVE ANALYSIS AND RESULTS

The purpose of this chapter is to present the quantitative results of the long-run event studies that serve as a basis for the dissertation along with the results of the methods used to test the hypothesized relationships. Chapter 4 contains five sections. The first section provides the characteristics of the study sample. Section 2 details the procedures of the event study methodology and presents the results of the long-run event study. The third section outlines the results of path modeling used to link reshoring events to positive abnormal returns. This is followed by the fourth section, which summarizes the quantitative results. The final section provides a post-hoc analysis to further explain unexpected results.

4.1 Sample Characteristics

The sample for this study consists of firms incorporated in the United States that have relocated some or all manufacturing operations to the United States from any foreign country since the global recession occurred in 2007. To be included in the sample, firms must have publicly available financial reports, which means the majority of the sample are firms publicly traded within the United States. To reduce the possibility that transplants or startups might alter the results, both the product or product type and the previous country of origin were identified for all firms in the sample.

To identify the sample used in this study, an event search was conducted using the company screening function of the S&P Capital IQ software. The initial parameters of the event screen included all key development announcements concerning business expansion, downsizing, or discontinued operations made between the years 2005 and 2015. To screen primarily for manufacturing operations, results were also filtered to include firms traded on major exchanges, including subsidiaries, with SIC codes beginning with either two or three. This initial screen returned 98,330 key development announcements. The search was then filtered to include only firms or subsidiaries incorporated in the United States. This filter limited the results to 21,363 events, which yielded the data set used for the study. While the sample firms used in the study were identified from this data set, the previous set of 98,330 events also proved to be useful and necessary to verify the actual movement of manufacturing to the United States from outside domestic borders.

From the set of 21,363 events, over 11,000 were discarded because the actions occurred solely beyond U.S. borders. In these events, manufacturing operations were either expanded overseas, offshored from the U.S., or moved from one foreign country to a different offshore location. Conversely, nearly 2000 events were classified as domestic realignments or downsizing operations, and thus eliminated from consideration. In these type events, manufacturing operations were opened in the U.S., but the expansion came primarily from layoffs or closures at other U.S. locations. Over 200 more events were either identified as start-ups or eliminated due to difficulty in identifying the previous country of origin.

Many other announcements were purged because the event was outside the parameters of reshoring as defined for this dissertation. Many of these could be easily recognized and eliminated. For instance, over 1,200 announcements came from manufacturing firms, but were related to sales or service personnel. Another 1,300 were classified as maintenance or and technical support. Over 500 key developments were directly concerned with mining and exploration, although classified as chemical manufacturing. Several of these were also primarily related to utilities, rather than electrical equipment production.

The remaining data were used to identify the sample firms for this dissertation. Each of the roughly 5,000 key development announcements remaining were carefully analyzed in an attempt to identify as many reshoring events as possible. Care was also taken to ensure that each firm chosen fit the parameters of the event study. For example, around 300 announcements regarding research and development were purged to focus primarily on manufacturing, while many research and development announcements specifically stated an increase in manufacturing capacity for prototypes or final production. All firms under bankruptcy protection during the period of study were eliminated from the sample. Many other firms had no financial data listed for crucial measures or fiscal years.

The remaining searchable events yielded 137 firms with reshoring activity which constituted the beginning sample in the early stages of the quantitative study. However, not all of the initial sample could be retained throughout the study. A number of these firms were eliminated during the process of matching and calculating abnormal returns. For instance, 22 were excluded when attempts to find all needed financial information failed. Three firms were purchased or delisted from a stock exchange during the span of interest. Seven more firms were eliminated because no previous country of origin could be identified. Finally, nine firms were eliminated due to delays in the reshoring process. For these firms, manufacturing was originally scheduled to begin by 2013, but actual production did not commence until 2014 or later. This process left a total of 96 reshoring events for the final sample. Descriptive statistics for firms in the final sample are presented in Table 5.

As shown in Table 5, the most significant year for reshoring activity for this sample is 2011. For some reason, reshoring appears to occur more in odd-numbered years. Ellram et al. (2013) suggest that this trend is likely due to even-year election cycles in the U.S. Other reasons could be the unusually large number of global supply chain disruptions that occurred globally in 2011 (Revilla & Sáenz, 2014). Studies conducted by the Boston Consulting Group find similar trends during the same period of time (“U.S. Executives Remain Bullish on American Manufacturing,” 2014).

Table 5: Frequency of Reshoring Occurrences by Year and Industrial Classification

N=96		Count	Percentage			Count	Percentage
Reshoring Year	2007	1	1.00%	2-Digit SIC Code	2600	3	3.13%
	2008	4	5.00%		2800	22	22.92%
	2009	18	23.00%		3000	4	4.17%
	2010	12	35.00%		3300	5	5.21%
	2011	24	59.00%		3500	12	12.50%
	2012	14	73.00%		3600	17	17.71%
	2013	23	96.00%		3700	22	22.92%
					3800	2	2.08%
					3900	2	2.08%
					Other	7	7.29%
	Total	96	100.0%		Total	96	100.0%

Industry classification also appears to influence reshoring decisions, as well. The reshoring trend is somewhat contained to a few specific industries. Firms with SIC codes beginning with 2800 and 3700 comprise the most populous segments with 22% of the sample each. The 2800 classification is given to all firms that produce chemicals and plastics, while 3700 is primarily designated for automobile or aerospace production.

Available data from reshorenow.org also finds these to be the largest segments of reshoring firms ("Reshoring Initiative Data Report," 2015). The U.S. government currently keeps no data to quantify reshoring activity.

4.2 Longitudinal Event Study Methodology

4.2.1 Industry Control Groups

Once the sample firms have been identified, it is necessary to determine the change in performance specific to the reshoring event. Thus, the next step in the event study methodology involves the creation of industry-controlled matching groups, which will provide the baseline used to measure abnormal changes in performance. Matching group creation follows the guidelines set forth by Barber and Lyon (1996). The format for this section closely resembles those adopted in previous long-run event studies (Jacobs et al., 2015; Kinney & Wempe, 2002; Swink & Jacobs, 2012).

This study uses three different matching groups based on the three most statistically significant matching methods identified by Barber and Lyon (1996) in their simulation study on determining abnormal performance. These three techniques match firms on the basis of performance, size, and industry classification. Prior performance is by far the most significant predictor, while industry classification has the lowest effect of these three. Barber and Lyon (1996) also found that a sample with sufficient size and generalizability to the its population has more statistical and theoretical relevance than industry classification. Thus, to dilute the effect of potential outliers and reduce the possibility of sample firms being discarded, filters for industry classification are adjusted for any cell containing only one firm.

The first method involves matching firms on the basis of matching year firm performance and industry classification. Performance matching includes all firms whose ROA is within 10% of the sample firm, while industry matching includes firms with the same 2-digit SIC code. The matching year is the lag year preceding the first year of analysis. This study uses the two years prior to reshoring as a comparison, so the lag or matching year is Y-3 where Y0 is the year in which reshored production begins. Thus, the performance and industry (PI) matching group consists of all firms with in the same 2-digit SIC codes and matching year ROA within 10% of the sample firm. The PI matching screen produced 2,733 total matches to be used to create performance baselines for firms in the target sample. For firms with insufficient matches, a second screen was applied which included all firms with the same 4-digit SIC code, and ROA within 10% of the sample firm. This second step produced an additional 70 matches, totaling 2,803 matches firms for 96 sample firms. Median group size for the PI matching group is 24, with only three sample firms matched with only one firm.

The second industry group matches firms on the basis of industry classification and median performance levels for the three fiscal years prior to analysis. Thus, median performance and industry (MPI) matching group includes all firms with the same 2-digit SIC code whose median ROA for the fiscal years Y-5, Y-4, and Y-3 are with 10% of the median ROA for the sample firm over the same three fiscal years. Screening for the MPI matching group yielded 2,815 total firm matches. The second step provided an additional 64 firms, totaling 2,879 matched firms. The median size for the MPI matching group is 22 with only 2 sample firms matched against single firms.

The final and most stringent matching group adds the additional requirement that matched firms should have median value of total assets within a factor of 25 of sample firm median total assets for years -5, -4, and -3. Thus, this group is essentially a subset of the MPI matching group. This initial screen returned 1,710 initial firm matches, while step two yielded eight more matches. This resulted in 1,718 total matched firms for the 96 reshoring events in the study sample. Median group size for the MPIS matching group is 12, with only two firms matched against single firms.

Table 6: Matching Process and Industry Control Group Statistics

		Matching Group		
N=96		Performance and Industry (PI)	Median Performance and Industry (MPI)	Median Performance, Size, and Industry (MPIS)
Matching Statistics	Step 1 Matches	2733	2815	1710
	Step 2 Matches	70	64	8
	Total Matched Firms	2803	2879	1718
	Median Group Size	24	22.5	12.0
	Mean Group Size	29.19	29.98	17.89
	Maximum Group Size	75	67	60
	Single-Firm Groups	3	2	2

The results of the matching process appear in Table 6, while Table 7 provides descriptive statistics for each of the three matching groups. To distinguish between reshoring and non-reshoring firms, all firms used in the study sample were purged from the matching groups. To further dilute the possibility that domestic firms within matching groups might have reshored upstream activities that cannot be identified, as many suitable matches as possible were needed in each matching group for each firm. As shown in Table 6, both the mean and median group sizes are greater than 10 for all three matching groups. A maximum of three firms are compared to only one firm for any group, and the most stringent method (MPIS) only contains two firms with single-firm groups. Table 7 shows the wide variance in size, market share, and wealth for both the sample and matching group firms. This further supports the generalizability of the sample and matched firms to the population of reshoring firms in all manufacturing industries.

Table 7: Descriptive Statistics for Matching Group Companies in Year 2011

	Total Enterprise Value ($M)	Market Cap ($M)	Total Assets ($M)	Total Revenue ($M)	Operating Income ($M)	Employees
Reshoring Sample						
Count	90.00	90.00	96.00	96.00	96.00	87
Median		4442.10	8782.10	7778.40	670.15	25540
Mean	37954.13	23096.99	43588.80	30949.13	2500.38	62639
Standard Deviation	86915.26	48547.01	99163.40	50705.30	4490.59	83925
Minimum	46.00	56.30	42.20	6.65	-557.00	42
Maximum	649438.20	376410.60	718189.00	229212.40	33790.00	348877
Performance and Industry (PI) Matching Group						
Count	1649	1650	1712	1712	1712	1324
Median	331.20	302.00	548.00	493.85	32.60	2368
Mean	3722.18	3122.00	4337.57	3664.52	346.81	11372
Standard Deviation	14493.03	12443.47	16038.41	15527.47	1585.70	29895
Minimum	-887.30	0.18	0.38	0.00	-1658.10	4
Maximum	254053.60	233083.60	337474.00	470171.00	43764.00	460000
Median Performance and Industry (MPI) Matching Group						
Count	1778.00	1781.00	1831.00	1833.00	1833.00	1438
Median	408.95	354.20	637.30	569.40	36.10	2638
Mean	4835.19	4067.89	5451.32	4527.19	458.16	13200
Standard Deviation	20072.23	17574.05	21918.03	19299.51	2118.29	37161
Minimum	-887.30	0.18	1.32	0.00	-2250.10	18
Maximum	350458.60	376410.60	359840.30	470171.00	43764.00	552810
Median Performance, Size, and Industry (MPIS) Matching Group						
Count	1219.00	1240.00	1258.00	1257.00	1260.00	1055
Median	877.60	760.85	1305.10	1140.70	85.30	4090
Mean	6995.88	5678.26	16395.88	6146.37	647.58	17049
Standard Deviation	29166.44	20469.77	119219.11	19106.06	2309.79	43033
Minimum	-887.30	4.92	10.60	1.60	-2250.10	10
Maximum	649438.20	376410.60	2553144.50	317863.50	33790.00	552810

4.2.2 Calculations and Treatment of Outliers

Changes in abnormal return on assets (ROA) were calculated using the difference between the changes in a sample firm's actual and expected performance for a given period. Several steps are involved in this calculation. First, the ROA for each period of analysis is computed for each firm. Then, changes in ROA are calculated by subtracting the returns from the lag year, or year prior to the period of analysis. The median value of changes in ROA for the firms matched with each sample firm provides the expected returns for sample firms relative to each matching group. Finally, the expected change in ROA for each matching group is subtracted from the actual change in sample firm ROA for each year and multi-year period of analysis.

Statistical significance of the changes in abnormal ROA were examined using Wilcoxon Signed Rank tests. This nonparametric test is used to determine if the median value of a sample is significantly different from zero (Wilcoxon, 1945). Since the premise of this study assumes positive changes in abnormal returns, a one-tailed Wilcoxon test is used. Similar to a paired t-test, this method is used to determine if the difference between actual and expected returns is significantly greater than zero. To control for the possibility of extreme outliers commonly found in financial data, the results are trimmed at 2.5% for each tail for every calculation.

For robustness, two additional measures were also used. Binomial Sign tests are used to determine if the percentage of positive changes in abnormal returns were significantly greater than 50. In addition to these tests which use the median value, paired t-tests were also executed to determine if the mean value of changes in abnormal returns was significantly greater than zero. Each of these tests was performed using

SPSS 24. This process was then repeated using the same control groups to calculate changes in abnormal return on sales (ROS).

Under normal circumstances, operating efficiency and firm profitability should be highly correlated. Thus, to provide greater breadth to the study, and to help control for potential endogeneity, this study also considers the changes in abnormal return on sales (ROS) over the same periods (Hendricks & Singhal, 2005a; Sharma, 2005). To allow for comparison within and across firms, the same matching groups are used to calculate both abnormal ROA and abnormal ROS. As stated in the previous section, comparing changes in returns offers more statistical power than comparing actual returns for a given period (Barber & Lyon, 1996). Thus, this section analyzes the significance of changes in abnormal ROS over the same years and multi-year periods before and after reshoring. The quantitative results of the changes in abnormal returns and each of the empirical tests appear in Table 8 and Table 9 for changes in abnormal ROA and abnormal ROS, respectively.

4.2.3 Abnormal Return on Assets

The first and perhaps most obvious observation is the noticeable change from negative returns before reshoring to positive returns during and after the reshoring event. As expected, changes in abnormal ROA were positive and significant across all three matching groups for the multi-year periods following reshoring. For each matching group, abnormal returns increased roughly 0.5 percent for the two-year period following the reshoring year. Abnormal returns rose more than a full percentage point relative to all three matching groups for the three-year period which includes the reshoring year. Over the same period, around 66% of firms showed positive changes in abnormal ROA across all three matching groups.

Table 8: Annual changes in abnormal ROA for year -2 through year +2

From Year	N	Median %	Z-Statistic[a]	Mean %	t-Statistic	%Positive	Z-Statistic[b]
Panel A: *Performance Industry Matching Group*							
-3 to -2	90	-0.0031	-.563	-0.0012	-.149	50.00%	.000
-2 to -1	90	0.0025	.219	-0.0021	-.432	55.56%	.949
-1 to 0	90	0.0023	1.092	0.0034	.822	55.56%	.949
0 to +1	93	-0.0001	.098	-0.0012	-.292	49.46%	.000
+1 to +2	93	0.0002	.795	0.0045	1.080	53.93%	.207
-3 to 0	89	0.0025	.404	0.0035	.593	53.93%	.746
0 to +2	91	0.0068	1.860**	0.0045	.982	62.64%	2.306***
-1 to +2	93	0.0108	2.604***	0.0110	2.680***	65.59%	2.903***
Panel B: *Median Performance Industry Matching*							
-3 to -2	91	-0.0027	-1.464*	-0.0159	-1.882**	42.86%	-1.258
-2 to -1	94	-0.0052	-.681	-0.0079	-1.033	50.00%	.000
-1 to 0	90	0.0036	2.042**	0.0083	1.969**	58.89%	1.581*
0 to +1	93	0.0055	1.063	0.0010	.229	55.91%	1.037
+1 to +2	93	-0.0005	.661	0.0036	.834	49.46%	.000
-3 to 0	90	-0.0030	-.871	-0.0054	-.836	47.78%	-.316
0 to +2	91	0.0057	1.872**	0.0060	1.266	59.34%	1.677**
-1 to +2	92	0.0133	3.275***	0.0132	3.428***	66.30%	3.023***
Panel C: *Median Performance Size and Industry*							
-3 to -2	90	-0.0047	-1.125	-0.0139	-1.685**	41.11%	-1.581*
-2 to -1	94	-0.0023	-.669	-0.0071	-.908	48.94%	-.103
-1 to 0	90	0.0059	2.444***	0.0098	2.408***	62.22%	2.214**
0 to +1	93	0.0035	.347	-0.0003	-.065	55.91%	1.037
+1 to +2	93	0.0021	1.312*	0.0060	1.330*	54.84%	.830
-3 to 0	90	-0.0041	-1.032	-0.0060	-.874	47.78%	-.316
0 to +2	91	0.0058	1.583*	0.0024	.494	57.14%	1.258
-1 to +2	92	0.0133	3.232***	0.0129	3.309***	65.22%	2.815***

[a] Z-Statistics for medians are obtained using Wilcoxon Signed-Rank tests.
[b] Z-Statistics for % positive are obtained using Binomial Sign tests.
*Significance is one-tailed: p≤.10
**Significance is one-tailed: p≤.05.
***Significance is one-tailed: p≤.01

Both the magnitude and statistical significance of the changes in abnormal ROA increased with the rigor of the matching techniques used to identify industry matching groups. For instance, the most stringent matching group (MPIS) showed significant and positive changes in annual abnormal ROA in two different years as well as for both multi-year periods after the reshoring event. The most significant increase occurred for the three-year period during and after reshoring, which had a median change of +1.33% with a z-score of 3.232. By comparison, the least conservative matching group (PI) produced no significant results for single-year periods. While both multiple-year periods following reshoring were significant, the highest z-score or the PI matching group was 2.604 with a three-year median increase of 1.08%.

While significant differences do exist across the three matching groups, the results are similar for all groups in all periods of analysis. A noticeable trend emerges when consecutive annual results are viewed over time. Sample firms outpaced firms in all three matching groups during the reshoring year, generating median changes in abnormal ROA from year -1 to year zero of +0.23%, +0.36, and +0.59%. Abnormal returns were still positive, yet much less pronounced in the following two years, possibly due additional costs in closing operations abroad. Compared to the most closely matched MPIS group, abnormal returns were more evenly dispersed with each year showing nearly 55% positive abnormal returns and significant ($p<.1$) growth in the second year (+1 to +2). Changes in abnormal ROA were also positive and significant for multiple-year periods following reshoring which include the reshoring year as well as those that do not. Thus, abnormal gains are not solely driven by local incentive programs or borrowing power. The changes in abnormal ROA are also similar and significant for mean-based t-tests as well, suggesting that the results are robust.

4.2.4 Abnormal Return on Sales

Changes in abnormal ROS closely resembled the results for abnormal ROA. All groups show negative changes that are not significant in the years leading up to reshoring. Again, the largest single year change occurred during the reshoring year, and changes in abnormal returns were positive for each year following reshoring. Returns were also positive and significant ($p<.05$) for each multiple-year period following the reshoring event.

One notable difference should be mentioned, though. Changes in abnormal ROA are slightly larger with more predictive power than changes in abnormal ROS. Median changes in abnormal ROS for the three-year period during and after reshoring were +0.96%, +0.67, and +0.97% for the PI, MPI, and MPIS groups, respectively. Binomial sign tests showed that roughly 63% of firms posted positive changes in abnormal ROS over this same period, while z-scores from Wilcoxon Signed Rank tests were significant at 2.355, 2.822, and 2.925 for PI, MPI, and MPIS, respectively.

Table 9: Annual changes in abnormal ROS for year -2 through year +2

From Year	N	Median %	Z-Statistic[a]	Mean %	t-Statistic	%Positive	Z-Statistic[b]
Panel A: *Performance Industry Matching Group*							
-3 to -2	90	-0.0024	-.986	-0.0055	-.533	42.22%	-1.173
-2 to -1	89	0.0030	.820	0.0010	.158	56.18%	1.060
-1 to 0	93	0.0038	.416	-0.0008	-.114	52.69%	.415
0 to +1	93	0.0013	.962	0.0040	.669	53.76%	.730
+1 to +2	93	0.0003	.518	0.0228	1.157	52.75%	.104
-3 to 0	91	0.0014	.493	0.0073	.801	52.75%	.527
0 to +2	93	0.0044	1.741**	0.0112	1.673**	62.37%	2.398***
-1 to +2	94	0.0097	2.355***	0.0070	1.108	62.77%	2.372***
Panel B: *Median Performance Industry Matching*							
-3 to -2	95	-0.0020	-.442	0.0060	.310	46.32%	-.616
-2 to -1	95	0.0032	.223	-0.0022	-.249	51.58%	.205
-1 to 0	94	0.0035	1.669**	0.0173	1.514*	57.45%	1.452*
0 to +1	93	0.0035	1.508*	0.0037	.623	58.06%	1.452*
+1 to +2	96	-0.0001	.515	0.0469	1.424*	50.00%	.000
-3 to 0	93	0.0002	-.312	-0.0091	-.946	50.54%	.000
0 to +2	94	0.0043	1.914**	0.0146	1.797**	57.45%	1.341*
-1 to +2	93	0.0069	2.822***	0.0140	1.866**	63.44%	2.489***
Panel C: *Median Performance Size and Industry*							
-3 to -2	95	-0.0030	-.505	0.0038	.199	45.26%	-.821
-2 to -1	95	-0.0006	-.100	-0.0011	-.117	48.42%	-.205
-1 to 0	92	0.0041	1.604*	0.0070	.923	57.61%	1.355*
0 to +1	94	0.0012	.782	-0.0002	-.032	51.06%	.103
+1 to +2	94	0.0004	.764	0.0118	1.507*	53.19%	.516
-3 to 0	93	0.0015	-.228	-0.0084	-.846	53.76%	.622
0 to +2	94	0.0041	1.789**	0.0136	1.557*	56.38%	1.135
-1 to +2	93	0.0096	2.925***	0.0141	1.815**	62.37%	2.281***

[a] Z-Statistics for medians are obtained using Wilcoxon Signed-Rank tests.

[b] Z-Statistics for % positive are obtained using Binomial Sign tests.

*Significance is one-tailed: $p \leq .10$

**Significance is one-tailed: $p \leq .05$

***Significance is one-tailed: $p \leq .01$

4.3 Linking Reshoring to Superior Firm Performance

4.3.1 Study Characteristics

4.3.1.1 Control variables. Several measures are used to control for potential selection bias in the sample. Firm size is an obvious source of potential bias in many cases. This is because the possibility exists that only larger firms have access to the capital necessary to relocate production to a different hemisphere (Sharma, 2005). Thus, larger firms are more likely to be successful with reshoring events in certain industries. This study controls for firm size by using the natural log of total enterprise value for the fiscal year in which reshoring took place (Y0) (Jacobs et al., 2015). Because relocation is a capital-intensive activity that affects certain industries more than others, this study also controls for the percentage of revenues devoted to capital expenditures in each of the three years following reshoring. This also helps to control for the uneven distribution of government incentives to relocate to the United States.

To control for the possibility that abnormal returns might be a continuation of previous firm performance, two additional measures are included as control variables. These prior performance control variables are created using the methodology found in the event study performed by Swink and Jacobs (2012). To create the control terms for prior performance, Dunn and Bradstreet industry performance measures for each 3-digit SIC code in the matching year (Y-3) provide generic baselines for each sample firm. To control for prior positive performance, a variable is created by assigning the industry-adjusted performance as the value for all firms with positive results and zero as the value for all firms with performance below the industry baseline. Conversely, a negative prior performance term is created by assigning the industry-adjusted performance as the value for all firms with performance below the baseline, and zero for all firms that outperformed the industry (Jacobs et al., 2015).

4.3.1.2 Exogenous variables. This study utilizes single-item measures for the four variables of interest and both moderating variables. The proxy measures used for the independent variables were each taken from multi-item measures created for this study. Results were similar for models using multiple- and single-item measures. Models with multiple measurement items failed to produce noticeable improvements in explained variance, effect sizes, or statistical power, so results for the more parsimonious model are presented and discussed in this study. Appendix F provides the measurement items and results for the alternative models.

Factor market rivalry was measured using the global competitive index scores for the previous country of origin for the product being reshored. This yearly index uses global respondents from multi-national firms to answer survey questions on the perceived economic competitiveness of 160 countries. Items are scored using a 7-point scale, with 1 indicating extremely non-competitive countries and 7 indicating extremely completive countries. Since factor market rivalry increases costs and decreases competitiveness, this item was reverse-scored. Geographic distance between countries provides the proxy measure for logistics costs. This measure was obtained using Google Maps, and represents the aerial miles between the center of the previous country of origin and the U.S. Strategic Risk Exposure was also measured at the country level using the previous country of origin measure for Control of Corruption from the World Governance Indicators index. This yearly index scores international governments using a 5-point scale, ranging from -2 for ineffective governments and +2 for effective governments

(Kaufmann, Kraay, & Mastruzzi, 2009). Since eliminating corruption reduces long-term risk, this item was reverse-scored by taking the negative value of the item. Finally, the country risk measure of the previous country of origin. Adopted from the FM Global Resilience Index, this measure assigns scores ranging from 1 to 100 to countries on the potential of a supply chain disruption due to faulty structures and machinery, probability of natural disasters, and natural resource shortage (FM Global Resilience Index, 2015).

Both moderating variables were measured using single-item measures. For all models, research and development (R&D) intensity was used to indicate the level of product innovativeness, while the percentage of revenues generated outside the U.S. provides the proxy measure for offshore relationship value. These items provided continuous measures at the firm level, which were used to determine if the direct effects were contingent upon firm-specific and industry-specific activities.

4.3.1.3 Endogenous variables. Superior operating efficiency and superior firm profitability both exist as ultimate outcomes in the conceptualization of reshoring success. To provide more descriptive information, the sensitivity analysis is conducted using the same structural models for both endogenous variables. Return on sales is a scaled measure of a firm's profit margin. Therefore, positive (negative) changes in abnormal ROS provide relevant measures for superior (inferior) firm profitability (Sharma, 2005). Likewise, positive changes in abnormal return on assets represent improvements in the efficient use of firm assets (Aaker & Jacobson, 1987). Thus, abnormal changes in ROA serve as proxy measures for superior operating efficiency.

When using changes in abnormal returns as an endogenous variable, results must be statistically significant for each measure across all matching groups dissertation

(Swink & Jacobs, 2012). The strongest change for all groups occurs over the three-year period after reshoring, which includes the year that domestic production began. This period also offers the most statistical power. Thus, the changes in abnormal returns from year -1 to year +2 were used as single-item indicators of the endogenous variables. This longer period also reduces the potential of outliers resulting from cross-sectional dependency and mean reversion (Hendricks & Singhal, 2005a). To further reduce the possibility that outliers might alter the results, the sample is winsorized at 2.5% for each tail.

4.3.1.4 Distribution of data. This section discusses the availability and distribution of the data that were used to determine the significant factors leading to reshoring success. Descriptive statistics for the variables of interest appear in Table 10. The final testable sample size for this study was 96. Missing data did not pose a major threat to reliability. A total of 18 items were missing in six cases. However, measures for the independent, dependent, and contingent variables in this sample contained no missing data items. The missing items were in the measures of firm size and capital expenditures that were used as control items. While still important, the percentage of missing items was relatively small for each measure and for the entire data set.

The distribution of data for the model was a primary factor in determining the statistical technique to use for empirical testing, because nonparametric data violates the assumptions of many regression-based techniques. Data distribution was especially important for the endogenous variables, because literature suggests that abnormal returns generally form nonparametric distribution patterns (Hendricks & Singhal, 2003). Statistics for skewness and kurtosis were used to assess normality of the data. For each measure, the absolute value should be below 1 for normal distributions (Hair et al., 2016). The statistics for skewness and kurtosis shown in Table 10 suggest that both endogenous terms have peaked distributions which are negatively skewed. Four of eight variables shown have skewness statistics with absolute values greater than one, while half of the kurtosis statistics also fall outside the range of -1 and +1.

Table 10: Measures of Central Tendency and Distribution of Data

	FMR	TLC	SRE	SCDR	PI	ORV	SOE[a]	SFP[b]
Valid N	96	96	96	96	96	96	96	96
Mean	1.913	4948.7	-1.05	32.96	3.68	61.71	.0150	.0297
Median	1.690	4882.0	-1.56	27.40	2.86	66.15	.0133	.0104
Mode	1.60	6303.0	-1.65	8.40	.00	77.00	.1794	.5101
Minimum	1.02	1192.0	-2.45	4.50	.00	.00	-.1126	-.3024
Maximum	2.92	9495.0	.60	87.50	31.85	95.20	.1794	.5101
Std. Dev.	.4312	2236.4	1.05	23.37	4.65	23.24	.0493	.1139
Skewness	.789	-.419	.560	1.156	3.77	-.840	1.001	2.359
-Std. Error	.246	.246	.246	.246	.246	.246	.246	.246
Kurtosis	-.419	-.711	-1.39	.470	18.18	.059	2.946	9.955
-Std. Error	.488	.488	.488	.488	.488	.488	.488	.488
Kolmogorov-Smirnov Test	.000[c,d]	.000[c,d]	.000[c,d]	.000[c,d]	.000[c,d]	.002[c,d]	.000[c,d]	.000[c,d]

FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, and ORV = Offshore Relationship Value.
[a.] Superior Operating Performance represents the abnormal return on assets for the MPIS matching group, Winsorized at 2.5% for each tail.
[b.] Superior Firm Profitability represents the abnormal return on sales for the MPIS matching group, Winsorized at 2.5% for each tail.
[c.] Test distribution is normal.
[d.] Lilliefors Significance Correction.

To provide additional analysis, the Kolmogorov-Smirnov (K-S) test was performed to determine if the data are normally distributed. As Table 10 shows, the results for all variables were highly significant ($p<.01$) to reject the null hypothesis that data are normal distributed ($\mu=0$, $\sigma^2=1$). Thus, results of the K-S test, along with the statistics for skewness and kurtosis, provide strong evidence that the data are not normally distributed. Hence, non-parametric statistical techniques were used for further analyses.

4.3.1.5 Analytical approach. Since the data do not form a normal distribution pattern, nonparametric analytical techniques are employed to empirically test the hypothesized relationships between the antecedents and outcomes of reshoring events. Partial least squares structural equation modeling (PLS-SEM) is therefore used to model and empirically test the hypothesized relationships affecting reshoring decisions. This variance-based method makes no assumptions regarding normality or sample size. However, the sample must be generalizable to the population and the sample size must be sufficient to achieve the desired statistical power (Hair et al., 2011). Using the G*Power 3 application (Faul, Erdfelder, Lang, & Buchner, 2007), the largest model in this study requires a sample size of 74 to achieve 95% power for a moderate effect size with critical t-value of 1.66. Path modeling in this dissertation is performed using the SmartPLS software package, version 3.2.4 (Ringle, Wende, & Becker, 2015).

For each endogenous term, three different structural models were tested. First, the effects of hypothesized variables and control measures were examined. Then, separate structural models were tested to analyze the moderating effects of the contingency variables. Thus, Structural Model 1 estimates the path coefficients for the four direct relationships hypothesized in the conceptual model. This model also includes a formative index variable comprised of the six control measures for firm size, prior performance, and capital expenditures. Finally, both moderating variables are also included in Structural Model 1 to reduce the likelihood omitted variable bias and to allow changes in explained variance to be examined in the other models.

Structural Model 2 is used to analyze the moderating effect of product innovativeness on the drivers of reshoring success. Using SmartPLS 3.2.4, moderation is analyzed by creating latent interaction terms between the moderating variable, product innovativeness, and each of the four exogenous variables: factor market rivalry, total logistics costs, strategic rick exposure, and supply chain disruption risk (Chin et al., 2003; Rigdon, Ringle, & Sarstedt, 2010). For each endogenous term, Structural Model 2 estimates the path coefficients of the direct effects, while the latent interaction terms are added separately. This same process is then repeated to create latent interaction terms for the third model, which analyzes moderating effect of offshore relationship value. Thus, Structural Model 3 estimates the path coefficients of the control variable, the moderating variables, all four hypothesized direct effects, and the four latent interaction terms for the moderating variable, offshore relationship value, and each of the four exogenous variables.

Each calculation is performed using both endogenous terms for all three matching groups for breadth and rigor. However, abnormal changes in returns for firms matched according to median performance, size, and industry classification (MPIS matching group) offer the most statistical power across all years for ROA and ROS. Thus, for brevity and clarity, only the results from analyses based on MPIS calculations are presented for the remainder of this dissertation. The quantitative results of calculations for each of the three matching groups, along with all figures and tables, are provided in the appendices for each respective matching group.

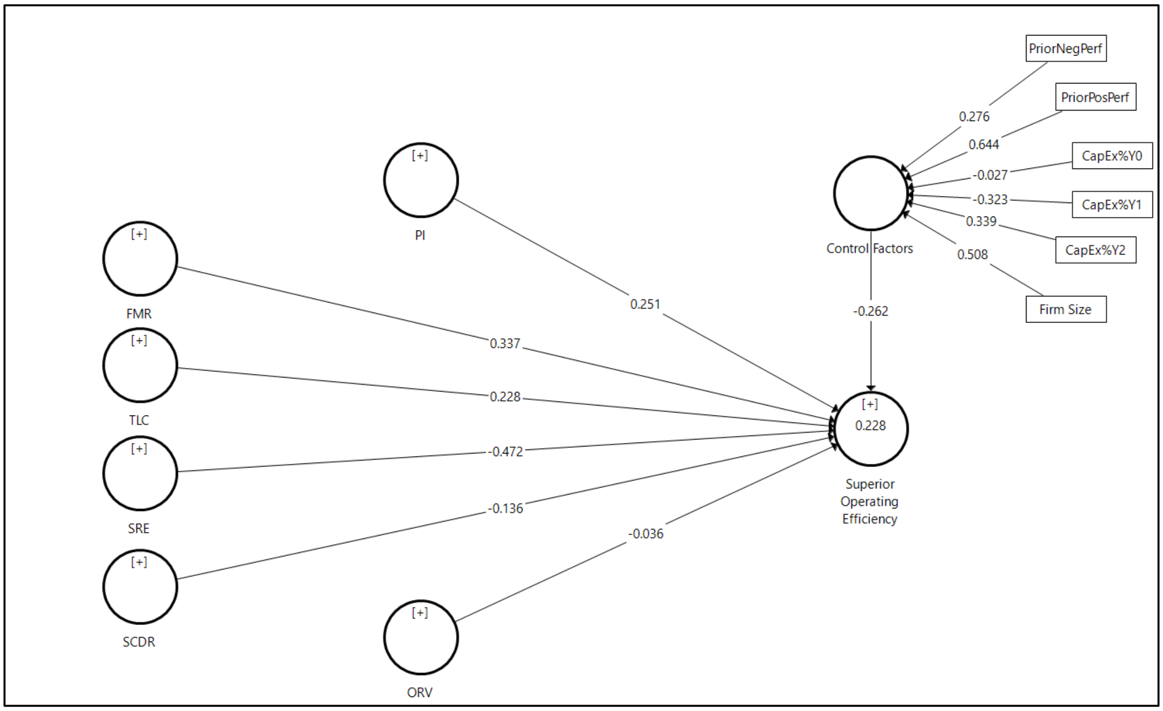
4.3.2 Estimating Superior Operating Efficiency

4.3.2.1 Structural Model 1 – direct effects.

4.3.2.1.1 Estimating the model. Partial Least Squares Simultaneous Equations Modeling (PLS-SEM) was employed to estimate and empirically test the structural model used to explain the variance in Superior Operating Efficiency. Using the SmartPLS 3.2.4 statistical software, the PLS algorithm was chosen to estimate the structural model (Ringle et al., 2015). Since missing items for all measures are below the 5% recommended threshold for using PLS-SEM, any of the algorithms for missing data are sufficient (Hair et al., 2017). Due to the relatively low sample size (n=96), pairwise deletion was selected as the treatment for missing data to maximize the use of available information. The path weighting scheme was selected, using default settings of 300 maximum iterations, a stop criterion of 7, and initial values equal to 1.

The model converged on the second iteration, explaining 22.8% of the variance in superior operating efficiency. However, both strategic rick exposure and supply chain disruption risk have negative, rather than positive valences. The magnitude and valence of the path coefficients reflect the proposed relationships for all other variables. The path coefficients and explained variance (R^2 = .228) for Structural Model 1 are presented in Figure 3.

Figure 3: Path Coefficients and R^2 for Structural Model 1



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, and ORV = Offshore Relationship Value.

4.3.2.1.2 Assessing the results. After the PLS algorithm converges, it is necessary to assess the results of the path model estimation. As with any statistical method, validity and reliability of the constructs and the model must be confirmed. Since no reflective constructs exist in this model, traditional measures of internal consistency and convergent validity are not appropriate and thus not performed (Hair et al., 2017). Single-item measures rely upon face validity as an indication of construct quality, therefore practical and theoretical justifications are more important for models utilizing proxy measures.

Traditional methods for assessing discriminant validity such as the Fornell-Larcker Criterion or cross-loadings are also invalid for single-item and formative constructs. However, the use of single-item measures does not guarantee that a construct is statistically different from any other. Thus, the heterotrait-monotrait (HTMT) ratio was used along with the inner variance inflation factors (VIF) to assess discriminant validity and collinearity for each model. The HTMT is the ratio of between trait correlations to the ratio of within-trait correlations, thereby estimating the true correlation between perfectly measured variables (Henseler, Ringle, & Sarstedt, 2015). If all HTMT ratios are below 1.0, then each item is more highly correlated with its own construct than with any other and discriminant validity has been established (Hair et al., 2017). To eliminate the possibility of measurement errors, a more conservative threshold of .90 is recommended of conceptually similar constructs and .85 for dissimilar constructs (Henseler et al., 2015). As seen in Table 11, the largest figure in the chart was 0.8315 indicating that discriminant validity has been met.

In addition to the HTMT numbers, the VIF figures were used to ensure that multicollinearity was not an issue. As an inverse function of tolerance, the variance inflation factor represents the squared value of an increase in standard error resulting from collinearity (Hair et al., 2011). Any VIF value above 1.0 indicates that some multicollinearity exists, while a VIF value above 10 indicates that extreme multicollinearity is present. When using PLS-SEM, adjustments to the model should be considered for any value of 5.0 or higher (Henseler, Ringle, & Sinkovics, 2009). With no reflective measures in the structural model, outer VIF numbers were of no concern. As shown in Table 11, VIF values were well below the critical threshold of five for all inner VIF values. Thus, it was determined that multicollinearity was not a significant factor in the model results.

Table 11: Measures of Discriminant Validity and Collinearity for Structural Model 1

Item	Inner VIF	Heterotrait-Monotrait Ratio (HTMT)					
	SOE	FMR	TLC	SRE	SCDR	PI	ORV
Control	1.043						
FMR	3.908						
TLC	1.839	0.076					
SRE	4.364	0.832	0.328				
SCDR	1.432	0.093	0.508	0.077			
PI	1.128	0.050	0.278	0.021	0.084		
ORV	1.124	0.047	0.206	0.030	0.242	0.160	
SOE	-	0.022	0.079	0.136	0.091	0.272	0.023

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SOE = Superior Operating Efficiency.

In addition to construct validity, it is also necessary to assess the reliability of the inner model. The primary objective of PLS-SEM is to maximize the amount of explained variance for endogenous constructs. Because PLS is a prediction-based technique, it provides no global measure of fit (Hair et al., 2017). Thus, the predictive capabilities of the structural model are used to indicate the quality of the model. The primary measure of model quality is the coefficient of determination (R^2) of endogenous constructs, although path coefficients (β) and individual effect sizes (f^2) are also necessary to assess model quality (Hair, Sarstedt, Ringle, et al., 2012). The statistical significance for each of these measures is determined by using bootstrapping. This nonparametric resampling procedure randomly selects a predetermined number of subsamples, which it uses to estimate the model parameters as well as the standard error, t-values, and p-values for the results (Hair et al., 2017). Assuming the number of subsamples is large enough to satisfy the central limit theorem, bootstrapping can return reliable estimates without imposing restrictions concerning sample size or normality.

To perform the analysis, all previous settings were retained from the model estimation, and pairwise deletion was again selected as the treatment for missing data. Complete bootstrapping was used because this method returns t-values, p-values, and confidence intervals for all quality measures of the model, unlike basic bootstrapping that only analyzes path coefficients and indicator weights (Ringle et al., 2015). Because relationships within the model were hypothesized as directional, one-tailed results were returned with bias corrected and accelerated confidence intervals and normalized data distribution. To ensure conditions of the central limits theorem were met, a large sample size of 5000 subsamples was selected, with item-level sign changes permitted. Results of bootstrapping for Structural Model 1 are presented in Table 12, while full tables with confidence intervals are provided in the respective appendix for each endogenous measure.

When assessing the results of bootstrapping, the reliability of the coefficient of determination must be considered. Results in Table 12 suggest that Structural Model 1 adequately explains the variance in superior operating efficiency for this sample with R^2 of .228 (p=.013) and adjusted R^2 of .167 (p=.067). Two of the control variables were also significant. Both firm size and prior positive performance had strong negative effects on operating efficiency. Both contingency variables were in the expected direction, but only product innovativeness was significant (β=.251, p=.018). Offshore relationship value was negative as expected, but insignificant (β=-.036, p=.301).

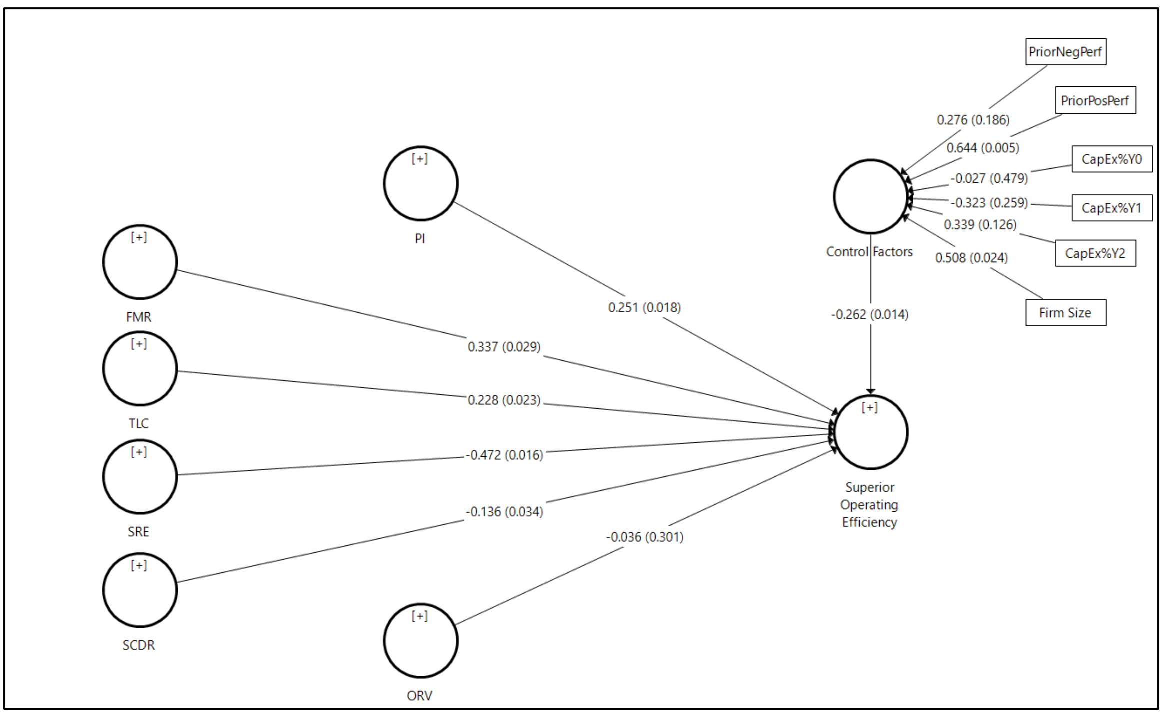
Table 12: Statistical Significance of Path Coefficients and R^2 for Structural Model 1

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Explained Variance (R^2) for Endogenous Variable Superior Operating Efficiency					
R^2	0.228	0.334	0.103	2.215	.013**
Adjusted R^2	0.167	0.281	0.111	1.499	.067*
Statistical Significance of Path Coefficients (β)					
Control Factors → SOE	-0.262	-0.344	0.120	2.190	.014**
PI → SOE	0.251	0.223	0.119	2.098	.018**
ORV → SOE	-0.036	-0.094	0.071	0.509	.301
FMR → SOE	0.337	0.306	0.183	1.844	.029**
TLC → SOE	0.228	0.195	0.113	2.020	.023**
SRE → SOE	-0.472	-0.417	0.223	2.111	.016**
SCDR → SOE	-0.136	-0.134	0.074	1.839	.034**
Calculated Effect Size (f^2) of Variables for Specified Paths					
Control Factors → SOE	0.085	0.180	0.140	0.607	.272
PI → SOE	0.072	0.084	0.077	0.933	.175
ORV → SOE	0.001	0.017	0.025	0.06	.476
FMR → SOE	0.038	0.048	0.054	0.703	.241
TLC → SOE	0.037	0.039	0.042	0.873	.191
SRE → SOE	0.066	0.078	0.080	0.823	.205
SCDR → SOE	0.017	0.024	0.024	0.705	.240

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SOE = Superior Operating Efficiency.
*Significance is one-tailed: p<.10
**Significance is one-tailed: p<.05
***Significance is one-tailed: p<.01

To determine the drivers of reshoring success, the path coefficients for the proposed relationships were examined next. The path coefficients and p-values for each structural path are presented in Figure 4 in addition to Table 12. Path coefficients were significant (p<.05) for each of the hypothesized direct effects. However, only two of these effects moved in the proposed direction. The direct path from factor market rivalry to superior operating efficiency was positive and significant (β=.337, p=.033), providing support for Hypothesis 1a. Likewise, the total logistics costs were shown to have a positive and significant impact (β=.228, p=.022) on superior operating efficiency. Thus, Hypothesis 2a is also supported. Both measures of long-term risk move in the opposite direction of the hypothesized relationships. Although strategic risk exposure was significant and produced the largest path coefficient in the model, the valence was negative (β=-.472, p=.016). While supply chain disruption risk had a much smaller path coefficient, results indicate that it also significantly reduced superior operating efficiency (β=-.136, p=.034). Therefore, neither Hypothesis 3a nor Hypothesis 4a were supported.

Figure 4: Path Coefficients and p-Values for Structural Model 1



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, and ORV = Offshore Relationship Value.

In addition to the statistical significance of the coefficient of determination and path coefficients, it is also suggested that the magnitude of these effects should also be considered. Smart PLS 3 calculates the effect sizes for each structural path using Cohen's (1988) f^2, which estimates the change in R^2 that would occur if a structural path were omitted from the model. Thus, calculated effect sizes were also examined for each of the structural paths, following Cohen's guidelines for interpreting f^2 values: .02 indicates a weak effect, .15 a moderate effect, and .35 a large effect (Cohen, 1992).

As shown in Table 12, two structural paths are below .02 and have no substantial effect, while all other paths were characterized as having small effect sizes. The two smallest effects on superior operating performance come from offshore relationship value (f^2=.001) and supply chain disruption risk (f^2=.017), both of which were too small to be considered relevant. Not surprisingly, the largest effect (f^2=.085) was derived from the control index, which contains six formative measures. This was followed by the direct path from product innovativeness to superior operating performance (f^2=.072). The final three direct paths to superior operating efficiency were also between .02 and .15, indicating small effect sizes: factor market rivalry (f^2=.038), total logistics costs (f^2=.037), and strategic risk exposure (f^2=.066). Thus, each of these proposed relationships was shown to be relevant to the model, yet no single variable substantially changes the level of operating efficiency.

4.3.2.1.3 Determining predictive validity. The final step in evaluating the results of PLS-SEM involves assessing the predictive validity of the structural model. SmartPLS 3 uses a technique called blindfolding to estimate Stone-Geisser's Q^2, which is a measure of external validity or predictive relevance of the structural model results (Ringle et al., 2015). Blindfolding is a resampling technique used by PLS-SEM which omits certain data, predicts the omitted data points, then uses the prediction error to cross-validate the model estimates (Tenenhaus, Vinzi, Chatelin, & Lauro, 2005).

Blindfolding is conducted by selecting an omission distance (D), which instructs the algorithm to omit every *d*th data point for *d* number of cases beginning with the subsequent data point for each case (Henseler et al., 2009). Thus for an omission distance with the default value of seven, SmartPLS 3 creates seven cases. Case 1 would start from the beginning and omit every seventh data point, while case 2 would start at the second data point and delete every seventh case. This pattern continues until all possible combinations are achieved (Hair et al., 2017). The algorithm then uses the model estimates to predict the omitted terms, and calculates cross validated redundancy using the sum of squared prediction error (SSE) and the sum of squares of the observation (SSO) for each of the seven cases. The ratio of SSE divided by SSO is then subtracted from 1 to generate the value of Q^2. The structural model of any endogenous latent variable with a Q^2 greater than zero provides predictive relevance (Henseler et al., 2009).

Since blindfolding can only be applied to endogenous latent variables with reflective measurement items (Henseler et al., 2009), valid results cannot be produced for Structural Model 1, which employs a single-item endogenous term. To circumvent this problem, a new endogenous variable was created using the three-year changes in abnormal ROA (-1 to +2) for each of the three matching groups as reflective indicators of superior operating value. This measure satisfied the requirement of reflective indicators, allowing the blindfolding procedure to validate the individual measures of superior operating value as well as the predictive relevance of the structural model. Using the same settings from the previous steps, the default value of seven was used as the omission distance for Structural Model 1. Table 13 shows that the model has external validity with a Q^2 of .141. As expected, the cross-validated redundancy increases with the stringency of each matching group with Q^2 values of .164 for the MPIS group, .139 for the MPI group, and .118 for the PI matching group. This suggests that Structural Model 1 adequately predicts superior operating efficiency.

Table 13: Predictive Validity of Structural Model 1

	SSO	SSE	Q^2 (1-SSE/SSO)
Construct Cross-Validated Redundancy			
SOE	288	247.485	0.141
Indicator Cross-Validated Redundancy			
AbROA MPIS Matching Group	96	80.215	0.164
AbROA MPI Matching Group	96	82.639	0.139
AbROA PI Matching Group	96	84.631	0.118

Where SSO = Sum of Squared Observations, SSE = Sum of Squared Prediction Errors, SOE = Superior Operating Efficiency, and AbROA = Abnormal Return on Assets

4.3.2.2 Structural Model 2 - interactions with product innovativeness.

4.3.2.2.1 Estimating the model. Building upon Structural Model 1, the second model uses path modeling to determine if the direct effects between the independent variables and superior operating efficiency are contingent upon the innovativeness of the product being manufactured. Moderation was tested by using PLS-SEM to estimate the amount of variance explained by interactions between product innovativeness and the other exogenous variables (Hair et al., 2017). Moderating effects were examined by creating latent variables to measure the interactions between product innovativeness and each of the four independent variables for the endogenous variable superior operating efficiency (Chin et al., 2003). Using SmartPLS 3, all four latent interaction terms were created using the two stage calculation method with standardized product term generation (Ringle et al., 2015). The PLS algorithm was then employed to estimate the structural path between each interaction variable and the endogenous term superior operating efficiency, followed by bootstrapping to determine the statistical significance of the effects.

Because PLS-SEM aims to reduce unexplained variance in the endogenous variable, only moderating effects that explain additional variance should be included in the structural model. Path modeling was performed separately for each interaction variable to determine the change in explained variance attributable to each moderating effect. Different combinations of moderating effects were also examined to identify the structural equation that maximizes explained variance in superior operating efficiency.

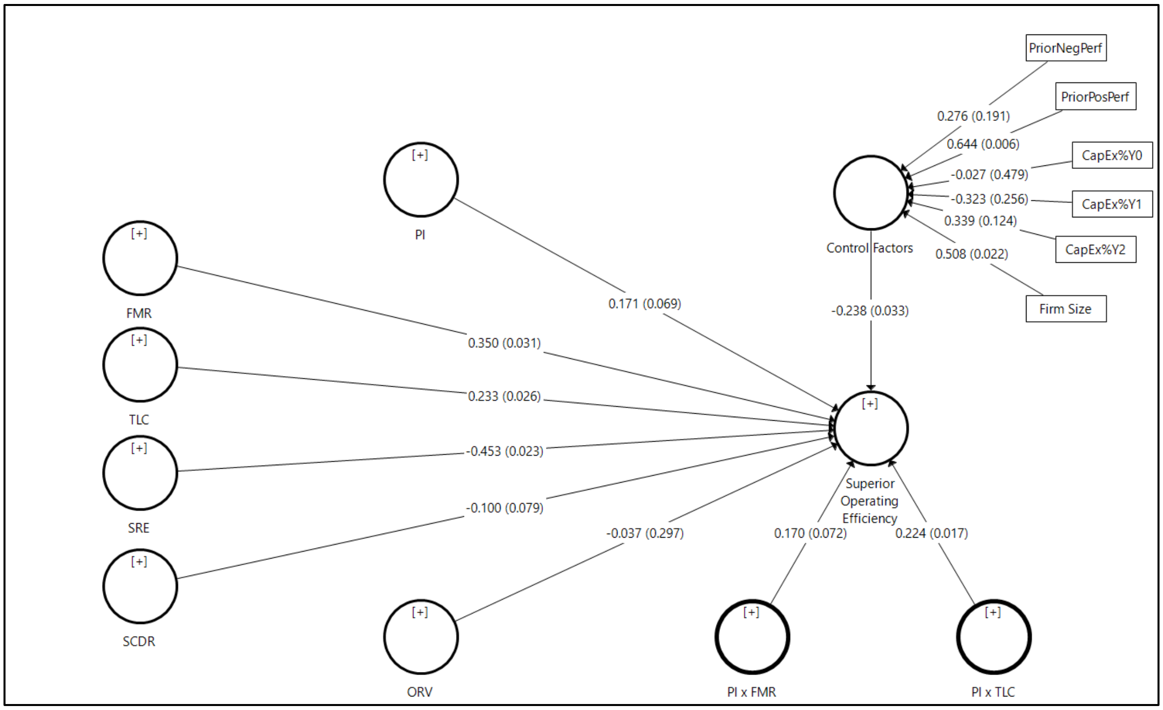
The PLS algorithm was used to estimate the structural paths and changes in R^2, while bootstrapping was performed to determine the statistical significance of the changes. Since quality measures were not needed for this initial assessment, basic bootstrapping was performed using 5,000 subsamples with one-tailed test results.

Results of this initial assessment indicate that only two of the four proposed moderating effects of product innovativeness are significant. As expected, both economic drivers of reshoring have greater impacts on superior operating efficiency when product innovativeness increases. The interaction between product innovativeness and total logistics costs produced the strongest effect, increasing the explained variance in superior operating efficiency from .228 in Structural Model 1 to .267. Thus, the moderating effect of product innovativeness on total logistics costs is positive and significant (β=.192, p=.048), explaining an additional 3.9% of the variance in superior operating efficiency. The interaction between product innovativeness and factor market rivalry was also positive and significant, although the effect on superior operating performance was much smaller. The moderating effect of product innovativeness on factor market rivalry increased the R^2 for superior operating efficiency to .281, explaining an additional 1.5% of the variance for the endogenous term.

Although product innovativeness significantly moderates both economic drivers of reshoring, virtually no interaction between product innovativeness and the strategic drivers of reshoring was detected for superior operating efficiency. The interaction between product innovativeness and strategic risk had no significant effect on superior operating efficiency (β=-.008, p=.489, f^2=.000). Likewise, the interaction between product innovativeness and supply chain disruption risk was not found to be a significant predictor of superior operating efficiency (β=-.038, p=.390, f^2=.001). Neither of these interaction variables increased the explained variance of superior operating efficiency when added to the structural model. Thus, both terms were excluded from the structural equation, leaving only two moderating effects to be examined in Structural Model 2. The path coefficients and p-values of the final model are shown in Figure 5.

4.3.2.2.2 Assessing the results. Structural Model 2 uses PLS-SEM to estimate the moderating effect of product innovativeness on factor market rivalry and total logistics costs for the endogenous term superior operating efficiency. The PLS algorithm was used to estimate path coefficients, effect sizes, and the coefficient of determination of superior operating efficiency. Pairwise deletion was selected as the treatment for missing values, and all calculations were performed using the path weighting scheme and initial values of one. Using a stopping criterion of seven, the model converged on the second iteration.

Figure 5: Path Coefficients and p-Values for Structural Model 2



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, and ORV = Offshore Relationship Value.

Structural Model 2 mirrors the first model except for the addition of two latent interaction variables used to measure moderating effects. As with single-item constructs, traditional measures of internal consistency and construct validity are invalid for latent interaction variables. Thus, the HTMT ratio and inner VIF values are used to assess discriminant validity and collinearity for Structural Model 2 with results provided in Table 14. All HTMT values were below .85, indicating that discriminant validity was achieved. Likewise, multicollinearity did not appear to be a significant issue as all inner VIF numbers were below the critical threshold of five.

Table 14: Measures of Discriminant Validity and Collinearity for Structural Model 2

Item	Inner VIF	Heterotrait-Monotrait Ratio (HTMT)							
		FMR	TLC	SRE	SCDR	PI	ORV	PI x FMR	PI x TLC
Control	1.072								
FMR	1.795								
TLC	1.118	0.076							
SRE	4.433	0.832	0.328						
SCDR	1.493	0.093	0.508	0.328					
PI	1.795	0.050	0.278	0.021	0.084				
ORV	1.118	0.047	0.206	0.030	0.242	0.160			
PI x FMR	1.129	0.000	0.009	0.049	0.098	0.000	0.046		
PI x TLC	1.804	0.121	0.062	0.156	0.123	0.598	0.079	0.224	
SOE	-	0.044	0.077	0.145	0.089	0.258	0.010	0.064	0.341

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SOE = Superior Operating Efficiency.

To assess the quality of Structural Model 2, complete bootstrapping was performed to calculate the statistical significance of the path coefficients in the inner model, the calculated effect sizes of the exogenous terms, and the coefficient of determination for the superior operating efficiency. Of particular concern to this model were the significance and effect sizes of the two moderating effects as well as the additional variance explained by moderation. Complete bootstrapping was conducted by selecting 5,000 subsamples and allowing item-level sign changes. Since positive moderation was hypothesized, one-tailed results were returned with bias corrected and accelerated confidence intervals and normalized data distribution. Results of complete bootstrapping for Structural Model 2 are presented in Table 15.

Table 15: Statistical Significance of Path Coefficients and R^2 for Structural Model 2

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Explained Variance (R^2) for Endogenous Variable Superior Operating Efficiency					
R^2	0.281	0.385	0.106	2.645	.004***
Adjusted R^2	0.206	0.320	0.117	1.754	.039**
Statistical Significance of Path Coefficients (β)					
Control Factors → SOE	-0.238	-0.312	0.128	1.861	.031**
PI → SOE	0.067	0.120	0.087	0.766	.222
ORV → SOE	-0.037	-0.090	0.068	0.534	.297
FMR → SOE	0.353	0.315	0.190	1.858	.032**
TLC → SOE	0.233	0.207	0.119	1.949	.026**
SRE → SOE	-0.453	-0.405	0.225	2.010	.022**
SCDR → SOE	-0.100	-0.114	0.072	1.396	.081*
PI x FMR → SOE	0.170	0.097	0.060	1.423	.072*
PI x TLC → SOE	0.224	0.204	0.109	2.056	.017**
Calculated Effect Size (f^2) of Variables for Specified Paths					
Control Factors → SOE	0.073	0.152	0.127	0.574	.283
PI → SOE	0.003	0.018	0.023	0.149	.441
ORV → SOE	0.002	0.017	0.026	0.065	.474
FMR → SOE	0.044	0.056	0.065	0.677	.249
TLC → SOE	0.041	0.046	0.048	0.842	.200
SRE → SOE	0.064	0.081	0.089	0.724	.235
SCDR → SOE	0.009	0.018	0.020	0.463	.322
PI x FMR → SOE	0.020	0.034	0.043	0.453	.325
PI x TLC → SOE	0.069	0.055	0.054	1.268	.100*

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SOE = Superior Operating Efficiency.
*Significance is one-tailed: p<.10
**Significance is one-tailed: p<.05
***Significance is one-tailed: p<.01

The coefficient of determination for is the first measure used to assess the quality of Structural Model 2. Results in Table 15 indicate that Structural Model 2 explains 28.1% of the variance in superior operating efficiency, with R^2 of .281 (p=.004) and adjusted R^2 of .206 (p=.039). Thus, Structural Model 2 explains more variance in superior operating efficiency and has more statistical power than Structural Model 1, which explained 22.8% of the variance in superior operating efficiency with R^2 of .228 (p=.013) and adjusted R^2 of .167 (p=.067). Hence, Structural Model 2 is a better predictor of superior operating efficiency, suggesting that product innovativeness is a significant moderator of factor market rivalry and total logistics costs.

Next, the path coefficients of the moderating effects must be evaluated along with the calculated effect sizes of the latent interaction terms (Hair et al., 2016). Results in Table 15 show that the interaction between product innovativeness and total logistics costs has positive and significant effect on superior operating efficiency (β=.224, p=.017, f^2=.069). The moderating effect also produces the largest calculated effect size in the model for superior operating efficiency, providing support for Hypothesis 6a.

The results show that the interaction between product innovativeness and factor market rivalry is positive, yet marginally significant with a very small calculated effect size (β=.170, p=.072, f^2=.020). However, .02 still falls within the acceptable range for small effects (Cohen, 1992), and the addition of the interaction increases the variance explained by the model. Therefore, the results offer marginal support for Hypothesis 5a. Interactions with strategic risk exposure and supply chain disruption risk were excluded from the structural equation, offering no support for Hypothesis 7a or Hypothesis 8a.

4.3.2.2.3 Determining predictive validity. Blindfolding was performed to assess the predictive validity of Structural Model 2 for the endogenous term superior operating efficiency. The omission distance was again set at seven, and changes in abnormal return on assets for all three matching groups were used as reflective indicators of superior operating efficiency. As shown in Table 16, the results indicate that the model has predictive relevance with a Q^2 of .182 for the endogenous construct. Cross-validated redundancies for the reflective indicators were also positive with Q^2 values of .135 for PI matching group, .194 for the MPI group, and .218 for the MPIS matching group results. Thus, results were consistent for all three matching groups whether examined in unison or independently, thereby substantiating the measures and providing external validity for the model.

Table 16: Predictive Validity of Structural Model 2

	SSO	SSE	Q^2 (1-SSE/SSO)
Construct Cross-Validated Redundancy			
SOE	288.000	235.525	0.182
Indicator Cross-Validated Redundancy			
AbROA MPIS Matching Group	96.000	75.077	0.218
AbROA MPI Matching Group	96.000	77.401	0.194
AbROA PI Matching Group	96.000	83.048	0.135

Where SSO = Sum of Squared Observations, SSE = Sum of Squared Prediction Errors, SOE = Superior Operating Efficiency, and AbROA = Abnormal Return on Assets.

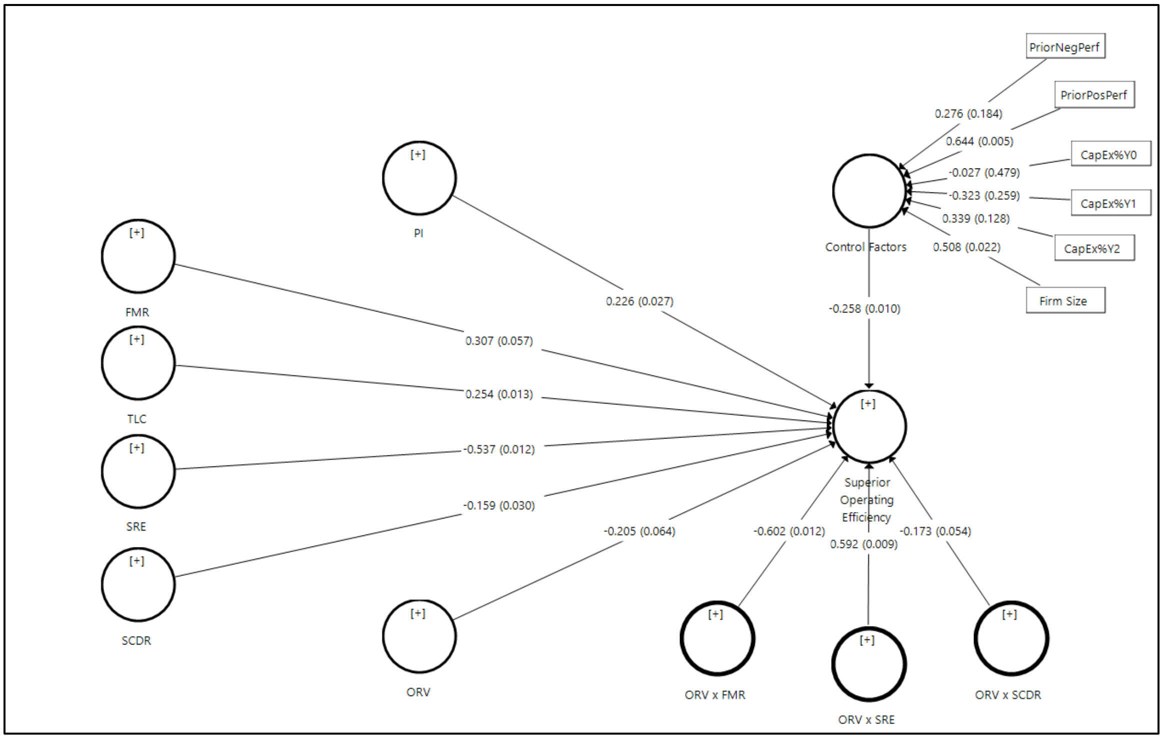
4.3.2.3 Structural Model 3 - interactions with offshore relationship value.

4.3.2.3.1 Estimating the model. Structural Model 3 uses PLS-SEM to determine if relationships between the independent variables and superior operating efficiency are contingent upon the value of offshore relationships for the reshoring firms (Hair et al., 2016). Moderation was again tested by creating four latent interaction variables to capture the moderating effects of offshore relationship value on and each of the four independent variables for the endogenous variable superior operating efficiency (Chin et al., 2003). Using SmartPLS 3, all four latent interaction terms were created using the two stage calculation method with standardized product term generation (Ringle et al., 2015). The PLS algorithm was then employed to estimate the moderating effects and changes in explained variance for superior operating efficiency. Bootstrapping was employed to identify the interaction variables to include in Structural Model 3. For simplicity, basic bootstrapping was performed using 5,000 subsamples with one-tailed test results.

Results of this initial assessment indicate that three of the four proposed moderating effects explain additional variance in superior operating efficiency. The interaction between offshore relationship value and strategic risk exposure was significant ($\beta = .491$, $p = .013$, $f^2 = .088$), explaining roughly 3.2% of the variance in superior operating efficiency. The moderating effect of offshore relationship value on factor market rivalry also appears to be significant for the endogenous term ($\beta = -.526$, $p = .015$, $f^2 = .076$), increasing R^2 by another 3%. These two interactions share similar effect sizes, and taken together increase R^2 from .228 to .292. Finally, the interaction between offshore relationship value and supply chain disruption risk explains an additional 1.7% of the variance in superior operating efficiency, increasing the value of R^2 from .292 to .309.

Total logistics cost was the only independent variable unaffected by the variance in offshore relationship value. The interaction between total logistics costs and offshore relationship value was not a significant predictor of superior operating efficiency ($\beta = .031$, $p = .339$, $f^2 = .001$), and was therefore excluded from the structural equation. Thus Structural Model 3 includes the endogenous variables from Structural Model 1 plus three latent variables used to calculate the moderating effect of offshore relationship value on factor market rivalry, strategic risk exposure, and supply chain disruption risk for the endogenous term superior operating efficiency. The path coefficients and p-values of the final model are shown in Figure 6.

Figure 6: Path Coefficients and p-Values for Structural Model 3



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, and ORV = Offshore Relationship Value.

4.3.2.3.2 Assessing the results. Structural Model 3 uses PLS-SEM to estimate the moderating effect of offshore relationship value on factor market rivalry, strategic risk exposure, and supply chain disruption risk for the endogenous term superior operating efficiency. The PLS algorithm was used to estimate path coefficients, effect sizes, and the coefficient of determination of superior operating efficiency. Pairwise deletion was selected as the treatment for missing values, and all calculations were performed using the path weighting scheme and initial values of one. Using a stopping criterion of seven, the model converged on the second iteration.

As previously mentioned, traditional measures of internal consistency and construct validity are invalid for latent interaction variables and single-item constructs. Thus, the HTMT ratio and inner VIF values are used to assess discriminant validity and collinearity for Structural Model 3 with results provided in Table 17. All HTMT values were below .85, indicating that discriminant validity was achieved. Likewise, multicollinearity did not appear to be a significant issue as all inner VIF numbers were below the critical threshold of five.

Table 17: Measures of Discriminant Validity and Collinearity for Model 3

Item	Inner VIF	Heterotrait-Monotrait Ratio (HTMT)								
		FMR	TLC	SRE	SCDR	PI	ORV	ORV x FMR	ORV x SRE	ORV x SCDR
Control	1.044									
FMR	4.075									
TLC	1.927	0.076								
SRE	4.494	0.832	0.328							
SCDR	1.730	0.093	0.508	0.077						
PI	1.148	0.050	0.278	0.021	0.084					
ORV	1.531	0.047	0.206	0.030	0.242	0.160				
ORV x FMR	4.359	0.011	0.183	0.087	0.268	0.148	0.266			
ORV x SRE	4.163	0.062	0.101	0.000	0.083	0.076	0.000	0.806		
ORV x SCDR	1.507	0.260	0.060	0.191	0.267	0.043	0.165	0.090	0.240	
SOE	-	0.022	0.079	0.136	0.091	0.272	0.023	0.006	0.096	0.081

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SOE = Superior Operating Efficiency.

Complete bootstrapping was performed to calculate the statistical significance of the path coefficients in the inner model, the calculated effect sizes of the exogenous terms, and the coefficient of determination for the superior operating efficiency. Structural Model 3 primarily focuses on the significance and effect sizes of the latent interaction variables that represent the three moderating effects as well as the additional variance explained by moderation. Complete bootstrapping was conducted using 5,000 subsamples and allowing item-level sign changes. Since negative moderation was hypothesized, one-tailed results were returned with bias corrected and accelerated confidence intervals and normalized data distribution. Results of complete bootstrapping for Structural Model 3 are presented in Table 18.

The coefficient of determination for is the first measure used to assess the quality of Structural Model 3. Results in Table 18 indicate that Structural Model 3 explains 30.9% of the variance in superior operating efficiency, with R^2 of .309 (p=.002) and adjusted R^2 of .227 (p=.025). Thus, Structural Model 3 explains more variance in superior operating efficiency and has more statistical power than Structural Model 1, which explained 22.8% of the variance in superior operating efficiency with an R^2 of .228 (p=.013) and adjusted R^2 of .167 (p=.067). Hence, Structural Model 3 is a better predictor of superior operating efficiency, suggesting that the effects of factor market value, strategic risk exposure, and supply chain disruption risk on superior operating efficiency are contingent upon offshore relationship value.

Next, the path coefficients of the moderating effects as well as the calculated effect sizes of the latent interaction terms must be evaluated (Hair et al., 2016). Results in Table 18 show that each of the three moderating effects for Structural Model 3 are statistically significant. However, two of the interactions are products of exogenous terms with unexpected valences, and the moderating effect of offshore relationship and strategic risk exposure is in the wrong direction. Thus, the magnitude, direction, and statistical significance of the interaction terms must all be assessed to provide empirical support for moderation (Chin et al., 2003).

Table 18: Significance of Path Coefficients and R^2 for Structural Model 3

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Explained Variance (R^2) for Endogenous Variable Superior Operating Efficiency					
R^2	0.309	0.410	0.104	2.962	.002***
Adjusted R^2	0.227	0.341	0.116	1.952	.025**
Statistical Significance of Path Coefficients (β)					
Control Factors → SEO	-0.258	-0.321	0.109	2.365	.009***
PI → SOE	0.226	0.211	0.116	1.947	.026**
ORV → SOE	-0.205	-0.192	0.137	1.495	.067*
FMR → SOE	0.307	0.303	0.195	1.577	.057*
TLC → SOE	0.254	0.218	0.117	2.180	.015**
SRE → SOE	-0.537	-0.477	0.236	2.271	.012**
SCDR → SOE	-0.159	-0.148	0.084	1.888	.030**
ORV x FMR → SOE	-0.602	-0.495	0.266	2.261	.012**
ORV x SRE → SOE	0.025	0.021	0.010	2.367	.009***
ORV x SCDR → SOE	-0.173	-0.162	0.108	1.604	.054*
Calculated Effect Size (f^2) of Variables for Specified Paths					
Control Factors → SEO	0.092	0.154	0.100	0.921	.179
PI → SOE	0.034	0.052	0.063	0.529	.299
ORV → SOE	0.049	0.051	0.051	0.951	.171
FMR → SOE	0.093	0.106	0.105	0.885	.188
TLC → SOE	0.021	0.026	0.027	0.768	.221
SRE → SOE	0.064	0.078	0.073	0.888	.187
SCDR → SOE	0.040	0.052	0.067	0.591	.277
ORV x FMR → SOE	0.096	0.088	0.089	1.078	.141
ORV x SRE → SOE	0.113	0.114	0.110	1.032	.151
ORV x SCDR → SOE	0.024	0.031	0.037	0.656	.256

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SOE = Superior Operating Efficiency.

*Significance is one-tailed: $p<.10$

**Significance is one-tailed: $p<.05$

***Significance is one-tailed: $p<.01$

First, the interaction between offshore relationship value and factor market rivalry has a significant and negative effect on superior operating efficiency (β=-.602, p=.012, f^2=.096). The inverse relationship was hypothesized and the calculated effect size of .096 suggests that the interaction is responsible for much of the increase in explained variance. Thus, Hypothesis 9a is supported. No interaction was found between total logistics costs and offshore relationship value. Therefore, the latent interaction term was excluded from the structural equation, offering no support for Hypothesis 10a.

The interaction between offshore relationship value and strategic risk exposure also significantly impacts superior operating efficiency (β=.025, p=.009, f^2=.113). However, the effect of the interaction is positive when negative moderation was proposed. From a quantitative perspective, the interaction does weaken the relationship between strategic risk exposure and superior operating performance, thereby supporting Hypothesis 11a. However, no argument has been made in this dissertation to support an increase in efficiency as offshore relationships strengthen. The direction of these structural paths was not affected by the inclusion of the moderating effect, as the simple effect of strategic risk exposure was also negative. Thus, no practical or theoretical justification exists to support the hypothesis.

The final hypothesized moderating effect in this model concerns the moderation of supply chain disruption risk by offshore relationship value. This interaction had a small, yet significant negative effect on superior operating efficiency (β=-.173, p=.054, f^2=.024). The calculated effect size and p-value of the moderating effect were both sufficient and path coefficient is negative, as hypothesized. However, the expected valence for supply chain disruption risk was not as expected. Therefore, the moderating effect actually strengthens the relationship between supply chain disruption risk and superior operating performance as the slope becomes steeper and inverted. Thus, this study offers no support for Hypothesis 12a.

4.3.2.3.3 Determining the predictive validity. Blindfolding was performed to assess the predictive validity of Structural Model 3 for the endogenous term superior operating efficiency. The omission distance was again set at seven, and changes in abnormal return on assets for all three matching groups were used as reflective indicators of superior operating efficiency. As shown in Table 19, the results indicate that the model has predictive relevance with Q^2 of .217 for the endogenous variable. The cross-validated redundancies for the reflective indicators were also positive with Q^2 values of .192 for PI matching group, .220 for the MPI group, and .239 for the MPIS matching group results. As expected, scores were similar for all matching groups and increased with the stringency of each matching technique, suggesting that the model adequately predicts superior operating efficiency.

Table 19: Predictive Validity of Structural Model 3

	SSO	SSE	Q^2 (1-SSE/SSO)
Construct Cross-Validated Redundancy			
SOE	288.000	225.458	0.217
Indicator Cross-Validated Redundancy			
AbROA MPIS Matching Group	96.000	73.087	0.239
AbROA MPI Matching Group	96.000	74.833	0.220
AbROA PI Matching Group	96.000	77.538	0.192

Where SSO = Sum of Squared Observations, SSE = Sum of Squared Prediction Errors, SOE = Superior Operating Efficiency, and AbROA = Abnormal Return on Assets

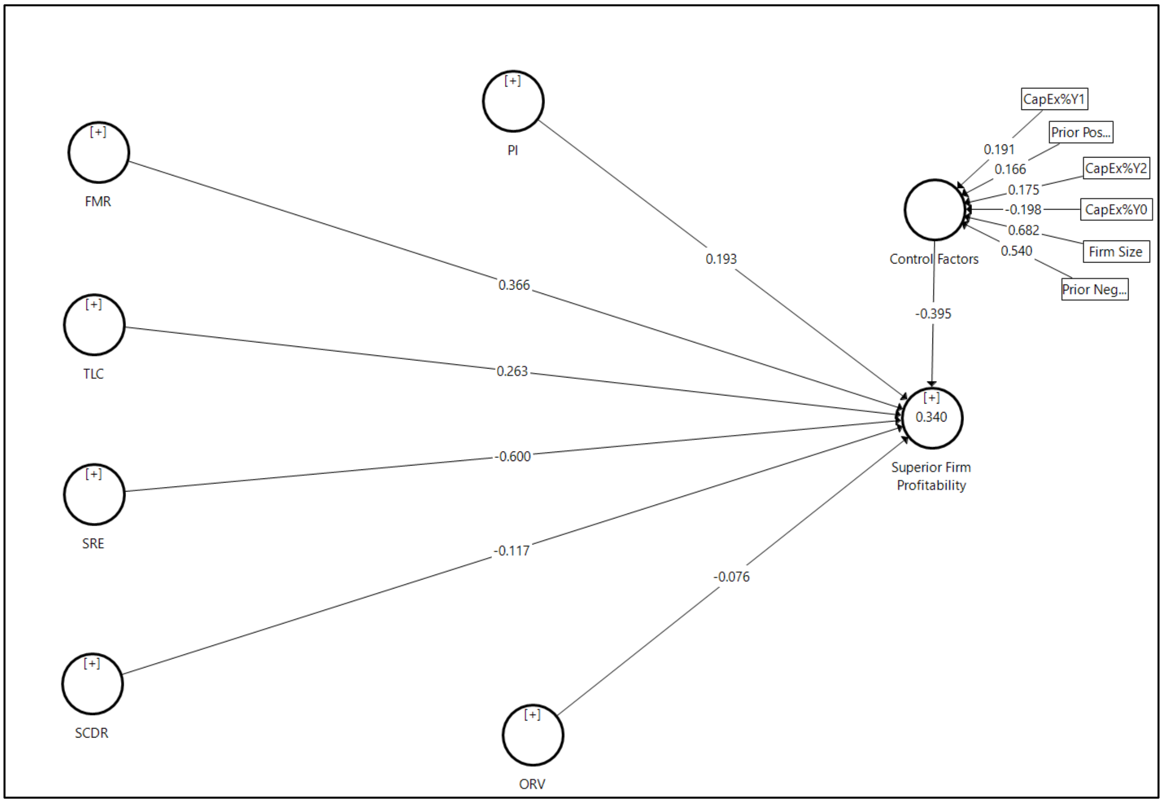
4.3.3 Estimating Superior Firm Profitability

4.3.3.1 Structural Model 4 - direct effects.

4.3.3.1.1 Estimating the model. Structural Model 4 exists to estimate and empirically test the structural model used to explain the variance in superior firm profitability. The model uses the same exogenous variables and structural paths as Structural Model 1 to estimate the endogenous variable superior firm profitability. As with Structural Model 1, the PLS algorithm was chosen to estimate the structural model, while pairwise deletion was selected as the treatment for missing data (Ringle et al., 2015). The path weighting scheme was selected, using default settings of 300 maximum iterations, a stop criterion of 7, and initial values equal to 1. The model converged on the second iteration, explaining 34.0% of the variance in superior firm profitability.

The results for superior firm profitability closely resemble those of superior operating efficiency in Structural Model 1. However, the path coefficients and the coefficient of determination for superior firm profitability are slightly larger for this model than for Structural Model 1. Also of importance, both strategic rick exposure and supply chain disruption risk have negative, rather than positive valences. Thus, both long-term strategic variables negatively affect superior firm profitability in Structural Model 4, just as they did in Structural Model 1. The magnitude and valance of the path coefficients reflect the proposed relationships for all other variables. The path coefficients and explained variance (R^2 = .340) for Structural Model 4 are provided in Figure 7.

Figure 7: Path Coefficients and R^2 for Structural Model 4



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, and ORV = Offshore Relationship Value.

4.3.3.1.2 Assessing the results. Structural Model 4 uses the same exogenous constructs, measurement items, and structural paths as Structural Model 1 to estimate the path coefficients and explained variance for the endogenous variable superior firm performance. Thus, the same statistical techniques are used to assess the validity of the model. The HTMT ratio and inner VIF values are used to assess discriminant validity and collinearity for Structural Model 4 with results provided in Table 20. All HTMT values were below .85, indicating that discriminant validity was achieved. All inner VIF numbers were below the critical threshold of five, suggesting that multicollinearity did not invalidate the results.

Table 20: Measures of Discriminant Validity and Collinearity for Structural Model 4

Item	Inner VIF	Heterotrait-Monotrait Ratio (HTMT)					
	SFP	FMR	ORV	PI	SCDR	SRE	SFP
Control	1.140						
FMR	3.848						
ORV	1.210	0.047					
PI	1.142	0.050	0.160				
SCDR	1.432	0.093	0.242	0.084			
SRE	4.302	0.832	0.030	0.021	0.077		
SFP	-	0.099	0.144	0.253	0.115	0.226	
TLC	1.855	0.076	0.206	0.278	0.508	0.328	0.011

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

In lieu of viable fit measures for PLS-SEM, the predictive capabilities of the structural model are used to indicate the quality of the model (Hair, Sarstedt, Ringle, et al., 2012). Thus, bootstrapping was performed to assess the statistical significance of the coefficient of determination (R^2) of endogenous constructs, path coefficients (β) and calculated effect sizes (f^2). Complete bootstrapping was used to determine t-values, p-values, and confidence intervals for all quality measures of the model (Ringle et al., 2015). The same settings were retained from the PLS algorithm, and pairwise deletion was selected as a treatment for missing data items. To ensure a large enough sample size, 5000 subsamples were selected, with item-level sign changes permitted. Because relationships within the model were hypothesized, one-tailed results were returned with bias corrected and accelerated confidence intervals and normalized data distribution. Results of bootstrapping for Structural Model 4 are presented in Table 21.

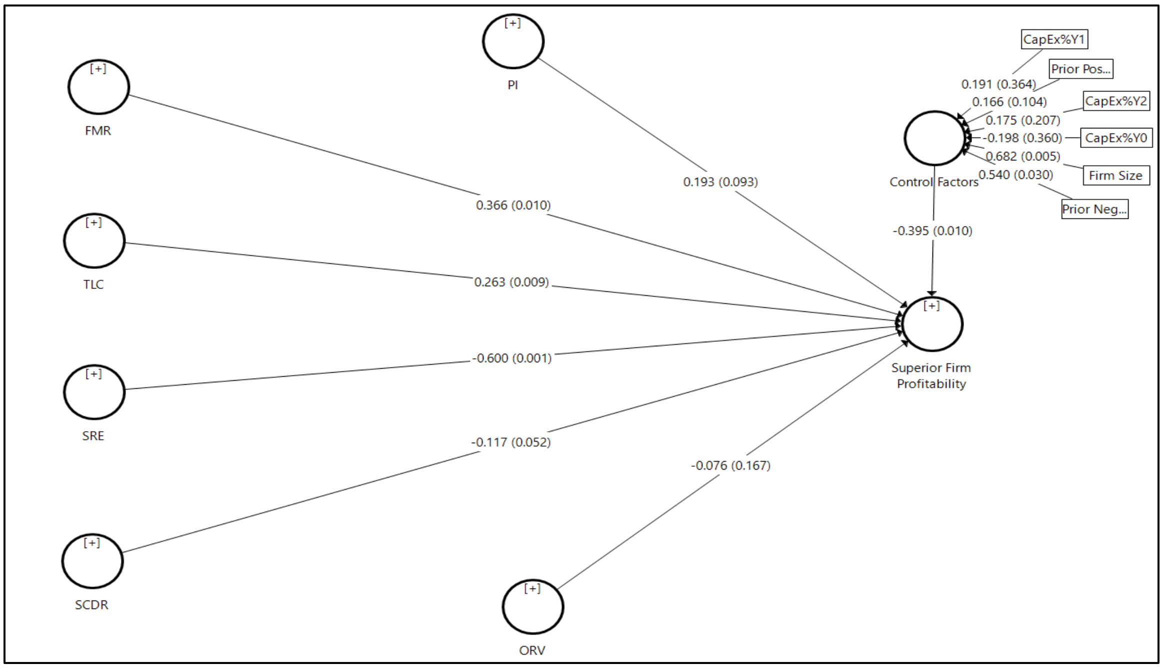
The coefficient of determination for is the first measure used to assess the quality of Structural Model 4. Results in Table 21 indicate that Structural Model 4 explains 34.0% of the variance in superior firm profitability, with R^2 of .340 (p=.009) and adjusted

R^2 of .288 (p=.031). Both the coefficient of determination and the adjusted R^2 for superior firm profitability were significant, suggesting that the model accurately predicts superior firm profitability. The direct effects model also explains more variance for superior firm profitability in Structural Model 4 than for superior operating performance in Structural Model 1.

To determine the drivers of reshoring success, the path coefficients for the proposed relationships between the independent variables and superior firm profitability were next examined (Hair et al., 2017) . In addition to the statistical significance of the path coefficients, the calculated effect sizes much also be considered to determine the effect that each structural path has on the coefficient of determination of the exogenous variables (Cohen, 1988). The path coefficients and p-values for each structural path are presented in Figure 8 while the all three measures are shown in Table 21.

The direct path from factor market rivalry to superior operating efficiency was positive and significant (β=.337, p=.033, f^2=.053), providing support for Hypothesis 1b. Likewise, total logistics costs were shown to have a positive and significant impact (β=.263, p=.009, f^2=.057) on superior operating efficiency. Thus, Hypothesis 2b is also supported. Both measures of long-term risk move in the opposite direction of the hypothesized relationships. Although strategic risk exposure was significant and produced the largest path coefficient in the model, the valence was negative (β=-.600, p=.001, f^2= .127). Thus, Hypothesis 3b is not supported. Although supply chain disruption risk had a much smaller path coefficient, results indicate that it also significantly reduced superior operating efficiency (β=-.117, p=.052, f^2=.014). The calculated effect size for this structural path is also below .02, suggesting that supply chain disruption risk not a significant predictor of superior firm profitability. Therefore, Hypotheses 4a was not supported.

Figure 8: Path Coefficients and p-Values for Structural Model 4



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

Path coefficients were significant for each of the hypothesized direct effects, although two moved opposite the proposed direction. Both of these long-term strategic predictors were also negative for superior operating performance. Similarly, all effect sizes were above the lower bound for relevant small effects (Cohen, 1992) with the exception of two, which were both below .02 in Structural Model 1. This suggests that both endogenous terms are similar, and the measures and structural models are robust.

Table 21: Statistical Significance of Path Coefficients and R^2 for Structural Model 1

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Explained Variance (R^2) for Endogenous Variable Superior Firm Profitability					
R^2	0.340	0.481	0.143	2.374	.009***
Adjusted R^2	0.288	0.439	0.155	1.860	.031**
Statistical Significance of Path Coefficients (β)					
Control Factors → SFP	-0.395	-0.485	0.171	2.313	.010***
PI → SFP	0.193	0.201	0.146	1.320	.093*
ORV → SFP	-0.076	-0.108	0.079	0.965	.167
FMR → SFP	0.366	0.310	0.156	2.342	.010***
TLC → SFP	0.263	0.194	0.111	2.365	.009***
SRE → SFP	-0.600	-0.494	0.188	3.186	.001***
SCDR → SFP	-0.117	-0.115	0.072	1.628	.052*
Calculated Effect Size (f^2) of Variables for Specified Paths					
Control Factors → SFP	0.208	0.511	0.504	0.412	.340
PI → SFP	0.050	0.101	0.133	0.373	.355
ORV → SFP	0.007	0.028	0.038	0.194	.423
FMR → SFP	0.053	0.058	0.051	1.043	.148
TLC → SFP	0.057	0.049	0.048	1.175	.120
SRE → SFP	0.127	0.124	0.089	1.431	.076*
SCDR → SFP	0.014	0.025	0.027	0.532	.298

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

*Significance is one-tailed: p<.10

**Significance is one-tailed: p<.05

***Significance is one-tailed: p<.01

4.3.3.1.3 Determining the predictive validity. Blindfolding was performed to assess the predictive validity of Structural Model 4 for the endogenous term superior firm profitability. The omission distance was again set at seven, and changes in abnormal return on sales for all three matching groups were used as reflective indicators of superior operating efficiency. As shown in Table 22, the results indicate that the model has predictive relevance with Q^2 of .210 for the endogenous variable. The cross-validated redundancies for the reflective indicators were also positive with Q^2 values of .145 for PI matching group, .238 for the MPI group, and .249 for the MPIS matching group results. The results were positive for the construct as well as for each matching group, suggesting that the model adequately predicts superior firm profitability.

Table 22: Predictive Validity of Structural Model 4

	SSO	SSE	Q^2 (1-SSE/SSO)
Construct Cross-Validated Redundancy			
SFP	288.000	227.385	.210
Indicator Cross-Validated Redundancy			
AbROS MPIS Matching Group	96.000	72.114	.249
AbROS MPI Matching Group	96.000	73.150	.238
AbROS PI Matching Group	96.000	82.121	.145

Where SSO = Sum of Squared Observations, SSE = Sum of Squared Prediction Errors, SFP = Superior Firm Profitability and AbROS = Abnormal Return on Sales

4.3.3.2 Structural Model 5 - interactions with product innovativeness

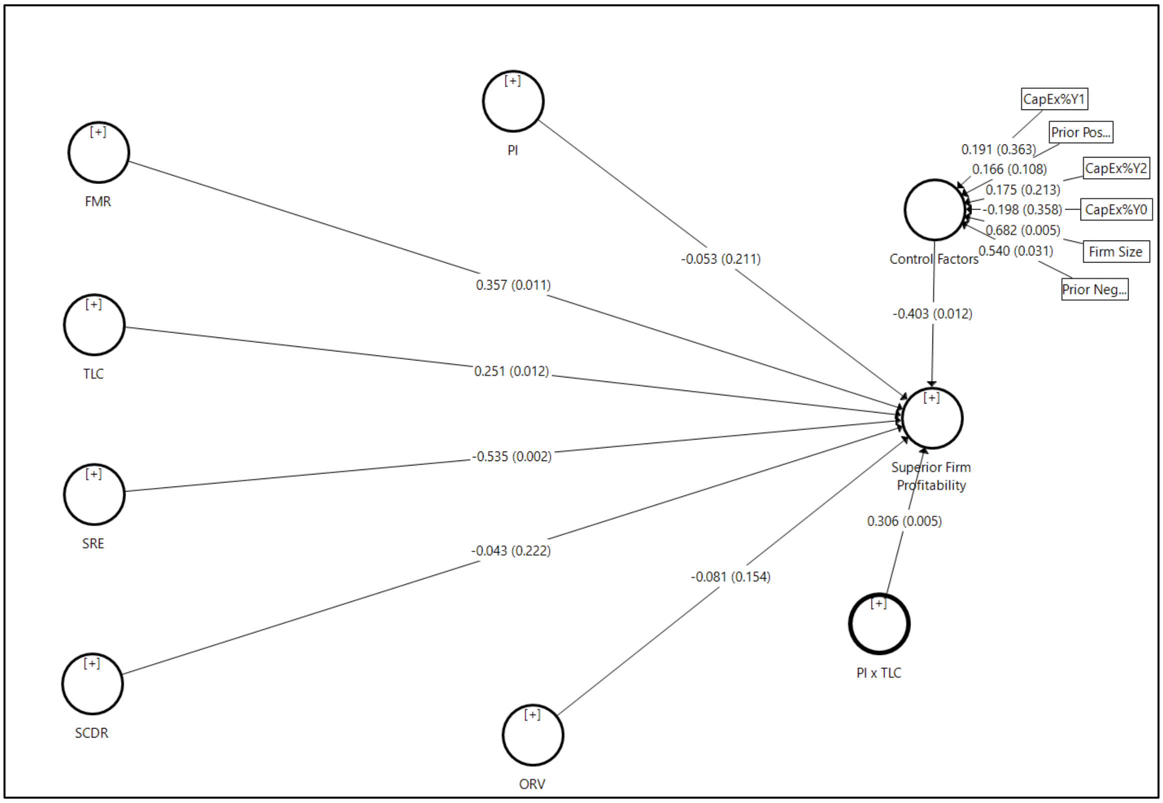
4.3.3.2.1 Estimating Model 5. Building upon the previous model, Structural Model 5 uses path modeling to determine if the relationships between the independent variables and superior firm profitability are contingent upon the innovativeness of the product being manufactured. Moderation was tested by using PLS-SEM to estimate the variance in superior firm profitability explained by interactions between product innovativeness and the other exogenous variables (Hair et al., 2016). Moderating effects were examined using the four latent interaction variables that were created in Structural Model 2. The PLS algorithm was then employed to estimate the structural path between each interaction variable and the endogenous term superior operating efficiency, followed by bootstrapping to determine the statistical significance of the effects.

The PLS algorithm was used to estimate the structural paths and changes in R^2, while bootstrapping was performed to determine the statistical significance of the moderating effects. Since quality measures were not needed for this initial assessment, basic bootstrapping was performed using 5,000 subsamples with one-tailed test results.

Results of this initial assessment indicate that only one of the four proposed moderating effects of product innovativeness are significant. The interaction between product innovativeness and total logistics costs produced the only significant effect, increasing the explained variance in superior firm profitability from .340 in Structural Model 4 to .440. Thus, the moderating effect of product innovativeness on total logistics costs is positive and significant (β=.306, p=.005), explaining an additional 10.0% of the variance in superior firm profitability.

The interaction between product innovativeness and factor market rivalry was not significant (β=-.036, p=.406, f^2=.001), and had no effect on the R^2 of superior firm performance. Thus, the moderating effect of product innovativeness on factor market rivalry was not included in the model. The interaction between product innovativeness and strategic risk had no significant effect on superior firm performance (β=-.122, p=.249, f^2=.011). Likewise, the interaction between product innovativeness and supply chain disruption risk was not found to be a significant predictor of superior firm performance (β=-.124, p=.216, f^2=.015). Neither of these interaction variables increased the explained variance of superior operating efficiency when added to the structural model. Thus, both terms were excluded from the structural equation, leaving only one moderating effects to be examined in Structural Model 5. The path coefficients and p-values of the final model are shown in Figure 9.

Figure 9: Path Coefficients and p-Values for Structural Model 5



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

Structural Model 5 uses PLS-SEM to estimate the moderating effect of product innovativeness on total logistics costs for the endogenous term superior firm profitability. The PLS algorithm was used to estimate path coefficients, effect sizes, and the coefficient of determination of superior firm profitability. Pairwise deletion was selected as the treatment for missing values, and all calculations were performed using the path weighting scheme and initial values of one. Using a stopping criterion of seven, the model converged on the second iteration.

Structural Model 5 uses the same exogenous constructs and measures as Structural Model 2. Thus, the same statistical tests and assessments are used to determine the discriminate validity of the model for the endogenous term superior firm profitability. The HTMT ratio and inner VIF values are used to assess discriminant validity and collinearity for Structural Model 5 with results provided in Table 23. All HTMT values were below .85, indicating that discriminant validity was achieved. Multicollinearity did not appear to be a significant issue as all inner VIF numbers were below the critical threshold of five.

Table 23: Measures of Discriminant Validity and Collinearity of Structural Model 5

Item	Inner VIF	Heterotrait-Monotrait Ratio (HTMT)						
	SFP	FMR	ORV	PI	PI x TLC	SCDR	SRE	SFP
Control	1.141							
FMR	3.849							
ORV	1.210	0.047						
PI	1.750	0.050	0.160					
PI x TLC	1.682	0.121	0.079	0.598				
SCDR	1.486	0.093	0.242	0.084	0.123			
SRE	4.344	0.832	0.030	0.021	0.156	0.077		
SFP	-	0.099	0.144	0.253	0.441	0.115	0.226	
TLC	1.856	0.076	0.206	0.278	0.062	0.508	0.328	0.011

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

4.3.3.2.2 Assessing the results. To assess the quality of Structural Model 5, complete bootstrapping was performed to calculate the statistical significance of the path coefficients in the inner model, the calculated effect sizes of the exogenous terms, and the coefficient of determination for the superior firm profitability. Of particular concern to this model is the significance and effect sizes of the moderating effect as well as the additional variance explained by moderation. Complete bootstrapping was conducted by selecting 5,000 subsamples and allowing item-level sign changes. Since positive moderation was hypothesized, one-tailed results were returned with bias corrected and accelerated confidence intervals and normalized data distribution. Results of complete bootstrapping for Structural Model 5 are presented in Table 24.

The coefficient of determination is the first measure used to assess the quality of Structural Model 5. Results in Table 24 indicate that Structural Model 5 explains 44.0% of the variance in superior firm profitability, with R^2 of .440 (p=.001) and adjusted R^2 of .389 (p=.005). Thus, Structural Model 5 explains more variance in superior firm profitability and has more statistical power than Structural Model 4, which explained 34.0% of the variance in superior firm profitability, with R^2 of .340 (p=.009) and adjusted R^2 of .288 (p=.031). Hence, Structural Model 5 is a better predictor of superior firm profitability, suggesting that product innovativeness is a significant moderator of total logistics costs.

Next, the path coefficients of the moderating effects must be evaluated along with the calculated effect sizes of the latent interaction terms (Hair et al., 2017). Results in Table 24 show that the interaction between product innovativeness and total logistics costs has positive and significant effect on superior firm profitability (β=.306, p=.005, f^2=.178). The moderating effect also produces the largest calculated effect size in the model for superior firm profitability, providing support for Hypothesis 6b. Interactions with factor market rivalry, strategic risk exposure, and supply chain disruption risk were excluded from the structural equation, offering no support for Hypothesis 5b, Hypothesis 7b or 8b.

Table 24: Statistical Significance of Path Coefficients and R^2 for Structural Model 2

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Explained Variance (R^2) for Endogenous Variable Superior Firm Profitability					
R^2	0.440	0.546	0.139	3.155	.001***
Adjusted R^2	0.389	0.504	0.152	2.552	.005***
Statistical Significance of Path Coefficients (β)					
Control Factors → SFP	-0.403	-0.473	0.179	2.257	.012**
PI → SFP	-0.053	-0.080	0.066	0.804	.211
ORV → SFP	-0.081	-0.107	0.079	1.022	.154
FMR → SFP	0.357	0.302	0.156	2.290	.011**
TLC → SFP	0.251	0.197	0.112	2.246	.012**
SRE → SFP	-0.535	-0.450	0.188	2.844	.002***
SCDR → SFP	-0.043	-0.075	0.057	0.765	.222
PI x TLC → SFP	0.306	0.266	0.119	2.563	.005***
Calculated Effect Size (f^2) of Variables for Specified Paths					
Control Factors → SFP	0.254	0.548	0.530	0.479	.316
PI → SFP	0.003	0.012	0.017	0.165	.435
ORV → SFP	0.010	0.031	0.042	0.230	.409
FMR → SFP	0.059	0.063	0.057	1.046	.148
TLC → SFP	0.060	0.056	0.056	1.079	.140
SRE → SFP	0.118	0.121	0.093	1.261	.104
SCDR → SFP	0.002	0.013	0.018	0.129	.449
PI x TLC → SFP	0.178	0.156	0.130	1.367	.086*

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

*Significance is one-tailed: p<.10

**Significance is one-tailed: p<.05

***Significance is one-tailed: p<.01

4.3.3.2.3 Determining the predictive validity. Blindfolding was performed to assess the predictive validity of Structural Model 5 for the endogenous term superior firm profitability. The omission distance was again set at seven, and changes in abnormal return on sales for all three matching groups were used as reflective indicators of superior operating efficiency. As shown in Table 25, the results indicate that the model has predictive relevance with Q^2 of .301 for the endogenous variable. The cross-validated redundancies for the reflective indicators were also positive with Q^2 values of .179 for PI matching group, .361 for the MPI group, and .362 for the MPIS matching group results. The results were positive for the construct as well as for each matching group, suggesting that the model adequately predicts superior firm profitability.

Table 25: Predictive Validity of Structural Model 5

	SSO	SSE	Q^2 (1-SSE/SSO)
Construct Cross-Validated Redundancy			
SFP	288.000	201.453	.301
Indicator Cross-Validated Redundancy			
AbROS MPIS Matching Group	96.000	61.226	.362
AbROS MPI Matching Group	96.000	61.379	.361
AbROS PI Matching Group	96.000	78.878	.179

Where SSO = Sum of Squared Observations, SSE = Sum of Squared Prediction Errors, SFP = Superior Firm Profitability and AbROS = Abnormal Return on Sales

4.3.3.3 Structural Model 6 - moderating effect of offshore relationship value.

4.3.3.3.1 Estimating the model. Structural Model 6 exists to determine if direct effects of superior firm profitability are contingent upon the value of offshore relationships for the reshoring firms (Hair et al., 2016). This model uses the exogenous measures and structural paths from Structural Model 3 to determine the explained variance for the endogenous variable superior firm performance. Moderation was tested using the same four latent interaction variables from Structural Equation 3 to capture the moderating effects of offshore relationship value on each of the four independent variables for the endogenous variable superior firm profitability (Chin et al., 2003).

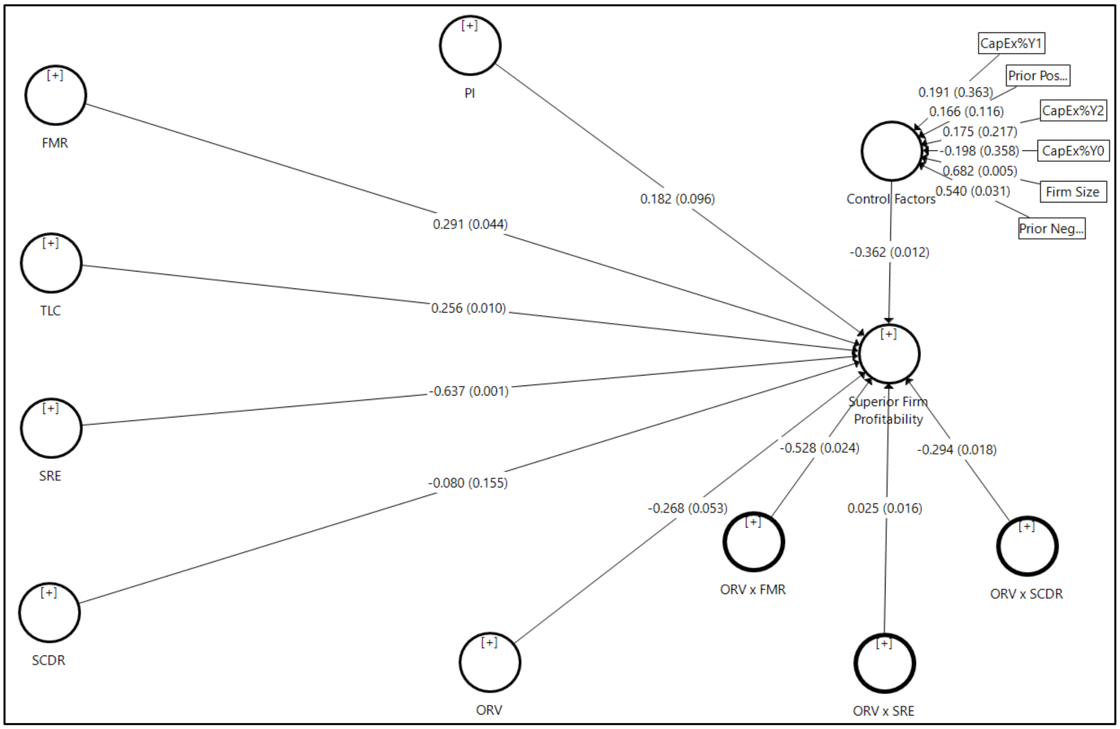
The PLS algorithm was employed to estimate the moderating effects and changes in explained variance for superior firm profitability. To determine which interaction terms to include in the model, path modeling was performed separately for each interaction variable to identify the change in explained variance attributable to each moderating effect. Different combinations of moderating effects were also examined to identify the structural equation that maximizes explained variance in superior firm profitability. Bootstrapping was utilized to identify the interaction variables to include in Structural Model 6. For simplicity, basic bootstrapping was performed using 5,000 subsamples with one-tailed test results.

Results of this initial assessment indicate that three of the four proposed moderating effects explain additional variance in superior operating efficiency. Total logistics cost was the only independent variable in Structural Model 6 virtually unaffected by the variance in offshore relationship value. The interaction between total logistics costs and offshore relationship value was not a significant predictor of superior operating efficiency (β = -.021, p = .380, f^2=.002), and the interaction had no effect on the R^2 for superior firm profitability. Thus, the latent interaction variable was excluded from the structural equation, summarily rejecting Hypothesis 9b. The other three interactions were significant and increased the explained variance in the endogenous term.

The interaction between offshore relationship value and supply chain disruption risk produces the smallest moderating effect in the model (β =-.149, p =.054, f^2=.023), yet the interaction is significant. The addition of this latent interaction term explains an additional 1.5% of the variance in superior firm profitability, increasing the value of R^2

from .340 to .355. Next, interaction between offshore relationship value and strategic risk exposure was significant (β =.195, p =.056, f^2=.051), explaining roughly 3.1% of the variance in superior operating efficiency. The inclusion of the interaction between offshore relationship value and strategic risk exposure increased R^2 from .355 to .386 for superior firm profitability. Finally, the interaction between offshore relationship value and factor market rivalry was significant (β=-.528, p=.024, f^2=.090), with the greatest effect on the endogenous term. The addition of this moderating effect increased the value of R^2 from .386 to .437, explaining an additional 4.1% of the variance in superior firm performance. Thus, Structural Model 6 includes the endogenous variables from Structural Model 4 plus three latent variables used to calculate the moderating effect of offshore relationship value on factor market rivalry, strategic risk exposure, and supply chain disruption risk for the endogenous term superior operating efficiency. The path coefficients and p-values of the final model are shown in Figure 10.

Figure 10: Path Coefficients and p-Values for Structural Model 6



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

4.3.3.3.2 Assessing the results. Structural Model 6 uses the same exogenous constructs and structural paths as Structural Model 3 to estimate the path coefficients and explained variance for the endogenous term superior firm profitability. Therefore, the same statistical tests and techniques are also used to assess model and measurement quality. As previously mentioned, traditional measures of internal consistency and construct validity are invalid for latent interaction variables and single-item constructs. Thus, the HTMT ratio and inner VIF values are used to assess discriminant validity and collinearity for Structural Model 6 with results provided in Table 26. All HTMT values were below .85, indicating that discriminant validity was achieved. All inner VIF numbers were below the critical threshold of five, suggesting that multicollinearity was not factor in the results.

Table 26: Measures of Discriminant Validity and Collinearity for Model 6

Item	Inner VIF	Heterotrait-Monotrait Ratio (HTMT)								
	SFP	FMR	ORV	ORV x FMR	ORV x SCDR	ORV x SRE	PI	SCDR	SRE	SFP
Control	1.165									
FMR	4.018									
ORV	1.653	0.047								
ORV x FMR	4.395	0.011	0.266							
ORV x SCDR	1.507	0.260	0.165	0.090						
ORV x SRE	4.232	0.062	0.000	0.806	0.240					
PI	1.162	0.050	0.160	0.148	0.043	0.076				
SCDR	1.730	0.093	0.242	0.268	0.267	0.083	0.084			
SRE	4.433	0.099	0.144	0.097	0.093	0.162	0.253	0.115		
SFP	-	0.832	0.030	0.087	0.191	0.000	0.021	0.077	0.226	
TLC	1.937	0.076	0.206	0.183	0.060	0.101	0.278	0.508	0.011	0.328

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

Complete bootstrapping was performed to calculate the statistical significance of the path coefficients in the inner model, the calculated effect sizes of the exogenous terms, and the coefficient of determination for superior firm profitability. Structural Model 6 primarily focuses on the significance and effect sizes of the latent interaction variables that represent the three moderating effects as well as the additional variance explained by moderation. Complete bootstrapping was conducted using 5,000 subsamples and allowing item-level sign changes. Since negative moderation was hypothesized, one-tailed results were returned with bias corrected and accelerated confidence intervals and normalized data distribution. Results of complete bootstrapping for Structural Model 6 are presented in Table 27.

Table 27: Significance of Path Coefficients and R^2 for Structural Model 6

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Explained Variance (R^2) for Endogenous Variable Superior Operating Efficiency					
R^2	0.437	0.564	0.126	3.470	.000***
Adjusted R^2	0.370	0.513	0.141	2.634	.004***
Statistical Significance of Path Coefficients (β)					
Control Factors → SFP	-0.362	-0.439	0.161	2.252	.012**
PI → SFP	0.182	0.197	0.140	1.306	.096*
ORV → SFP	-0.268	-0.226	0.165	1.618	.053*
FMR → SFP	0.291	0.266	0.170	1.707	.044**
TLC → SFP	0.256	0.191	0.110	2.320	.010***
SRE → SFP	-0.637	-0.531	0.204	3.126	.001***
SCDR → SFP	-0.080	-0.109	0.079	1.015	.155
ORV x FMR → SFP	-0.528	-0.417	0.268	1.971	.024**
ORV x SRE → SFP	0.025	0.021	0.012	2.135	.016**
ORV x SCDR → SFP	-0.294	-0.255	0.141	2.094	.018**
Calculated Effect Size (f^2) of Variables for Specified Paths					
Control Factors → SFP	0.199	0.403	0.342	0.584	.280
PI → SFP	0.051	0.107	0.135	0.377	.353
ORV → SFP	0.077	0.093	0.124	0.622	.267
FMR → SFP	0.037	0.051	0.059	0.635	.263
TLC → SFP	0.060	0.052	0.054	1.102	.135
SRE → SFP	0.162	0.157	0.112	1.446	.074*
SCDR → SFP	0.007	0.021	0.028	0.237	.406
ORV x FMR → SFP	0.090	0.089	0.103	0.877	.190
ORV x SRE → SFP	0.143	0.153	0.167	0.856	.196
ORV x SCDR → SFP	0.086	0.095	0.089	0.970	.166

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.
*Significance is one-tailed: $p<.10$
**Significance is one-tailed: $p<.05$
***Significance is one-tailed: $p<.01$

The coefficient of determination is the first measure used to assess the quality of Structural Model 6. Results in Table 27 indicate that Structural Model 6 explains 43.7%

of the variance in superior firm profitability, with R^2 of .437 ($p<.000$) and adjusted R^2 of .370 ($p=.004$). Thus, Structural Model 6 explains more variance in superior firm profitability and has more statistical power than Structural Model 4, which explained 34.0% of the variance in superior firm profitability with R^2 of .340 ($p=.013$) and adjusted R^2 of .288 ($p=.031$). Hence, Structural Model 6 is a better predictor of superior firm profitability, suggesting that the effects of factor market value, strategic risk exposure, and supply chain disruption risk on superior firm profitability are contingent upon offshore relationship value.

Next, the path coefficients of the moderating effects as well as the calculated effect sizes of the latent interaction terms must be evaluated (Hair et al., 2016). Results in Table 27 show that each of the three moderating effects for Structural Model 6 are statistically significant. However, two of the interactions are products of exogenous terms with unexpected valences, and the moderating effect of offshore relationship and strategic risk exposure is in the wrong direction. Thus, the magnitude, direction, and statistical significance of the interaction terms must all be assessed to provide empirical support for moderation (Chin et al., 2003).

First, the interaction between offshore relationship value and factor market rivalry has a significant and negative effect on superior firm profitability ($\beta=-.528$, $p=.024$, $f^2=.090$). Negative moderation was hypothesized, while the calculated effect size of .096 suggests that the interaction is responsible for much of the increase in explained variance. Thus, Hypothesis 9b is supported. No interaction was found between total logistics costs and offshore relationship value. Therefore, the latent interaction term was excluded from the structural equation, providing no support for Hypothesis 10b.

The interaction between offshore relationship value and strategic risk exposure also significantly impacts superior operating efficiency (β=.025, p=.016, f^2=.143). However, the effect of the interaction is positive when negative moderation was proposed. From a quantitative perspective, the interaction does weaken the relationship between strategic risk exposure and superior operating performance, thereby supporting Hypothesis 11b. However, no argument has been made in this dissertation to support an increase in domestic efficiency as offshore relationships strengthen. The direct relationship was not affected by the inclusion of the moderating effect, as the simple effect of strategic risk exposure was also negative. Thus, no practical or theoretical justification exists to support the hypothesis without further analysis.

The final hypothesized moderating effect in this model concerns the moderation of supply chain disruption risk by offshore relationship value. This interaction had a small, yet significant negative effect on superior firm performance (β=-.294, p=.018, f^2=.086). The calculated effect size and p-value of the moderating effect were both sufficient, and path coefficient is negative, as hypothesized. However, the expected valence for supply chain disruption risk was not as expected. Therefore, the moderating effect actually strengthens the relationship between supply chain disruption risk and superior operating performance as the slope becomes steeper and inverted. Thus, this study offers no support for Hypothesis 12a.

4.3.3.3.3 Determining the predictive validity. Blindfolding was performed to assess the predictive validity of Structural Model 6 for the endogenous term superior firm profitability. The omission distance was set at seven, and changes in abnormal return on sales for all three matching groups were used as reflective indicators of superior operating efficiency. As shown in Table 28, the results indicate that the model has predictive relevance with Q^2 of .274 for the endogenous variable. The cross-validated redundancies for the reflective indicators were also positive with Q^2 values of .196 for PI matching group, .309 for the MPI group, and .317 for the MPIS matching group results. The results were positive for the construct as well as for each matching group, suggesting that the model adequately predicts superior firm profitability.

Table 28: Predictive Validity of Structural Model 6

	SSO	SSE	Q^2 (1-SSE/SSO)
Construct Cross-Validated Redundancy			
SFP	288.000	209.079	.274
Indicator Cross-Validated Redundancy			
AbROS MPIS Matching Group	96.000	65.521	.317
AbROS MPI Matching Group	96.000	66.356	.309
AbROS PI Matching Group	96.000	77.202	.196

Where SSO = Sum of Squared Observations, SSE = Sum of Squared Prediction Errors, SFP = Superior Firm Profitability and AbROS = Abnormal Return on Sales

4.3.4 Summary of Results

Table 29: Summary of Hypothesized Relationships and Quantitative Results

	Path	Dir	Results[a]	Conclusion
H1a	FMR → SOE	(+)	β = .337, p = .033	Supported
H1b	FMR → SFP	(+)	β = .366, p = .010	Supported
H2a	TLC → SOE	(+)	β = .228, p = .022	Supported
H2b	TLC → SFP	(+)	β = .263, p = .009	Supported
H3a	SRE → SOE	(+)	β = -.472, p = .017	Not Supported
H3b	SRE → SFP	(+)	β = -.600, p = .001	Not Supported
H4a	SCDR → SOE	(+)	β = -.136, p = .033	Not Supported
H4b	SCDR → SFP	(+)	β = -.117, p = .052	Not Supported
H5a	PI*FMR → SOE	(+)	β = .170, p = .070; Sig. at p <.1	Marginal Support
H5b	PI*FMR → SFP	(+)	β = -.036, p = .406	Not Supported
H6a	PI*TLC → SOE	(+)	β = .224, p = .017	Supported
H6b	PI*TLC → SFP	(+)	β = .306, p = .005	Supported
H7a	PI*SRE → SOE	(+)	β = -.044, p = .368	Not Supported
H7b	PI*SRE → SFP	(+)	β = -.122, p = .249	Not Supported
H8a	PI*SCDR → SOE	(+)	β = -.031, p = .396	Not Supported
H8b	PI*SCDR → SFP	(+)	β = -.124, p = .216	Not Supported
H9a	ORV*FMR → SOE	(-)	β = -.602, p = .012	Supported
H9b	ORV*FMR → SFP	(-)	β = -.528, p = .024	Supported
H10a	ORV*TLC → SOE	(-)	β = .031, p = .339	Not Supported
H10b	ORV*TLC → SFP	(-)	β = .045, p = .359	Not Supported
H11a	ORV*SRE → SOE	(-)	β = .025, p = .009	Indeterminate
H11b	ORV*SRE → SFP	(-)	β = .025, p = .016	Indeterminate
H12a	ORV*SCDR → SOE	(-)	β = -.173, p = .054	Indeterminate
H12b	ORV*SCDR → SFP	(-)	β = -.294, p = .018	Indeterminate

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, SOE = Superior Operating Efficiency, and SFP = Superior Firm Profitability.

[a] Path coefficients and p-values (β, p) derived from partial least squares structural equation modeling and bootstrapping. Significance is one-tailed.

CHAPTER FIVE: DISCUSSION

The final chapter of this dissertation serves to discuss and explain the results of the empirical analyses and to use the information presented in the first three chapters to derive insights that may guide business decisions and future academic research. This chapter contains five sections. The first section provides a detailed analysis of the quantitative results relative to the purpose of the dissertation. Next, the second section outlines the academic contributions and managerial implications that may be derived from the study. Third, the limitations of the archival study are presented and potential opportunities for future research are proposed. The final section summarizes the dissertation and findings in the concluding remarks.

5.1 Findings

5.1.1 Event Study

The results of the long-run event study offer strong support for the theory that American firms can significantly improve performance by relocating manufacturing operations from offshore locations to the United States. Changes in abnormal returns were positive and statistically significant across all three matching groups for each multiple-year period following a reshoring event. This was in stark contrast to the negative changes in abnormal returns in the years leading up to reshoring. The changes in abnormal ROA were more powerful in all aspects than were the changes in abnormal ROS. However, results were similar for both changes in abnormal ROA and changes in abnormal ROS for all calculations across all fiscal periods.

Similar patterns appear over the same time periods in all groups for both measures. The strongest single-year change occurs during the year of reshoring. The median change in Abnormal ROA from year -1 to year was +0 .59%, compared to the MPIS group. The median change in ROS over the first year was .41%, relative to the MPIS group. Changes in abnormal returns steadily declined for both groups over the three-year period after reshoring. These changes must not be viewed as lost momentum, though. This study considers changes in abnormal returns rather than actual abnormal returns, therefore these gains are cumulative. In reality, abnormal ROA and abnormal ROS are both increasing at a decreasing rate in the three years following reshoring, which should provide a first-movers benefit that might create sustainable competitive advantages. Allowing the growth to pool over time shows that cumulative abnormal changes over the three-year period were +1.33% for ROA and 0.96% for ROS, relative to the MPIS matching group.

5.1.2 Path Modeling and Sensitivity Analysis

To determine the most significant predictors of these gains, second generation structural equations modeling was used to estimate the structural path of the proposed conceptual framework. The results of path modeling using PLS-SEM provided many interesting details about the reshoring decisions. As with the event study results, path analysis provided similar estimates for changes in ROA and changes in ROS. All path coefficient valences were the same for all models, while most variables have similar effect sizes across all models. Results are also similar for the additional measures and technique which are appended to the dissertation, offering further evidence that the measures and models are quite robust.

Both economic drivers of reshoring performed as expected. Results were positive and significant for both factor market rivalry and total logistics costs. This indicates the actual cost of ownership for goods produced offshore is much higher than the planned purchase price. The proposed interactions between product innovativeness and total logistics costs were supported. Product innovativeness also increased the effect of factor market rivalry, but to a much smaller degree. As expected, offshore relationship value was also found to attenuate the effect of factor market rivalry on foreign production costs, although no such effect was supported for total logistics costs.

Although the economic variables mainly produced expected results, neither none of the hypothesized relationships involving the risk variables were supported. Both strategic risk exposure and supply chain disruption risk were significant, but in the opposite direction. While it seems counterintuitive that increasing the level of long-term risk would increase firm performance, the cost of decreasing such risk could possibly outweigh the returns. While natural disasters and resource shortages have a huge impact on global firms, research indicates that these type threats are still viewed as truly random events (Ellram, Tate, & Petersen, 2013; Revilla & Sáenz, 2014). Thus, the reshoring decision would mainly depend of the risk aversion of the firm executives. Truly random events only become stochastic with increasing occurrences over a long enough timeline. Therefore, three years is quite possibly not long enough to capture the true outcomes relative to the entire industry.

Also possible is the fact that financial losses might be economic gains in many situations. For instance, many reshoring companies had a business model of performing research and development activities in the U.S., then outsourcing production to emerging economies (Moser, 2011; Pisano & Shih, 2012). Faced with counterfeiting, quality problems, or potential militant behavior, relocation to high-cost economies was necessary albeit costly. For these type firms, reshoring decisions could have been based on threats to longevity, thus the costs involved in reshoring may also be categorized as necessary expenditures (Platts & Song, 2010; N. Song et al., 2007).

A third possible explanation for the conflicting results emerges from the inability to obtain subjective reasons for reshoring using archival data. Many companies in this sample, as well as in the population, suffered substantial losses in offshore markets before moving production to the United States. For instance, The Boeing Company suffered huge losses due to problems before large portions of manufacturing were moved to North America (Denning, 2013a, 2013b). Since these losses cannot be recouped, the financial impact negatively affects accounting-based performance measures for many years (Ellram, Tate, & Feitzinger, 2013; Ellram, Tate, & Petersen, 2013; Tate, 2014; Tate et al., 2014). To provide a better understanding of these results, future studies should also distinguish between reshoring decisions made in anticipation of threats and those made in reaction to realized occurrences.

5.2 Academic Contributions and Managerial Implications

Although several of the proposed relationships in this study were not supported, the dissertation still contributes to the existing global supply chain management literature in many ways. Perhaps the most important contribution is the fact that this is the first study to date empirically linking reshoring to firm performance. In this way, the study provides evidence that reshoring is profitable in many situations. By finding strong support for the economic drivers, this dissertation confirms much of the early empirical work based subjective survey responses (Ellram, Tate, & Feitzinger, 2013; Ellram, Tate, & Petersen, 2013; Tate, 2014; Tate et al., 2014).

This dissertation also creates and empirically tests a conceptual framework for future manufacturing location decisions. The path modeling used in the sensitivity analysis demonstrates that the structural models explain a significant portion of the variance in the superior operating efficiency and superior firm profitability that lead to reshoring success. By using many of the same drivers of reshoring, the path analysis also serves to strengthen and extend the work current archival research existing in the literature (Ancarani et al., 2015; Fratocchi et al., 2014; Kinkel, 2014; Kinkel & Maloca, 2009).

5.2 Managerial Implications

This study has immediate practical implications, especially considering the potential benefits to be gained while taking into account the number of American firms currently producing in offshore markets. With the median change in abnormal ROA of 1.33% over three years, many firms should reconsider the total cost of producing offshore. To provide perspective, the median value of total assets for the sample firms in the study was $8,782.1M for sample firms in 2011. Thus, a +1.33% change in abnormal ROA equates to a $116.80M increase in operating income compared to the rest of the industry over the three-year period. Median operating income for sample firms in 2011 was $670.15M, equating to $2010.45M over the same three-year period. Thus, “Fictitious Median Company” could have reshored in 2011 and outperformed its industry by more than 10% through 2014, ceteris paribus. Perhaps even more astonishing, this fictitious company would have achieved these gains all why shouldering the costs of transferring production across the globe.

However, care must be taken when interpreting these results. It would be foolish to assume that every firm currently producing overseas will immediately benefit from reshoring. In fact, many multi-nationals have experience in offshore markets, are highly successful globally, and have no intention of transferring production to high-cost economies. While every possible measure was taken to control for selection bias, specialized studies such as this one require researchers to assess the results within the parameters of the targeted sample.

In this study, the majority of firms studied had already made detailed assessments and came to the conclusion that they would indeed be successful in North America. These results cannot be generalized across all American firms producing products abroad, as the study provides confirmation that firms expecting to be successful in reshoring actually did succeed. The study results are still quite useful, though. Survey data from Boston Consulting Group and the Reshoring Institute find that nearly half of all firms producing in China are considering exiting the country. More importantly, initial assessments indicate that at least 25% of firms manufacturing abroad would be more successful with American production. Thus, the path modeling results should also prove useful to those making reshoring decisions.

Firms most likely to immediately benefit are those with long costly supply chains. When all factors were considered, global logistics costs served as the strongest predictor of reshoring success. This is especially true for highly technical or innovative products. Given the low shelf life of innovative products, shorter supply chains reduce costly waste due to end of season sell-offs. Shorter transit time and closer echelons of research and production also allows for quicker updates and product changes. Proximity to suppliers, and more importantly, to market reduces lead time also provides more flexibility and customer responsiveness.

Firms facing higher production costs in offshore markets are also more likely to see successful reshoring outcomes. This type inflation results from increasing labor costs, increasing energy costs, natural resource availability, and even currency exchange rates between countries. With so many avenues for cost increases, factor market rivalry may go unnoticed until a detailed analysis of global procurement procedures is conducted. Also relevant is the finding that offshore relationship value greatly reduces the effect of factor market rivalry. Thus, firms with vast experience producing and selling in overseas markets might gain little by reshoring, while firms who ultimately over-extended by trying to compete abroad might easily reverse the negative effects by reshoring. At this time, this research cannot provide a definitive guide to decisions from a strategic standpoint, though. With unexpected results from both long-term variables, further research is needed to provide viable insights regarding risks and rewards involving strategic resources.

5.3 Limitations

As with all empirical research, this dissertation is subject to several limitations. Quite a few limitations result from the recency and immediacy of the reshoring phenomenon. Access to decision makers was also a great concern when designing the study. Because of these issues, the study was conducted using archival data, which presents many challenges. The recency of the phenomenon also contributes to a limited sample size and a smaller ranger of years to examine. Due to the limited size and scope of the target sample, single-item measures were used in the regression analysis. While additional measurements were also presented, proxy variables always increase the risk of measurement error. Although the longitudinal research design helps to limit these shortcomings and offers more predictive capability, the limited range of focus coupled with the potential for measurement error must still be considered.

Selection bias due to secondary data limited to publically traded companies. While quantitative models can effectively control for the influence of large firms, the impact that reshoring decisions on smaller, privately owned firms might not be accurately represented in this sample. Another source of potential bias of secondary research could be in the inability to conclude with certainty that control firms have not reshored or transplanted considerable portions of operations. While it is easy to search company histories, 10-K reports, and press releases, to determine if factories have opened or closed, there is no way to determine how much upstream purchasing might have been transferred to or from the U.S. However, any bias of this type would actually make the estimates more conservative.

Given the limitations involved in the current research and the wide-reaching implications of the study topic, many opportunities for future research exist. As the number of reshoring firms continues to grow, quantitative analysis using survey data should prove to be more insightful. The use of carefully designed questionnaires provides researchers the ability to derive specific answers that cannot be determined with archival data. This type of research will provide the ability to determine how the position within the supply chain affects a firm's manufacturing location. The impact of reshoring on procurement for retail and other distribution channels should also be considered. Most of these factors cannot be found consistently in public financial statements.

Even if subjective data becomes viable means of research, archival studies should not be abandoned. The need still exists for archival and qualitative analysis in the literature. For instance, this study could easily be broadened to include nearshoring as a preferred sourcing method. Given the narrow window of focus for this study, a replication would prove fruitful in two to four years. This would provide much better insights into the long-term effects of reshoring. It would also allow for a bigger sample size and broader range of years.

Opportunities also exist for research relative to public policy. With current calls for research on anti-consumption, reshoring should be a primary topic of interest for environmental sustainability. As reshoring creates shorter supply chains, the resultant production process should be leaner, involving much less wasteful production. Recent growth in closeout stores and discount chains relative to traditional retail chains should serve as a bellwether to indicate the overproduction caused by global outsourcing. Although slow-steaming dramatically reduces nautical emissions, marine pollution is still a serious concern considering the amount of ocean-borne traffic created by global outsourcing. Finally, environmental regulations are more stringent in high-cost economies. Thus, reshoring from emerging countries helps to ensure that pollution is prevented while global resources are better preserved.

5.5 Concluding Remarks

This study began with the purpose of developing a conceptual framework to identify the conditions leading to success in reshoring, the sustainability of success derived from reshoring, and any firm-facing or market-facing situations that might accelerate or attenuate success in reshoring. However, no conceptualization could be empirically tested without first determining the economic benefits of reshoring. To accomplish both tasks, an event study was conducted to isolate economic gains and losses attributable to reshoring, followed by second generation structural equation modeling utilized to determine the factors affecting the outcome of reshoring.

The results of the long-run event study offer strong support for the theory that American firms can significantly improve performance by relocating manufacturing operations from offshore locations to the United States. Of the 96 firms sampled in this study, 62% showed immediate positive changes in economic returns, with a median increase in ROA of .5% in the first year relative to industry control groups. Industry-controlled ROA continued to increase at a decreasing rate for all years included in this study, with two-thirds of the sample firms showing positive changes in economic returns in the three-year period following reshoring. These changes in economic returns are year over year improvements, and therefore represent cumulative gains. Thus, the benefits of reshoring appear to be sustainable for mid- and long-range strategic planning.

The proposed conceptual framework also proved beneficial, although additional research will be required to produce more detailed information. Path modeling results suggest that both economic drivers are reliable predictors of reshoring success. At the macro level, increasing factor market rivalry for the previous country of origin and higher total logistics costs prior to reshoring led to greater abnormal returns after the reshoring. Both were significant and positive in models, however the magnitude of the effect was contingent upon the market characteristics and the reshoring firm’s experience in global markets. Product innovativeness significantly increases the effect of total logistics costs, while offshore relationship value significantly reduces the impact of factor market rivalry in foreign markets. Both strategic drivers of reshoring, however, produced conflicting results. Both were significant, yet in the opposite direction. Thus, further research is needed to draw insights on the causal relationship.

The rigor involved in conducting an event study includes a strong qualitative element in case selection, a rigorous financial approach to industrial matching, as well as an objective quantitative data analysis. Thus, this dissertation is one of the earliest empirical papers on reshoring in the United States, and possibly the first to empirically link reshoring to any form of financial measure of firm performance. Considering the immediacy of the reshoring phenomenon, insights drawn from these results are directly applicable to current global supply chain decisions, but also serve as a springboard to generate future research on manufacturing locations.

REFERENCES

40 Force Majeure cases in Europe in only 4 months. (2015, July). Retrieved October 11, 2015, from http://www.plastics.gl/market/11-force-majeure-cases-in-europe-since-jan-2015/

Aaker, D. A., & Jacobson, R. (1987). The Role of Risk in Explaining Differences in Profitability. *The Academy of Management Journal*, *30*(2), 277–296. http://doi.org/10.2307/256274

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211.

Ancarani, A., Di Mauro, C., Fratocchi, L., Orzes, G., & Sartor, M. (2015). Prior to reshoring: A duration analysis of foreign manufacturing ventures. *International Journal of Production Economics*, *169*, 141–155.

Andersen, P. H., & Christensen, P. R. (2005). Bridges over troubled water: suppliers as connective nodes in global supply networks. *Journal of Business Research*, *58*(9), 1261–1273.

Anon. (2013). Deepwater, deep pockets. *Economist*, *408*(8844), 59–59.

Ansari, S. M., Fiss, P. C., & Zajac, E. J. (2010). Made to fit: How practices vary as they diffuse. *Academy of Management Review*, *35*(1), 67–92.

Arlbjørn, J. S., & Lüthje, T. (2012). Global operations and their interaction with supply chain performance. *Industrial Management & Data Systems*, *112*(7), 1044–1064.

Arvis, J.-F., Mustra, M. A., Ojala, L., Shepherd, B., & Saslavsky, D. (2012). *Connecting to Compete 2012: Trade Logistics in the Global Economy*. The World Bank.

Autry, C. W., & Bobbitt, L. M. (2008). Supply chain security orientation: conceptual development and a proposed framework. *International Journal of Logistics Management, The*, *19*(1), 42–64.

Autry, C. W., & Griffis, S. E. (2008). Supply chain capital: the impact of structural and relational linkages on firm execution and innovation. *Journal of Business Logistics*, *29*(1), 157–173.

Baldwin, R., & Venables, A. J. (2013). Spiders and snakes: offshoring and agglomeration in the global economy. *Journal of International Economics*, *90*(2), 245–254.

Barber, B. M., & Lyon, J. D. (1996). Detecting abnormal operating performance: The empirical power and specification of test statistics. *Journal of Financial Economics*, *41*(3), 359–399.

Barney, J. B. (1986). Strategic factor markets: Expectations, luck, and business strategy. *Management Science*, *32*(10), 1231–1241.

Barney, J. B. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, *17*(1), 99–120.

Barney, J. B. (2014). How marketing scholars might help address issues in resource-based theory. *Journal of the Academy of Marketing Science*, *42*(1), 24–26.

Barney, J. B., Wright, M., & Ketchen, D. J. (2001). The resource-based view of the firm: Ten years after 1991. *Journal of Management*, *27*(6), 625–641.

Barrett, P. M. (2014). BP's Lessons in Playing Nasty or Nice. *Business Week*, (4394), 26–27.

BCG - Press Release - U.S. Executives Remain Bullish on American Manufacturing, Study Finds. (2014). Retrieved December 1, 2014, from http://www.bcg.com/media/PressReleaseDetails.aspx?id=tcm:12-174453

Bell, J. E., Autry, C. W., Mollenkopf, D. A., & Thornton, L. M. (2012). A natural resource scarcity typology: theoretical foundations and strategic implications for supply chain management. *Journal of Business Logistics*, *33*(2), 158–166.

Bertrand, O., & Mol, M. J. (2013). The antecedents and innovation effects of domestic and offshore R&D outsourcing: The contingent impact of cognitive distance and absorptive capacity. *Strategic Management Journal*, *34*(6), 751–760.

Bhatnagar, R., & Sohal, A. S. (2005). Supply chain competitiveness: measuring the impact of location factors, uncertainty and manufacturing practices. *Technovation*, *25*(5), 443–456.

Bode, C., Hübner, D., & Wagner, S. M. (2014). Managing Financially Distressed Suppliers: An Exploratory Study. *Journal of Supply Chain Management*, *50*(4), 24–43.

Bode, C., Wagner, S. M., Petersen, K. J., & Ellram, L. M. (2011). Understanding responses to supply chain disruptions: insights from information processing and resource dependence perspectives. *Academy of Management Journal*, *54*(4), 833–856.

Boute, R. N., & Van Mieghem, J. A. (2015). Global Dual Sourcing and Order Smoothing: The Impact of Capacity and Lead Times. *Management Science*, *61*(9), 2080–2099.

Brandon-Jones, E., Squire, B., Autry, C. W., & Petersen, K. J. (2014). A Contingent Resource-Based Perspective of Supply Chain Resilience and Robustness. *Journal of Supply Chain Management*, *50*(3), 55–73.

Brutti, N. (2015). Public Awareness through Private Law Remedies: The Struggle for Information in the Samsung/Apple Case. *European Business Law Review*, *26*(3), 417–436.

Bygballe, L. E., Bø, E., & Grønland, S. E. (2012). Managing international supply: The balance between total costs and customer service. *Industrial Marketing Management*, *41*(3), 394–401.

Calantone, R. J., & Di Benedetto, C. A. (2012). The role of lean launch execution and launch timing on new product performance. *Journal of the Academy of Marketing Science*, *40*(4), 526–538.

Canis, B. (2011). *Motor Vehicle Supply Chain: Effects of the Japanese Earthquake and Tsunami*. DIANE Publishing.

Casson, M. (2013). Economic Analysis of International Supply Chains: An Internalization Perspective. *Journal of Supply Chain Management*, *49*(2), 8–13. http://doi.org/10.1111/jscm.12009

Cavusgil, S. T., & Cavusgil, E. (2012). Reflections on international marketing: destructive regeneration and multinational firms. *Journal of the Academy of Marketing Science*, *40*(2), 202–217.

Chang, M.-L., Cheng, C.-F., & Wu, W.-Y. (2012). How Buyer-Seller Relationship Quality Influences Adaptation and Innovation by Foreign MNCs' Subsidiaries. *Industrial Marketing Management*, *41*(7), 1047–1057.

Chen, I. J., & Paulraj, A. (2004). Towards a theory of supply chain management: the constructs and measurements. *Journal of Operations Management*, *22*(2), 119–150.

Chen, L., Olhager, J., & Tang, O. (2013). Manufacturing facility location and sustainability: A literature review and research agenda. *International Journal of Production Economics*.

Cheng, J.-H., & Sheu, J.-B. (2012). Inter-organizational relationships and strategy quality in green supply chains—Moderated by opportunistic behavior and dysfunctional conflict. *Industrial Marketing Management*, *41*(4), 563–572.

Chin, W. W., Marcolin, B. L., & Newsted, P. R. (2003). A partial least squares latent variable modeling approach for measuring interaction effects: Results from a Monte Carlo simulation study and an electronic-mail emotion/adoption study. *Information Systems Research*, *14*(2), 189–217.

Chopra, S., Reinhardt, G., & Mohan, U. (2007). The importance of decoupling recurrent and disruption risks in a supply chain. *Naval Research Logistics*, *54*(5), 544–555.

Chopra, S., & Sodhi, M. S. (2004). Supply-chain breakdown. *MIT Sloan Management Review*.

Christopher, M., Mena, C., Khan, O., & Yurt, O. (2011). Approaches to managing global sourcing risk. *Supply Chain Management: An International Journal*, *16*(2), 67–81.

Christopher, M., & Peck, H. (2004). Building the resilient supply chain. *The International Journal of Logistics Management*, *15*(2), 1–14.

Clarke, R. L. (1997). An analysis of the international ocean shipping conference system. *Transportation Journal*, 17–29.

Coase, R. H. (1937). The nature of the firm. *Economica*, *4*(16), 386–405.

Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences. 2nd edn. Hillsdale, New Jersey: L*. Erlbaum.

Cohen, J. (1992). A power primer. *Psychological Bulletin*, *112*(1), 155.

Conner, K. R. (1991). A historical comparison of resource-based theory and five schools of thought within industrial organization economics: do we have a new theory of the firm? *Journal of Management*, *17*(1), 121–154.

Danneels, E., & Kleinschmidtb, E. J. (2001). Product innovativeness from the firm's perspective: its dimensions and their relation with project selection and performance. *Journal of Product Innovation Management*, *18*(6), 357–373.

Davis, D. F., & Golicic, S. L. (2010). Gaining comparative advantage in supply chain relationships: the mediating role of market-oriented IT competence. *Journal of the Academy of Marketing Science*, *38*(1), 56–70.

de Treville, S., & Trigeorgis, L. (2010). It may be cheaper to manufacture at home. *Harvard Business Review*, *88*(10), 84–87.

Denning, S. (2013a). Boeing's offshoring woes: seven lessons every CEO must learn. *Strategy & Leadership*, *41*(3), 29–35.

Denning, S. (2013b). What went wrong at Boeing. *Strategy & Leadership*, *41*(3), 36–41.

Duray, R., Ward, P. T., Milligan, G. W., & Berry, W. L. (2000). Approaches to mass customization: configurations and empirical validation. *Journal of Operations Management*, *18*(6), 605–625.

Eggert, A., & Ulaga, W. (2010). Managing customer share in key supplier relationships. *Industrial Marketing Management*, *39*(8), 1346–1355.

Eisenhardt, K. M., & Martin, J. A. (2000). Dynamic Capabilities: What Are They? *Strategic Management Journal*, *21*(10/11), 1105–1121.

Elg, U., Deligonul, S. Z., Ghauri, P. N., Danis, W., & Tarnovskaya, V. (2012). Market-driving strategy implementation through global supplier relationships. *Industrial Marketing Management*, *41*(6), 919–928.

Elkins, D., Handfield, R. B., Blackhurst, J., & Craighead, C. W. (2005). 18 ways to guard against disruption. *Supply Chain Management Review*, *1*, 1.

Ellis, S. C., Henry, R. M., & Shockley, J. (2010). Buyer perceptions of supply disruption risk: a behavioral view and empirical assessment. *Journal of Operations Management*, *28*(1), 34–46.

Ellram, L. M. (1993). A framework for total cost of ownership. *International Journal of Logistics Management*, *The*, *4*(2), 49–60.

Ellram, L. M. (2013). Offshoring, Reshoring and the Manufacturing Location Decision. *Journal of Supply Chain Management*, *49*(2), 3–5. http://doi.org/10.1111/jscm.12023

Ellram, L. M., & Maltz, A. B. (1995). The use of total cost of ownership concepts to model the outsourcing decision. *International Journal of Logistics Management*, *The*, *6*(2), 55–66.

Ellram, L. M., Tate, W. L., & Feitzinger, E. G. (2013). Factor-Market Rivalry and Competition for Supply Chain Resources. *Journal of Supply Chain Management*, *49*(1), 29–46.

Ellram, L. M., Tate, W. L., & Petersen, K. J. (2013). Offshoring and Reshoring: An Update on the Manufacturing Location Decision. *Journal of Supply Chain Management*, *49*(2), 14–22. http://doi.org/10.1111/jscm.12019

Elzarka, S. M. (2013). Supply chain risk management: the lessons learned from the Egyptian revolution 2011. *International Journal of Logistics: Research & Applications*, *16*(6), 482–492.

Esper, T. L., Ellinger, A. E., Stank, T. P., Flint, D. J., & Moon, M. (2010). Demand and supply integration: a conceptual framework of value creation through knowledge management. *Journal of the Academy of Marketing Science*, *38*(1), 5–18.

Fahy, J., & Smithee, A. (1999). Strategic marketing and the resource based view of the firm. *Academy of Marketing Science Review*, *10*(1), 1–21.

Falkenberg, A. W. (1996). Marketing and the wealth of firms. *Journal of Macromarketing*, *16*(1), 4–24.

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G* Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, *39*(2), 175–191.

Fawcett, S. E., Calantone, R., & Smith, S. R. (1996). An investigation of the impact of flexibility on global reach and firm performance. *Journal of Business Logistics*, *17*, 167–196.

Feng, T., Sun, L., & Zhang, Y. (2010). The effects of customer and supplier involvement on competitive advantage: an empirical study in China. *Industrial Marketing Management*, *39*(8), 1384–1394.

Fine, C. (2013). Intelli-Sourcing to Replace Offshoring as Supply Chain Transparency Increases. *Journal of Supply Chain Management*, *49*(2), 6–7. http://doi.org/10.1111/jscm.12018

Fishbein, M. (1979). A theory of reasoned action: Some applications and implications. *Nebraska Symposium on Motivation*, *27*, 65–116.

Fishman, C. (2012). The insourcing boom. *The Atlantic*, *28*.

FM Global Resilience Index. (2015). Retrieved from http://www.fmglobal.com/page.aspx?id=04060300

Foss, K., & Foss, N. J. (2005). Resources and transaction costs: how property rights economics furthers the resource-based view. *Strategic Management Journal*, *26*(6), 541–553. http://doi.org/10.1002/smj.465

Fransoo, J. C., & Lee, C. (2013). The critical role of ocean container transport in global supply chain performance. *Production and Operations Management*, *22*(2), 253–268.

Fratocchi, L., Di Mauro, C., Barbieri, P., Nassimbeni, G., & Zanoni, A. (2014). When manufacturing moves back: Concepts and questions. *Journal of Purchasing and Supply Management*, *20*(1), 54–59.

Fu, F. Q., Jones, E., & Bolander, W. (2008). Product innovativeness, customer newness, and new product performance: a time-lagged examination of the impact of salesperson selling intentions on new product performance. *Journal of Personal Selling and Sales Management*, *28*(4), 351–364.

Fugate, B. S., Mentzer, J. T., & Stank, T. P. (2010). Logistics performance: efficiency, effectiveness, and differentiation. *Journal of Business Logistics*, *31*(1), 43–62.

Garcia, R., & Calantone, R. (2002). A critical look at technological innovation typology and innovativeness terminology: a literature review. *Journal of Product Innovation Management*, *19*(2), 110–132.

Gatignon, H., & Anderson, E. (1988). The multinational corporation's degree of control over foreign subsidiaries: An empirical test of a transaction cost explanation. *Journal of Law, Economics, & Organization*, 305–336.

Gereffi, G., & Lee, J. (2012). Why the world suddenly cares about global supply chains. *Journal of Supply Chain Management*, *48*(3), 24–32.

Geyskens, I., Steenkamp, J.-B. E., & Kumar, N. (2006). Make, buy, or ally: a transaction cost theory meta-analysis. *Academy of Management Journal*, *49*(3), 519–543.

Gianopoulos, K. M. (2015). Initial Disclosures Indicate Most Companies Were Unable to Determine the Source of Their Conflict Minerals. *GAO Reports*, 1.

Grappi, S., Romani, S., & Bagozzi, R. P. (2015). Consumer stakeholder responses to reshoring strategies. *Journal of the Academy of Marketing Science*, 1–19.

Gray, J. V., Roth, A. V., & Leiblein, M. J. (2011). Quality risk in offshore manufacturing: Evidence from the pharmaceutical industry. *Journal of Operations Management*, *29*(7), 737–752.

Gray, J. V., Skowronski, K., Esenduran, G., & Rungtusanatham, M. J. (2013). The Reshoring Phenomenon: What Supply Chain Academics Ought to know and Should Do. *Journal of Supply Chain Management*, *49*(2), 27–33. http://doi.org/10.1111/jscm.12012

Gunasekaran, A., Patel, C., & Tirtiroglu, E. (2001). Performance measures and metrics in a supply chain environment. *International Journal of Operations & Production Management*, *21*(1/2), 71–87.

Gylling, M., Heikkilä, J., Jussila, K., & Saarinen, M. (2015). Making decisions on offshore outsourcing and backshoring: A case study in the bicycle industry. *International Journal of Production Economics*, *162*, 92–100.

Hair, J. F., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling (PLS-SEM)* (2nd ed.). Sage Publications.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice*, *19*(2), 139–152.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2012). Editorial-Partial Least Squares: The Better Approach to Structural Equation Modeling? *Long Range Planning*, *45*(5–6), 312–319.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2013). Editorial-partial least squares structural equation modeling: Rigorous applications, better results and higher acceptance. *Long Range Planning*, *46*(1–2), 1–12.

Hair, J. F., Sarstedt, M., Pieper, T. M., & Ringle, C. M. (2012). The use of partial least squares structural equation modeling in strategic management research: a review of past practices and recommendations for future applications. *Long Range Planning*, *45*(5), 320–340.

Hair, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2012). An assessment of the use of partial least squares structural equation modeling in marketing research. *Journal of the Academy of Marketing Science*, *40*(3), 414–433.

Handley, S. M., & Benton, W. C. (2009). Unlocking the business outsourcing process model. *Journal of Operations Management*, *27*(5), 344–361.

Handley, S. M., & W. C., Benton. (2013). The influence of task-and location-specific complexity on the control and coordination costs in global outsourcing relationships. *Journal of Operations Management*, *31*(3), 109–128.

Hanlon, M., Lester, R., & Verdi, R. (2015). The effect of repatriation tax costs on US multinational investment. *Journal of Financial Economics*, *116*(1), 179–196.

Harland, C., Brenchley, R., & Walker, H. (2003). Risk in supply networks. *Journal of Purchasing and Supply Management*, *9*(2), 51–62.

Harrington, L. (2011). Is US Manufacturing Coming Back? *Inbound Logistics*, *31*(8).

Harris, K., de Carbonnel, G., & Bauman, K. (2014). Countdown to Conflict Minerals Reporting. *Supply Chain Management Review*, *18*(1), 42–49.

Hassini, E., Surti, C., & Searcy, C. (2012). A literature review and a case study of sustainable supply chains with a focus on metrics. *International Journal of Production Economics*, *140*(1), 69–82.

Hausman, W. H., Lee, H. L., & Subramanian, U. (2013). The impact of logistics performance on trade. *Production and Operations Management*, *22*(2), 236–252.

Hendricks, K. B., & Singhal, V. R. (2003). The effect of supply chain glitches on shareholder wealth. *Journal of Operations Management*, *21*(5), 501–522.

Hendricks, K. B., & Singhal, V. R. (2005a). An empirical analysis of the effect of supply chain disruptions on long-run stock price performance and equity risk of the firm. *Production and Operations Management*, *14*(1), 35–52.

Hendricks, K. B., & Singhal, V. R. (2005b). Association between supply chain glitches and operating performance. *Management Science*, *51*(5), 695–711.

Hendricks, K. B., & Singhal, V. R. (2008). The effect of product introduction delays on operating performance. *Management Science*, *54*(5), 878–892.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135.

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. *Advances in International Marketing*, *20*(1), 277–319.

Holcomb, T. R., & Hitt, M. A. (2007). Toward a model of strategic outsourcing. *Journal of Operations Management*, *25*(2), 464–481.

Homburg, C., Fürst, A., & Kuehnl, C. (2012). Ensuring international competitiveness: a configurative approach to foreign marketing subsidiaries. *Journal of the Academy of Marketing Science*, *40*(2), 290–312.

Huang, Y.-T., & Chu, W. (2010). Enhancement of product development capabilities of OEM suppliers: inter-and intra-organisational learning. *Journal of Business & Industrial Marketing*, *25*(2), 147–158.

Hult, G. T. M. (2012). A focus on international competitiveness. *Journal of the Academy of Marketing Science*, *40*(2), 195–201.

Hult, G. T. M., Hurley, R. F., & Knight, G. A. (2004). Innovativeness: Its antecedents and impact on business performance. *Industrial Marketing Management*, *33*(5), 429–438.

Hummels, D. (2007). Transportation costs and international trade in the second era of globalization. *The Journal of Economic Perspectives*, 131–154.

Hunt, S. D., & Morgan, R. M. (1995). The comparative advantage theory of competition. *The Journal of Marketing*, 1–15.

Hunt, S. D., & Morgan, R. M. (1996). The resource-advantage theory of competition: dynamics, path dependencies, and evolutionary dimensions. *The Journal of Marketing*, 107–114.

Jacobs, B. W., Swink, M., & Linderman, K. (2015). Performance effects of early and late Six Sigma adoptions. *Journal of Operations Management*, *36*, 244–257.

Joskow, P. L. (1988). Asset specificity and the structure of vertical relationships: empirical evidence. *Journal of Law, Economics, & Organization*, 95–117.

Kannan, V. R., & Tan, K. C. (2005). Just in time, total quality management, and supply chain management: understanding their linkages and impact on business performance. *Omega*, *33*(2), 153–162.

Kaufmann, D., Kraay, A., & Mastruzzi, M. (2009). Governance matters VIII: aggregate and individual governance indicators, 1996-2008. *World Bank Policy Research Working Paper*, (4978).

Kelley, L. (2014a). LyondellBasell lifts FM on acetic acid. *ICIS Chemical Business*, *286*(4), 19–19.

Kelley, L. (2014b). LyondellBasell’s high percentage of US force majeures. *ICIS Chemical Business*, *285*(24), 16–16.

Kinkel, S. (2014). Future and impact of backshoring—Some conclusions from 15 years of research on German practices. *Journal of Purchasing and Supply Management*, *20*(1), 63–65.

Kinkel, S., & Maloca, S. (2009). Drivers and antecedents of manufacturing offshoring and backshoring—A German perspective. *Journal of Purchasing and Supply Management*, *15*(3), 154–165.

Kinney, M. R., & Wempe, W. F. (2002). Further evidence on the extent and origins of JIT’s profitability effects. *The Accounting Review*, *77*(1), 203–225.

Klein, S. (1989). A transaction cost explanation of vertical control in international markets. *Journal of the Academy of Marketing Science*, *17*(3), 253–260.

Klein, S., Frazier, G. L., & Roth, V. J. (1990). A transaction cost analysis model of channel integration in international markets. *Journal of Marketing Research*, 196–208.

Knowler, G. (2014). Falling bunker price gets industry talking about speeding up ships. *JoC Online*, 1–1.

Kotabe, M. (1990). The relationship between offshore sourcing and innovativeness of US multinational firms: an empirical investigation. *Journal of International Business Studies*, 623–638.

Kotabe, M., & Murray, J. Y. (2004). Global sourcing strategy and sustainable competitive advantage. *Industrial Marketing Management*, *33*(1), 7–14. http://doi.org/10.1016/j.indmarman.2003.08.004

Kotha, S., & Srikanth, K. (2013). Managing a global partnership model: Lessons from the Boeing 787 "Dreamliner" program. *Global Strategy Journal*, *3*(1), 41–66.

Kozlenkova, I. V., Samaha, S. A., & Palmatier, R. W. (2014). Resource-based theory in marketing. *Journal of the Academy of Marketing Science*, *42*(1), 1–21.

Lall, S. (2001). Competitiveness indices and developing countries: an economic evaluation of the global competitiveness report. *World Development*, *29*(9), 1501–1525.

Lapierre, J. (2000). Customer-perceived value in industrial contexts. *Journal of Business & Industrial Marketing*, *15*(2/3), 122–145.

Larsen, M. M., Manning, S., & Pedersen, T. (2013). Uncovering the hidden costs of offshoring: The interplay of complexity, organizational design, and experience. *Strategic Management Journal*, *34*(5), 533–552.

Lau, A. K., Tang, E., & Yam, R. (2010). Effects of supplier and customer integration on product innovation and performance: empirical evidence in Hong Kong manufacturers. *Journal of Product Innovation Management*, *27*(5), 761–777.

Lee, C.-Y., Lee, H. L., & Zhang, J. (2015). The impact of slow ocean steaming on delivery reliability and fuel consumption. *Transportation Research Part E: Logistics and Transportation Review*, *76*, 176–190. http://doi.org/10.1016/j.tre.2015.02.004

Leiblein, M. J. (2003). The choice of organizational governance form and performance: Predictions from transaction cost, resource-based, and real options theories. *Journal of Management*, *29*(6), 937–961.

Li, Y., Wei, Z., & Liu, Y. (2010). Strategic Orientations, Knowledge Acquisition, and Firm Performance: The Perspective of the Vendor in Cross-Border Outsourcing. *Journal of Management Studies*, *47*(8), 1457–1482.

Liu, Y., Li, Y., Tao, L., & Wang, Y. (2008). Relationship stability, trust and relational risk in marketing channels: Evidence from China. *Industrial Marketing Management*, *37*(4), 432–446.

Liu, Y., Su, C., Li, Y., & Liu, T. (2010). Managing opportunism in a developing interfirm relationship: The interrelationship of calculative and loyalty commitment. *Industrial Marketing Management*, *39*(5), 844–852.

Luo, M., Fan, L., & Liu, L. (2009). An econometric analysis for container shipping market. *Maritime Policy & Management*, *36*(6), 507–523.

Macdonald, J. R., & Corsi, T. M. (2013). Supply chain disruption management: severe events, recovery, and performance. *Journal of Business Logistics*, *34*(4), 270–288.

Madalin, M. S. (2015). The Economic And Social Coordinates Of Developing A Sport Entrepreneurship Index–Current Challenges And Prerequisites. *Annals-Economy Series*, *3*, 224–229.

Makadok, R. (2001). Toward a synthesis of the resource-based and dynamic-capability views of rent creation. *Strategic Management Journal*, *22*(5), 387–401.

Mallik, S. (2010). Customer service in supply chain management. *The Handbook of Technology Management: Supply Chain Management, Marketing and Advertising, and Global Management*, *2*, 103–119.

Mann, C. L. (2012). Supply chain logistics, trade facilitation and international trade: A macroeconomic policy view. *Journal of Supply Chain Management*, *48*(3), 7–14.

Manuj, I., Esper, T. L., & Stank, T. P. (2014). Supply Chain Risk Management Approaches Under Different Conditions of Risk. *Journal of Business Logistics*, *35*(3), 241–258.

Manuj, I., & Mentzer, J. T. (2008a). Global supply chain risk management. *Journal of Business Logistics*, *29*(1), 133–155.

Manuj, I., & Mentzer, J. T. (2008b). Global supply chain risk management strategies. *International Journal of Physical Distribution & Logistics Management*, *38*(3), 192–223.

Markman, G. D., Gianiodis, P. T., & Buchholtz, A. K. (2009). Factor-market rivalry. *Academy of Management Review*, *34*(3), 423–441.

Marshall, V. B. (2012). Two Essays on the Degree of Globalization of a Firm: Measurement, Antecedents, and Consequences. *Dissertations, Theses and Capstone Projects*, Paper 536. http://doi.org/digitalcommons.kennesaw.edu.proxy.kennesaw.edu/etd/536

Martínez-Mora, C., & Merino, F. (2014). Offshoring in the Spanish footwear industry: A return journey? *Journal of Purchasing and Supply Management*, *20*(4), 225–237. http://doi.org/10.1016/j.pursup.2014.07.001

McCalman, P., & Spearot, A. (2013). Why trucks jump: Offshoring and product characteristics. *Journal of International Economics*, *91*(1), 82–95.

McIvor, R. (2009). How the transaction cost and resource-based theories of the firm inform outsourcing evaluation. *Journal of Operations Management*, *27*(1), 45–63.

McIvor, R. (2013). Understanding the Manufacturing Location Decision: The Case for the Transaction Cost and Capability Perspectives. *Journal of Supply Chain Management*, *49*(2), 23–26. http://doi.org/10.1111/jscm.12010

McMeekin, B., & McMackin, E. (2012). *Reshoring US Manufacturing: A Wave of the Present. Business Climate, viewed 08 March 2013*.

Mentzer, J. T., DeWitt, W., Keebler, J. S., Min, S., Nix, N. W., Smith, C. D., & Zacharia, Z. G. (2001). Defining supply chain management. *Journal of Business Logistics*, *22*(2), 1–25.

Miller, K. D. (1992). A framework for integrated risk management in international business. *Journal of International Business Studies*, 311–331.

Miller, K. D., & Bromiley, P. (1990). Strategic Risk and Corporate Performance: An Analysis of Alternative Risk Measures. *The Academy of Management Journal*, *33*(4), 756–779. http://doi.org/10.2307/256289

Min, H., LaTour, M. S., & Williams, A. (1994). Positioning against foreign supply sources in an international purchasing environment. *Industrial Marketing Management*, *23*(5), 371–382. http://doi.org/10.1016/0019-8501(94)90002-7

Minter, S. (2009). Offshoring by US companies doubles. *Industry Week*, *19*.

Mol, M. J., Pauwels, P., Matthyssens, P., & Quintens, L. (2004). A technological contingency perspective on the depth and scope of international outsourcing. *Journal of International Management*, *10*(2), 287–305.

Mol, M. J., van Tulder, R. J. M., & Beije, P. R. (2005). Antecedents and performance consequences of international outsourcing. *International Business Review*, *14*(5), 599–617. http://doi.org/10.1016/j.ibusrev.2005.05.004

Mooi, E. A., & Ghosh, M. (2010). Contract specificity and its performance implications. *Journal of Marketing*, *74*(2), 105–120.

Moser, H. (2011). Time to come home. *Supply Chain Quarterly*, *4*, 28–31.

Moser, H. (2012). Total Cost of Ownership Calculation-A key to bringing more manufacturing back to the USA. *Wire and Cable Technology International*, *40*(1), 62.

Nath, P., Nachiappan, S., & Ramanathan, R. (2010). The impact of marketing capability, operations capability and diversification strategy on performance: A resource-based view. *Industrial Marketing Management*, *39*(2), 317–329. http://doi.org/10.1016/j.indmarman.2008.09.001

Neves, L. W. de A., Hamacher, S., & Scavarda, L. F. (2014). Outsourcing from the perspectives of TCE and RBV: a multiple case study. *Production*, *24*(3), 687–699.

Nordås, H. K., Pinali, E., & Grosso, M. G. (2006). *Logistics and Time as a Trade Barrier*. OECD Publishing.

Notteboom, T., & Cariou, P. (2013). Slow steaming in container liner shipping: is there any impact on fuel surcharge practices? *International Journal of Logistics Management*, *24*(1), 73–86.

Pagano, A. (2009). The role of relational capabilities in the organization of international sourcing activities: A literature review. *Industrial Marketing Management*, *38*(8), 903–913.

Paladino, A. (2007). Investigating the Drivers of Innovation and New Product Success: A Comparison of Strategic Orientations*. *Journal of Product Innovation Management*, *24*(6), 534–553.

Peng, M. W. (2001). The resource-based view and international business. *Journal of Management*, *27*(6), 803–829.

Penrose, E. T. (1959). The Theory of the Growth of the Firm. *ME Sharpe, New York*.

Pereira, G. M., Sellitto, M. A., Borchardt, M., & Geiger, A. (2011). Procurement cost reduction for customized non-critical items in an automotive supply chain: An action research project. *Industrial Marketing Management*, *40*(1), 28–35.

Peteraf, M. A. (1993). The cornerstones of competitive advantage: A resource-based view. *Strategic Management Journal*, *14*(3), 179–191.

Pisano, G. P., & Shih, W. C. (2012). Does America really need manufacturing? *Harvard Business Review*, *90*(3), 94–+.

Platts, K. W., & Song, N. (2010). Overseas sourcing decisions-the total cost of sourcing from China. *Supply Chain Management: An International Journal*, *15*(4), 320–331.

Poppo, L., & Zenger, T. (1998). Testing alternative theories of the firm: transaction cost, knowledge-based, and measurement explanations for make-or-buy decisions in information services. *Strategic Management Journal*, *19*(9), 853–877.

Porter, M. E. (2008). The five competitive forces that shape strategy. *Harvard Business Review*, *86*(1), 25–40.

Porter, M. E., Delgado, M., Ketels, C., & Stern, S. (2008). Moving to a new global competitiveness index. *The Global Competitiveness Report*, *2009*, 43–63.

Prior, D. D. (2012). The effects of buyer-supplier relationships on buyer competitiveness. *Journal of Business & Industrial Marketing*, *27*(2), 100–114.

Rabinovich, E., & Cheon, S. (2011). Expanding horizons and deepening understanding via the use of secondary data sources. *Journal of Business Logistics*, *32*(4), 303–316.

Ramzy, A. (2013). Precious Holdings. *Time*, *181*(6), 10.

Reed, R., & DeFillippi, R. J. (1990). Causal ambiguity, barriers to imitation, and sustainable competitive advantage. *Academy of Management Review*, *15*(1), 88–102.

Rein, S., & Roy, J. (2012). The End of Cheap China. *The Economist Review*.

Reshoring Initiative Data Report: Reshoring and FDI Boost US Manufacturing in 2014. (2015). Retrieved January 28, 2016, from http://www.reshorenow.org/recent-data/

Revilla, E., & Sáenz, M. J. (2014). Supply chain disruption management: Global convergence vs national specificity. *Journal of Business Research*, *67*(6), 1123–1135.

Rigdon, E. E., Ringle, C. M., & Sarstedt, M. (2010). Structural modeling of heterogeneous data with partial least squares. *Review of Marketing Research*, *7*(7), 255–296.

Ringle, C. M., Wende, S., & Becker, J.-M. (2015). SmartPLS 3. Bönningstedt: SmartPLS. Retrieved May 27, 2016, from https://www.smartpls.com

Ritchie, B., & Brindley, C. (2007). Supply chain risk management and performance: A guiding framework for future development. *International Journal of Operations & Production Management*, *27*(3), 303–322.

Ritter, T., & Walter, A. (2012). More is not always better: The impact of relationship functions on customer-perceived relationship value. *Industrial Marketing Management*, *41*(1), 136–144.

Rugman, A. M., Oh, C. H., & Lim, D. S. (2012). The regional and global competitiveness of multinational firms. *Journal of the Academy of Marketing Science*, *40*(2), 218–235.

Rugman, A. M., & Verbeke, A. (2004). A perspective on regional and global strategies of multinational enterprises. *Journal of International Business Studies*, *35*(1), 3–18.

Sanders, N. R., Locke, A., Moore, C. B., & Autry, C. W. (2007). A multidimensional framework for understanding outsourcing arrangements. *Journal of Supply Chain Management*, *43*(4), 3–15.

Scheer, L. K., Miao, C. F., & Garrett, J. (2010). The effects of supplier capabilities on industrial customers' loyalty: the role of dependence. *Journal of the Academy of Marketing Science*, *38*(1), 90–104.

Schmeisser, B. (2013). A systematic review of literature on offshoring of value chain activities. *Journal of International Management*, *19*(4), 390–406.

Schoenherr, T., Rao Tummala, V. M., & Harrison, T. P. (2008). Assessing supply chain risks with the analytic hierarchy process: providing decision support for the offshoring decision by a US manufacturing company. *Journal of Purchasing and Supply Management*, *14*(2), 100–111.

Schwab, K. (2012). World Economic Forum.(2012). *The Global Competitiveness Report 2012-2013*.

Serra, A. P. (2004). Event study tests: a brief survey. *Gestão. Org-Revista Electrónica de Gestão Organizacional*, *2*(3), 248–255.

Seuring, S., & Gold, S. (2013). Sustainability management beyond corporate boundaries: from stakeholders to performance. *Journal of Cleaner Production*, *56*, 1–6.

Seuring, S., & Müller, M. (2008). From a literature review to a conceptual framework for sustainable supply chain management. *Journal of Cleaner Production*, *16*(15), 1699–1710.

Shafer, S. M., & Moeller, S. B. (2012). The effects of Six Sigma on corporate performance: An empirical investigation. *Journal of Operations Management*, *30*(7), 521–532.

Sharma, D. S. (2005). The association between ISO 9000 certification and financial performance. *The International Journal of Accounting*, *40*(2), 151–172.

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

Shelanski, H. A., & Klein, P. G. (1995). Empirical research in transaction cost economics: a review and assessment. *Journal of Law, Economics, & Organization*, 335–361.

Shih, W. C. (2014). What it takes to reshore manufacturing successfully. *Sloan Management Review*.

Shook, C. L., Adams, G. L., Ketchen Jr, D. J., & Craighead, C. W. (2009). Towards a “theoretical toolbox” for strategic sourcing. *Supply Chain Management: An International Journal*, *14*(1), 3–10.

Sichtmann, C., & Diamantopoulos, A. (2013). The impact of perceived brand globalness, brand origin image, and brand origin–extension fit on brand extension success. *Journal of the Academy of Marketing Science*, *41*(5), 567–585.

Sirkin, H. (2011). Is US Manufacturing Making a Comeback? *Harvard Business Review*.

Slepniov, D., Wæhrens, B. V., & Johansen, J. (2014). Dynamic roles and locations of manufacturing: imperatives of alignment and coordination with innovation. *Journal of Manufacturing Technology Management*, *25*(2), 198–217.

Smith, J. M. (1999). Item selection for global purchasing. *European Journal of Purchasing & Supply Management*, *5*(3), 117–127.

Song, D. P., & Dong, J. X. (2013). Long-haul liner service route design with ship deployment and empty container repositioning. *Transportation Research: Part B*, *55*, 188–211.

Song, N., Platts, K. W., & Bance, D. (2007). Total acquisition cost of overseas outsourcing/sourcing: a framework and a case study. *Journal of Manufacturing Technology Management*, *18*(7), 858–875.

Song, X. M., & Parry, M. E. (1999). Challenges of managing the development of breakthrough products in Japan. *Journal of Operations Management*, *17*(6), 665–688.

Spekman, R. E., & Davis, E. W. (2004). Risky business: expanding the discussion on risk and the extended enterprise. *International Journal of Physical Distribution & Logistics Management*, *34*(5), 414–433.

Steenkamp, J.-B. E., & Geyskens, I. (2012). Transaction cost economics and the roles of national culture: a test of hypotheses based on Inglehart and Hofstede. *Journal of the Academy of Marketing Science*, *40*(2), 252–270.

Stock, J. R., & Lambert, D. M. (2001). *Strategic logistics management* (Vol. 4). McGraw-Hill/Irwin Boston, MA.

Swink, M., & Jacobs, B. W. (2012). Six Sigma adoption: operating performance impacts and contextual drivers of success. *Journal of Operations Management*, *30*(6), 437–453.

Sydow, J., & Frenkel, S. J. (2013). Labor, Risk, and Uncertainty in Global Supply Networks—Exploratory Insights. *Journal of Business Logistics*, *34*(3), 236–247.

Talluri, S. S., Kull, T. J., Yildiz, H., & Yoon, J. (2013). Assessing the efficiency of risk mitigation strategies in supply chains. *Journal of Business Logistics*, *34*(4), 253–269.

Tang, C. S., Zimmerman, J. D., & Nelson, J. I. (2009). Managing new product development and supply chain risks: The Boeing 787 case. *Supply Chain Forum: An International Journal*, *10*, 74–86.

Tang, O., & Musa, S. N. (2011). Identifying risk issues and research advancements in supply chain risk management. *Leading Edge of Inventory Research*, *133*(1), 25–34. http://doi.org/10.1016/j.ijpe.2010.06.013

Tate, W. L. (2014). Offshoring and reshoring: US insights and research challenges. *Journal of Purchasing and Supply Management*, *20*(1), 66–68.

Tate, W. L., & Ellram, L. M. (2009). Offshore outsourcing: a managerial framework. *Journal of Business & Industrial Marketing*, *24*(3/4), 256–268.

Tate, W. L., Ellram, L. M., & Kirchoff, J. F. (2010). Corporate social responsibility reports: a thematic analysis related to supply chain management. *Journal of Supply Chain Management*, *46*(1), 19–44.

Tate, W. L., Ellram, L. M., Schoenherr, T., & Petersen, K. J. (2014). Global competitive conditions driving the manufacturing location decision. *Business Horizons*.

Teece, D. J. (1986). Transactions cost economics and the multinational enterprise An Assessment. *Journal of Economic Behavior & Organization*, *7*(1), 21–45.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, *18*(7), 509–533.

Tenenhaus, M., Vinzi, V. E., Chatelin, Y.-M., & Lauro, C. (2005). PLS path modeling. *Computational Statistics & Data Analysis*, *48*(1), 159–205.

Thornton, L. M., Autry, C. W., Gligor, D. M., & Brik, A. B. (2013). Does Socially Responsible Supplier Selection Pay Off for Customer Firms? A Cross-Cultural Comparison. *Journal of Supply Chain Management*, *49*(3), 66–89.

Tummala, R., & Schoenherr, T. (2011). Assessing and managing risks using the supply chain risk management process (SCRMP). *Supply Chain Management: An International Journal*, *16*(6), 474–483.

Ulaga, W., & Chacour, S. (2001). Measuring customer-perceived value in business markets: a prerequisite for marketing strategy development and implementation. *Industrial Marketing Management*, *30*(6), 525–540.

Ulaga, W., & Eggert, A. (2005). Relationship value in business markets: the construct and its dimensions. *Journal of Business-to-Business Marketing*, *12*(1), 73–99.

Ulaga, W., & Eggert, A. (2006). Value-based differentiation in business relationships: gaining and sustaining key supplier status. *Journal of Marketing*, *70*(1), 119–136.

Van den Bossche, P. (2014). Six Driving Forces in Manufacturing. *Supply Chain Management Review*, *18*(1), 50–51.

van Hoek, R. I. (2001). The rediscovery of postponement a literature review and directions for research. *Journal of Operations Management*, *19*(2), 161–184.

Wagner, S. M. (2010). Supplier traits for better customer firm innovation performance. *Industrial Marketing Management*, *39*(7), 1139–1149.

Wagner, S. M., & Bode, C. (2006). An empirical investigation into supply chain vulnerability. *Conference 2006, the Fourth Worldwide Symposium in Purchasing & Supply Chain Management*, *12*(6), 301–312. http://doi.org/10.1016/j.pursup.2007.01.004

Walker, G., & Weber, D. (1984). A transaction cost approach to make-or-buy decisions. *Administrative Science Quarterly*, 373–391.

Walker, G., & Weber, D. (1987). Supplier competition, uncertainty, and make-or-buy decisions. *Academy of Management Journal*, *30*(3), 589–596.

Walker, H., Huq, F. A., Stevenson, M., & Zorzini, M. (2014). Social sustainability in developing country suppliers: An exploratory study in the ready made garments industry of Bangladesh. *International Journal of Operations & Production Management*, *34*(5), 610–638.

Waller, M. A., & Fawcett, S. E. (2012). The total cost concept of logistics: one of many fundamental logistics concepts begging for answers. *Journal of Business Logistics*, *33*(1), 1–3.

Walter, A., Müller, T. A., Helfert, G., & Ritter, T. (2003). Functions of industrial supplier relationships and their impact on relationship quality. *Industrial Marketing Management*, *32*(2), 159–169.

Weber, L., & Mayer, K. (2014). Transaction cost economics and the cognitive perspective: Investigating the sources and governance of interpretive uncertainty. *Academy of Management Review*, *39*(3), 344–363.

Weddle, N. (2015). Unprecedented number of FMs hitting European crackers. *ICIS Chemical Business*, (3661), 8–8.

Wernerfelt, B. (1984). A resource-based view of the firm. *Strategic Management Journal*, *5*(2), 171–180.

Wernerfelt, B. (2014). On the role of the RBV in marketing. *Journal of the Academy of Marketing Science*, *42*(1), 22–23.

Wilcoxon, F. (1945). Individual comparisons by ranking methods. *Biometrics Bulletin*, 80–83.

Williamson, O. E. (1975). Markets and hierarchies. *New York*, 26–30.

Williamson, O. E. (1981). The economics of organization: The transaction cost approach. *American Journal of Sociology*, 548–577.

Williamson, O. E. (1985). *The Economic Institutions of Capitalism*. Simon and Schuster.

Williamson, O. E. (1991). Comparative economic organization: The analysis of discrete structural alternatives. *Administrative Science Quarterly*, 269–296.

Williamson, O. E. (2008). Outsourcing: Transaction Cost Economics and Supply Chain Management*. *Journal of Supply Chain Management*, *44*(2), 5–16.

Wu, X., & Zhang, F. (2014). Home or Overseas? An analysis of sourcing strategies under competition. *Management Science*.

Zeng, A. Z., & Rossetti, C. (2003). Developing a framework for evaluating the logistics costs in global sourcing processes: an implementation and insights. *International Journal of Physical Distribution & Logistics Management*, *33*(9), 785–803.

Zsidisin, G. A., & Ellram, L. M. (2003). An Agency Theory Investigation of Supply Risk Management. *Journal of Supply Chain Management*, *39*(2), 15–27.

Zsidisin, G. A., Ellram, L. M., Carter, J. R., & Cavinato, J. L. (2004). An analysis of supply risk assessment techniques. *International Journal of Physical Distribution & Logistics Management*, *34*(5), 397–413.

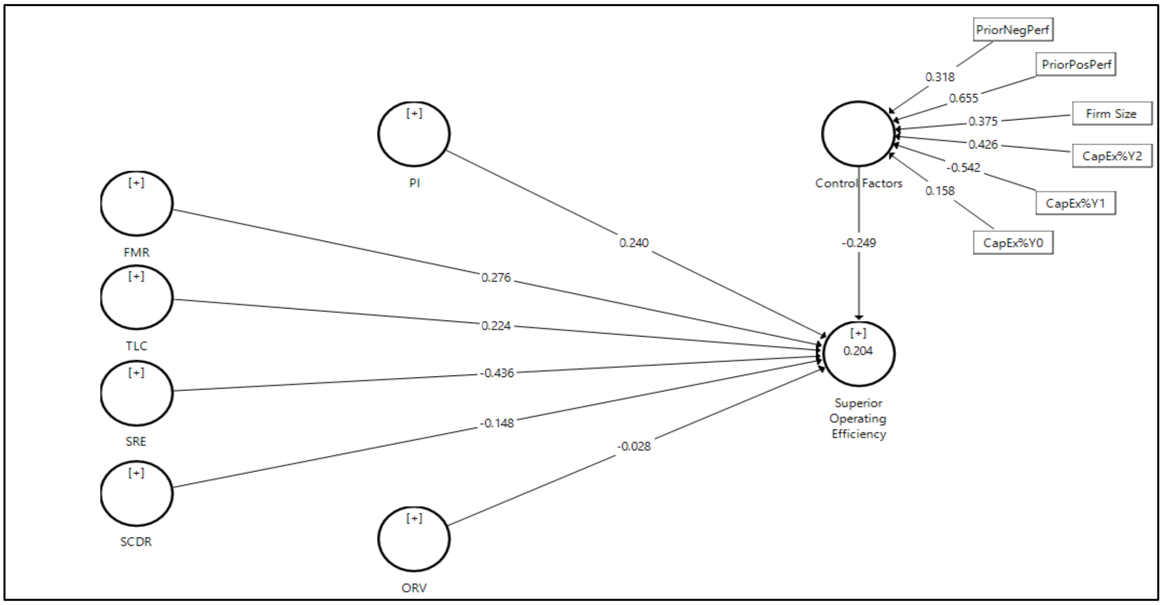
Zsidisin, G. A., Panelli, A., & Upton, R. (2000). Purchasing organization involvement in risk assessments, contingency plans, and risk management: an exploratory study. *Supply Chain Management: An International Journal*, *5*(4), 187–198.

APPENDICES

APPENDIX A – SUPERIOR OPERATING EFFICIENCY MPI MATCHING GROUP

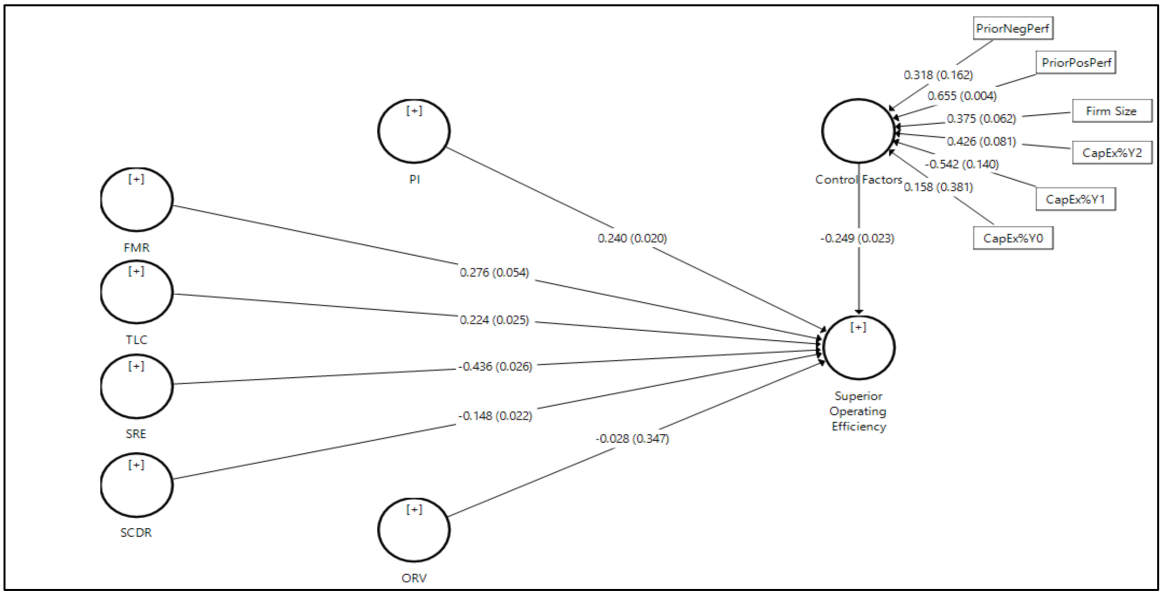
A.1 Path Modeling and Bootstrapping for Structural Model 1

Figure 11: Path Coefficients and R^2 of Model 1 for MPI Matching Group



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Operating Efficiency.

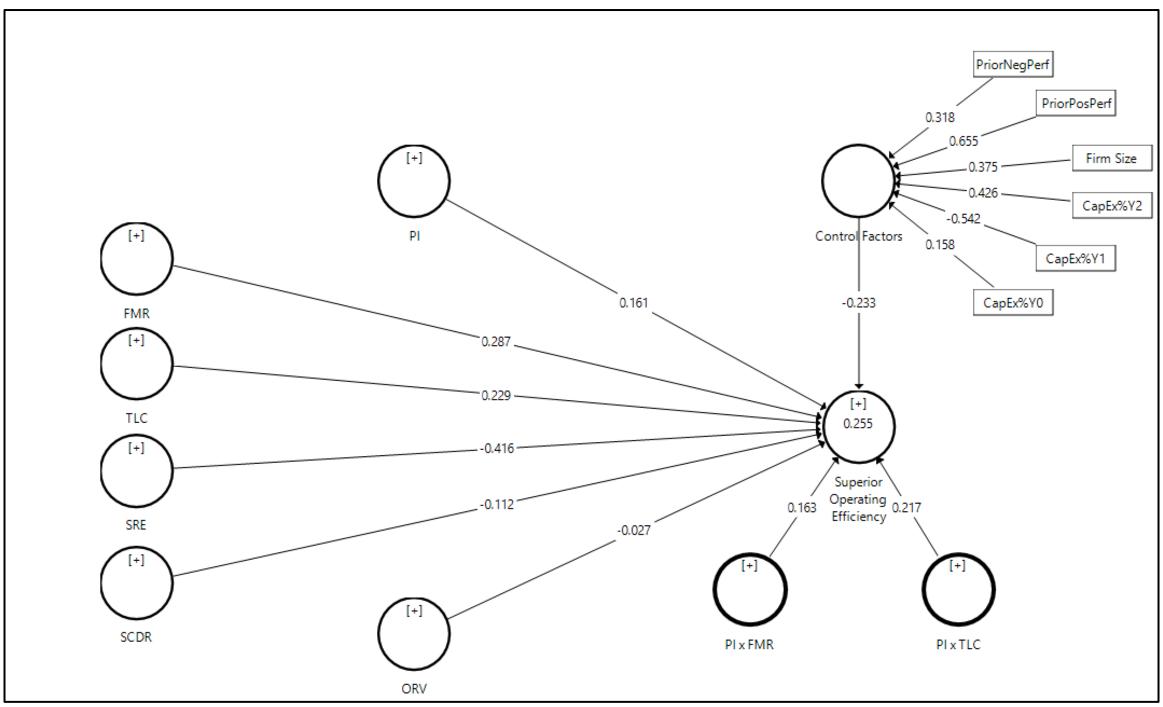
Figure 12: Path Coefficients and p-Values of Model 1 for MPI Group



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Operating Efficiency.

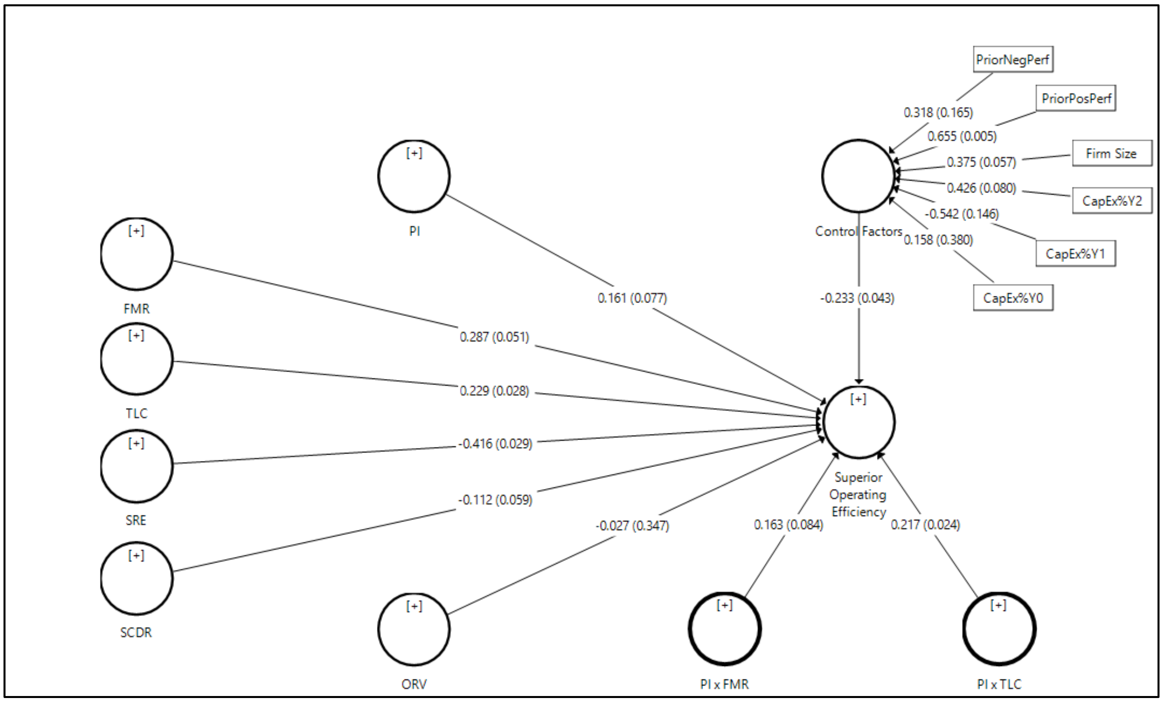
A.2 Path Modeling and Bootstrapping for Structural Model 2

Figure 13: Path Coefficients and R^2 of Model 2 for MPI Group



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Operating Efficiency.

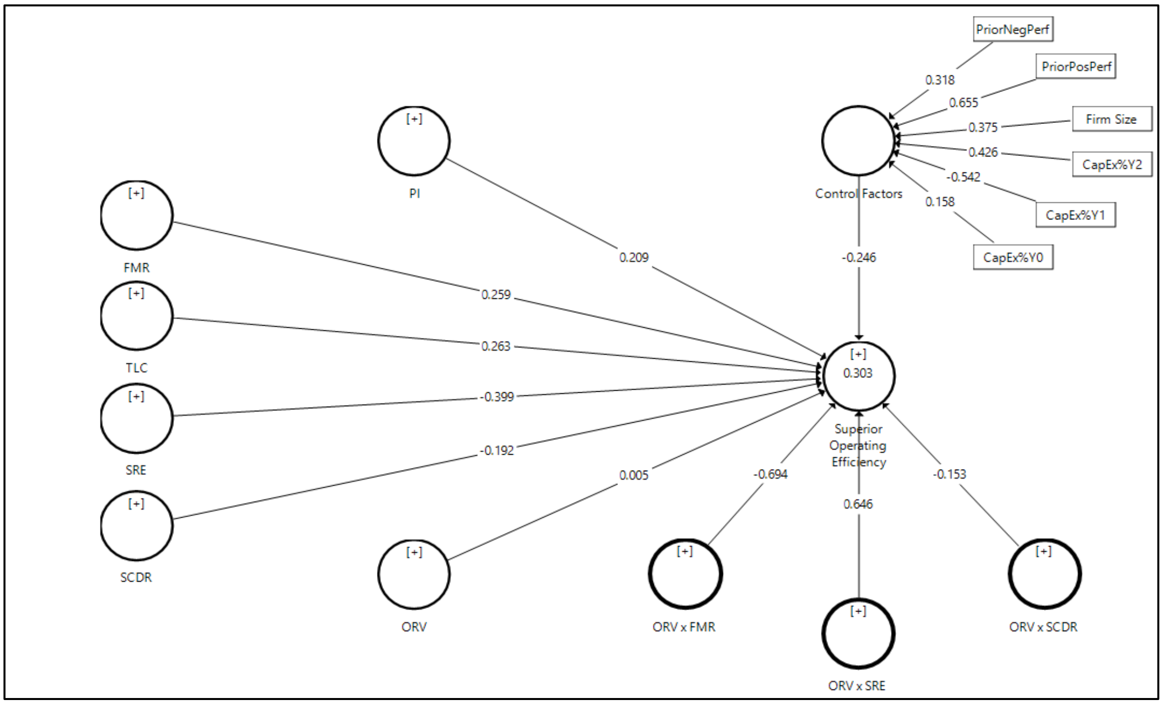
Figure 14: Path Coefficients and p-Values of Model 2 for MPI Group



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Operating Efficiency.

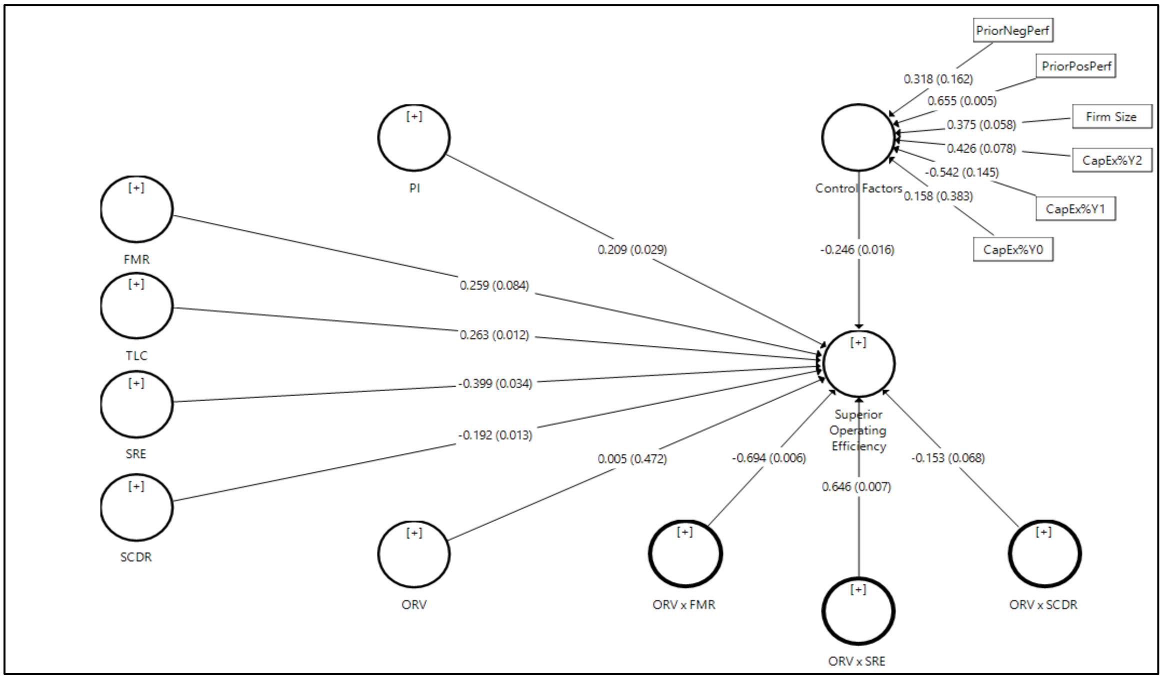
A.3 Path Modeling and Bootstrapping for Structural Model 3

Figure 15: Path Coefficients and R^2 of Model 3 for MPI Group



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Operating Efficiency.

Figure 16: Path Coefficients and p-Values of Model 3 for MPI Group

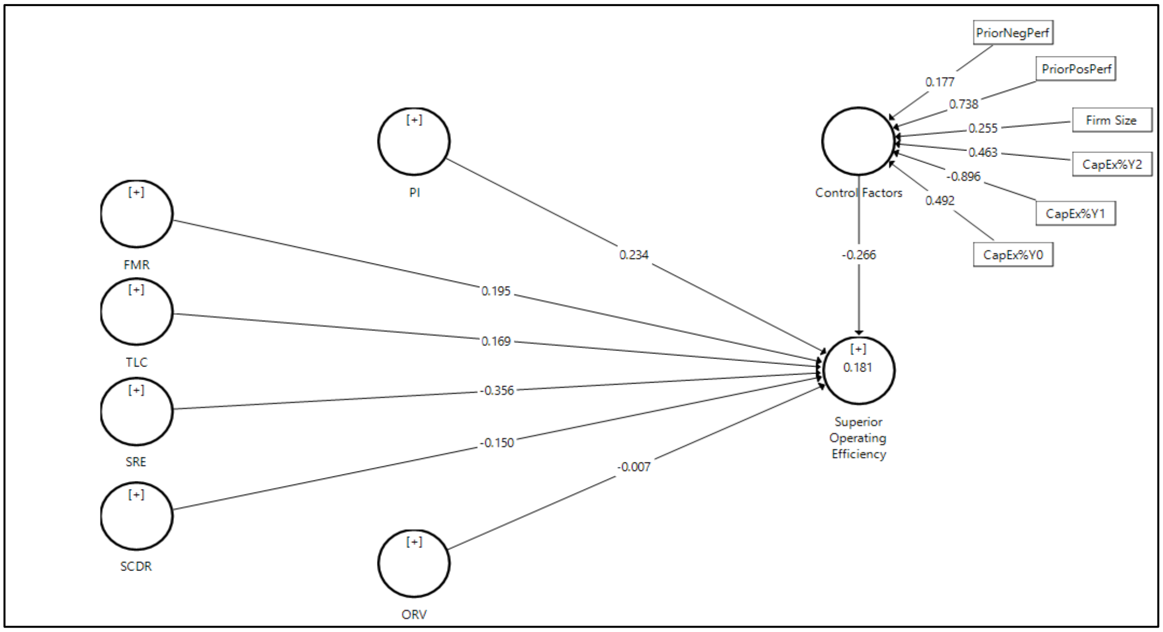


Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Operating Efficiency.

APPENDIX B – SUPERIOR OPERATING EFFICIENCY RELATIVE TO PI GROUP

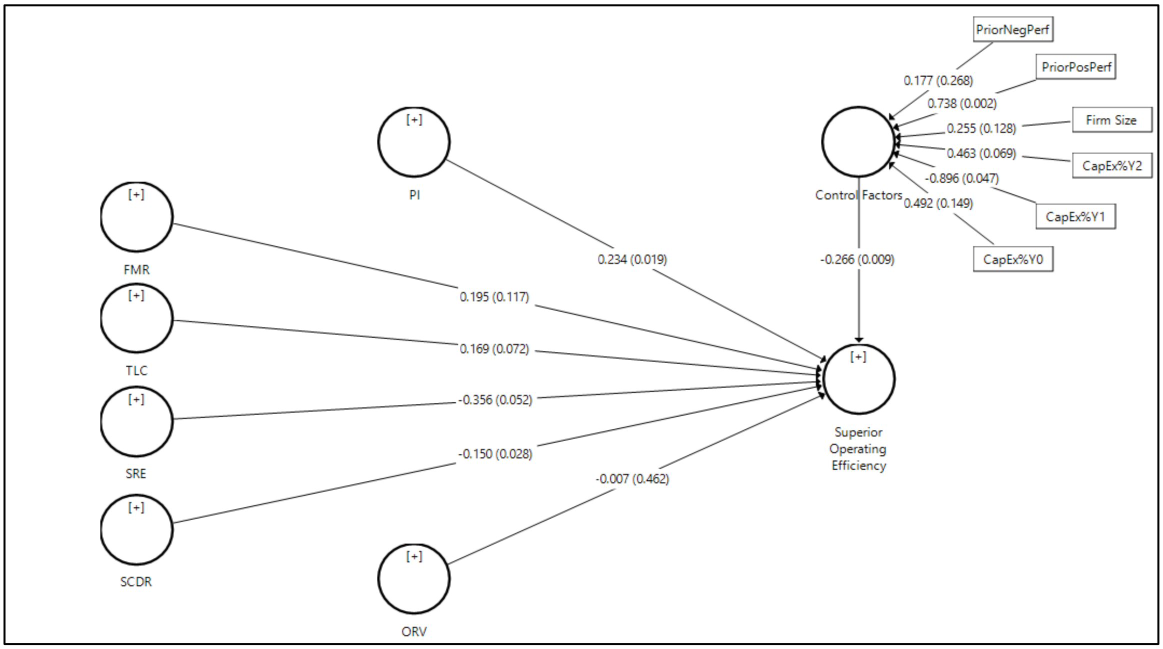
B.1 Path Modeling and Bootstrapping for Structural Model 1

Figure 17: Path Coefficients and R^2 of Model 1 for PI Group



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Operating Efficiency.

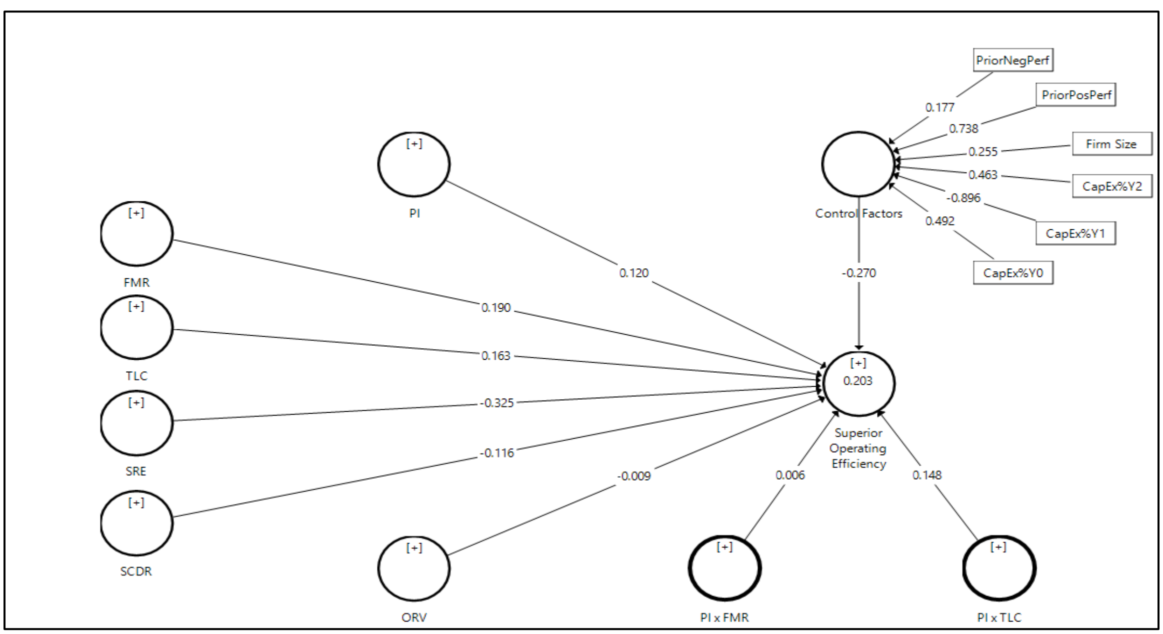
Figure 18: Path Coefficients and p-Values of Model 1 for PI Group



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Operating Efficiency.

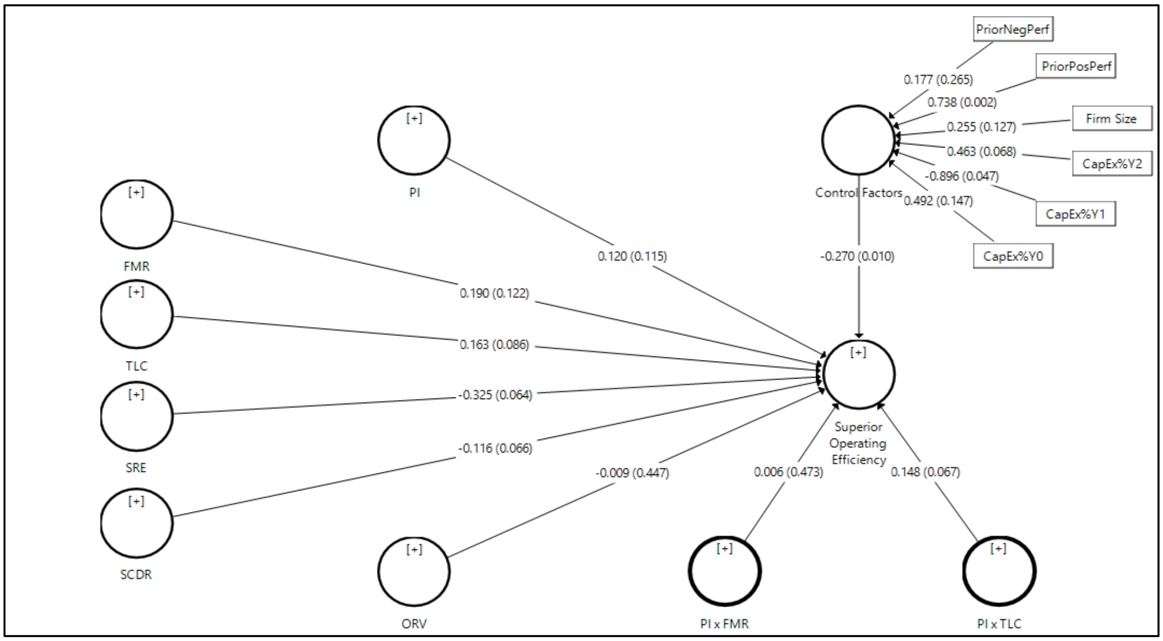
B.2 Path Modeling and Bootstrapping for Structural Model 2

Figure 19: Path Coefficients and R^2 of Model 2 for PI Group



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Operating Efficiency.

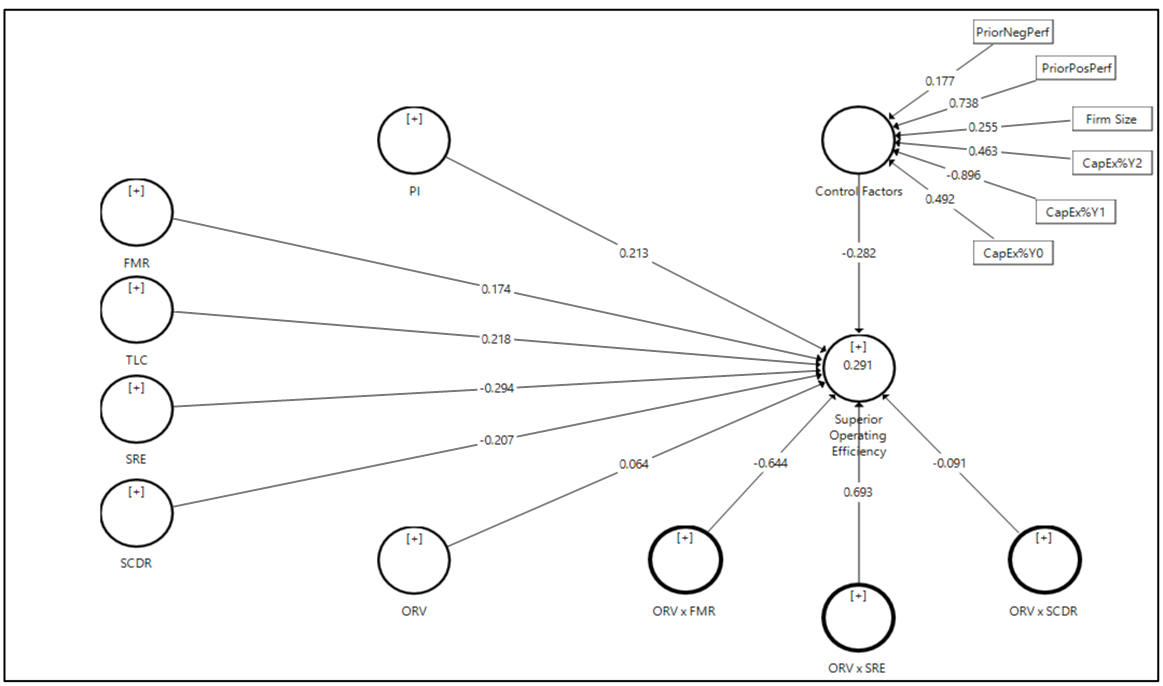
Figure 20: Path Coefficients and p-Values of Model 2 for PI Group



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Operating Efficiency.

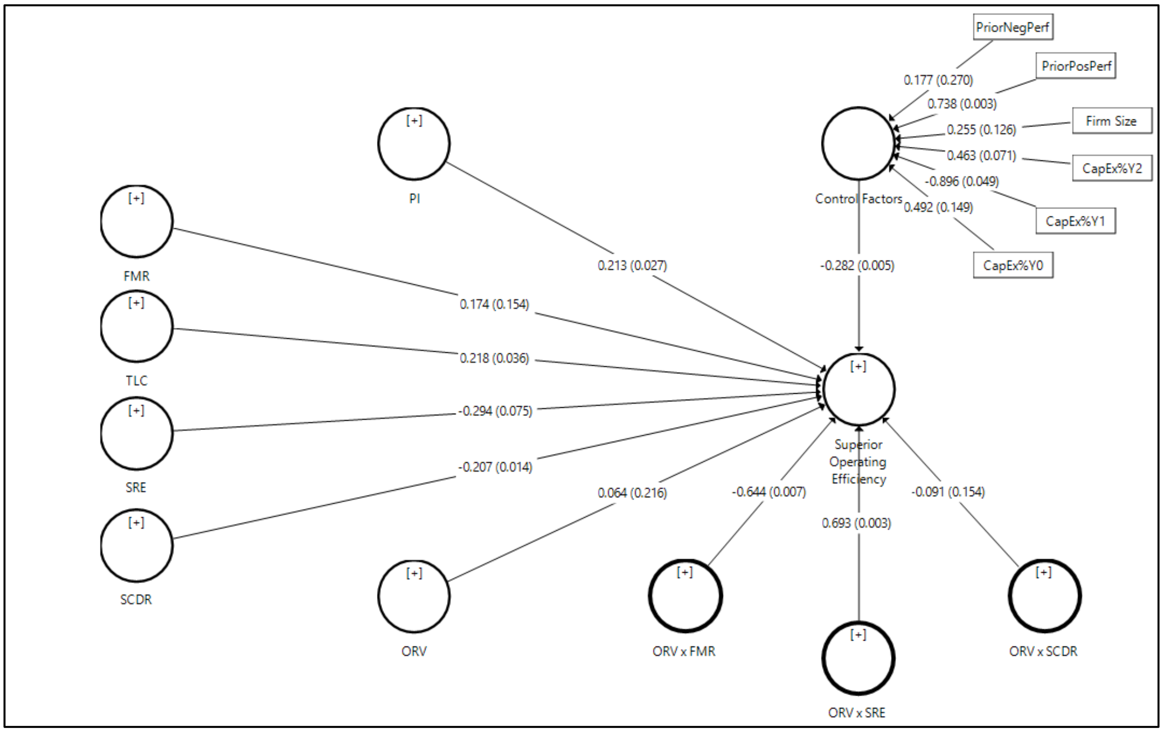
B.3 Path Modeling and Bootstrapping for Structural Model 3

Figure 21: Path Coefficients and R^2 of Model 3 for PI Group



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Operating Efficiency.

Figure 22: Path Coefficients and p-Values of Model 3 for PI Group

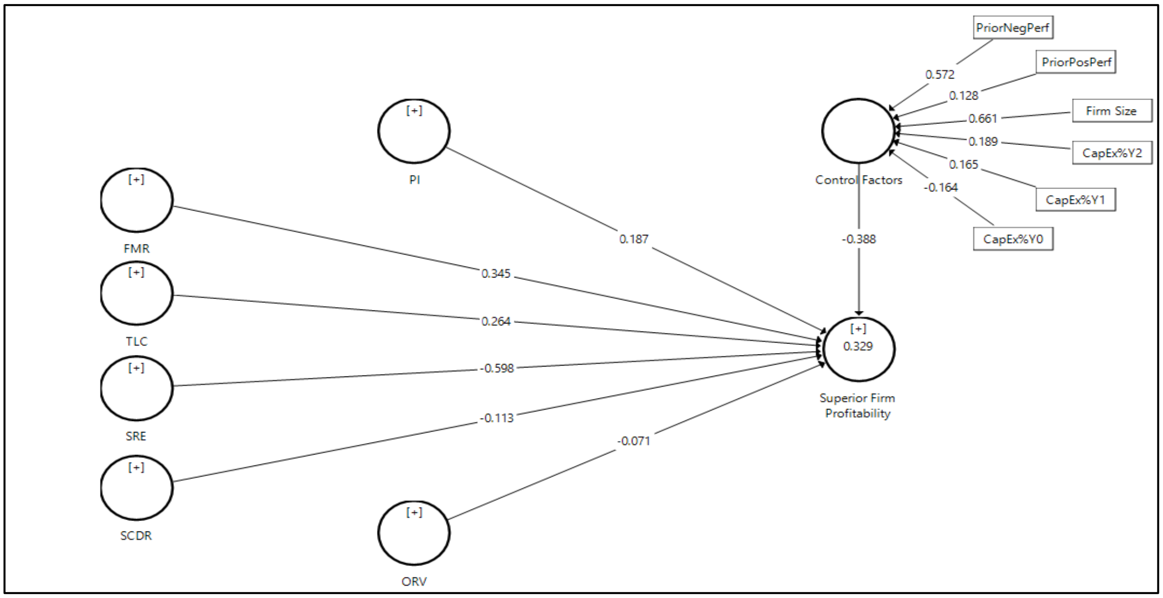


Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Operating Efficiency.

APPENDIX C – SUPERIOR FIRM PROFITABILITY RELATIVE TO MPI GROUP

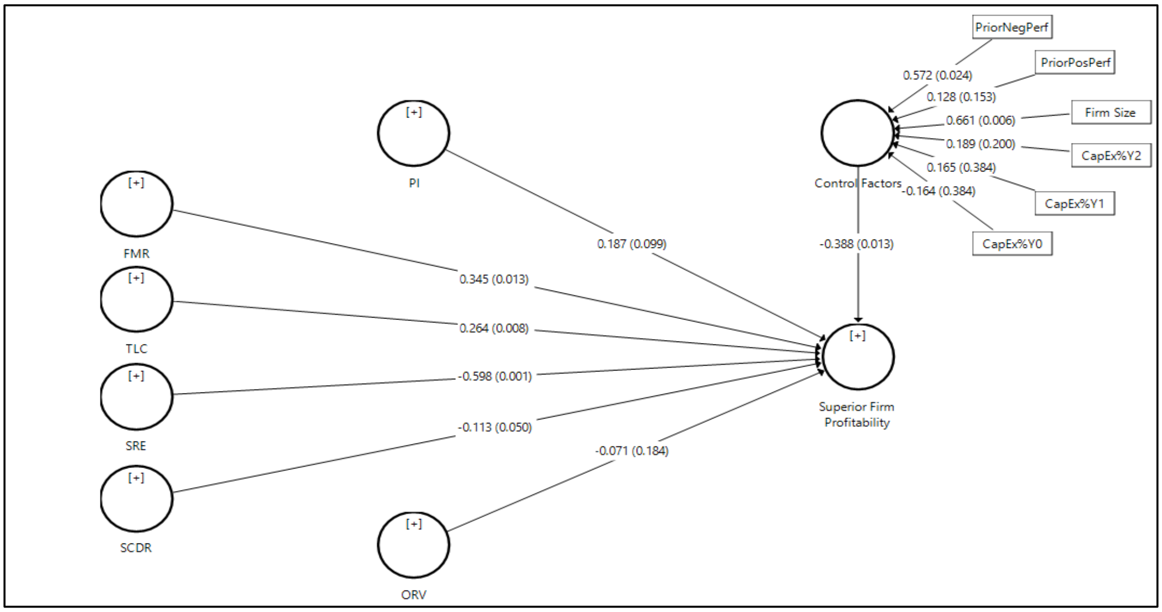
C.1 Path Modeling and Bootstrapping for Structural Model 4

Figure 23: Path Coefficients and R^2 of Model 4 for MPI Group



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Operating Efficiency.

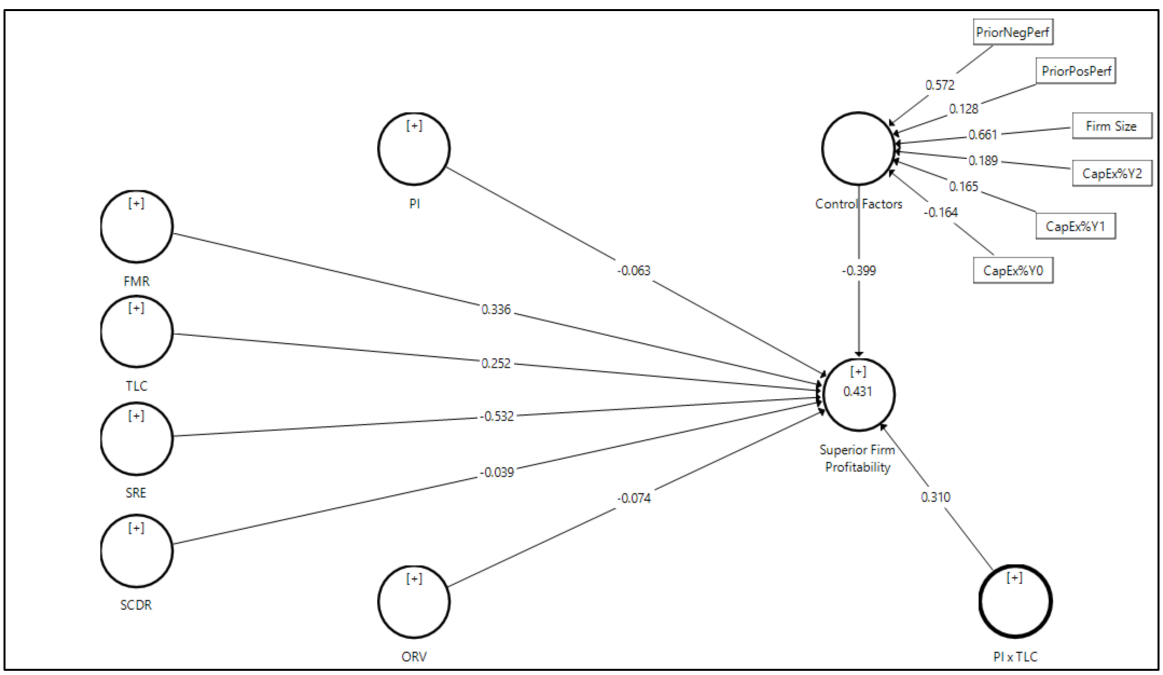
Figure 24: Path Coefficients and p-Values of Model 4 for MPI Group



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

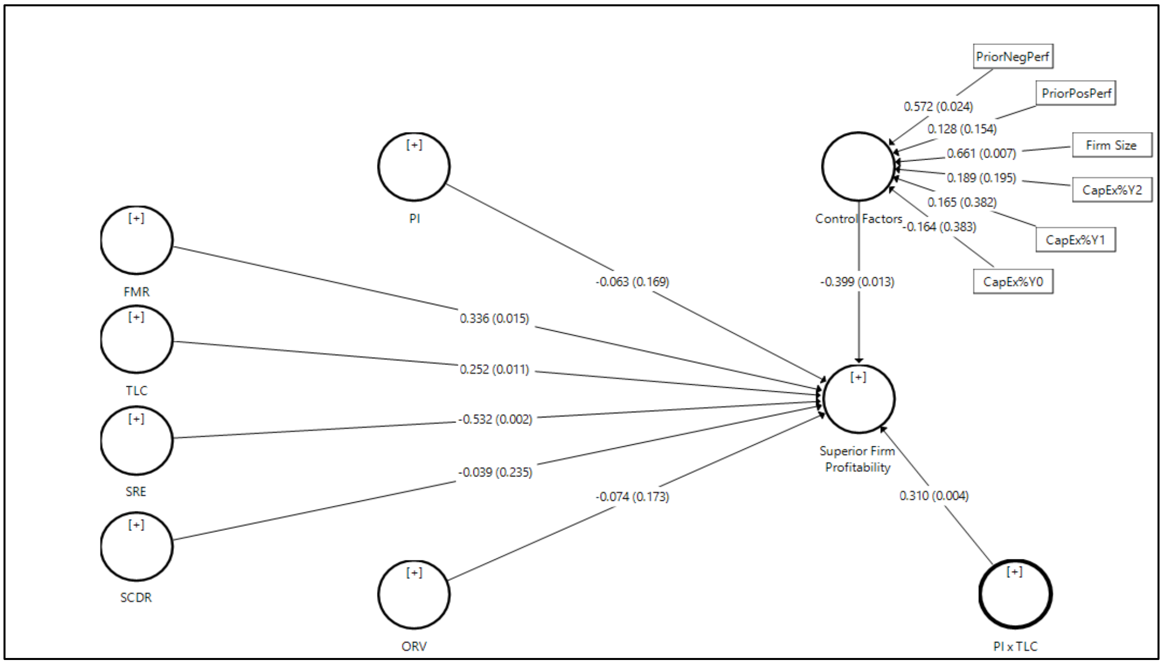
C.2 Path Modeling and Bootstrapping for Structural Model 5

Figure 25: Path Coefficients and R^2 of Model 5 for MPI Group



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

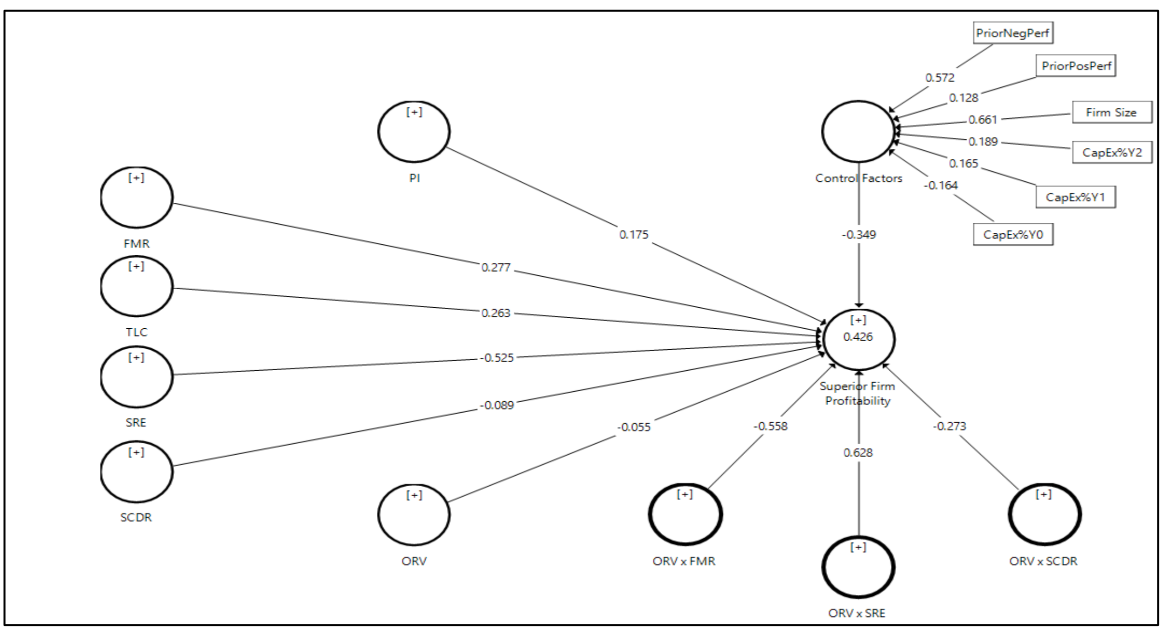
Figure 26: Path Coefficients and p-Values of Model 5 for MPI Group



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

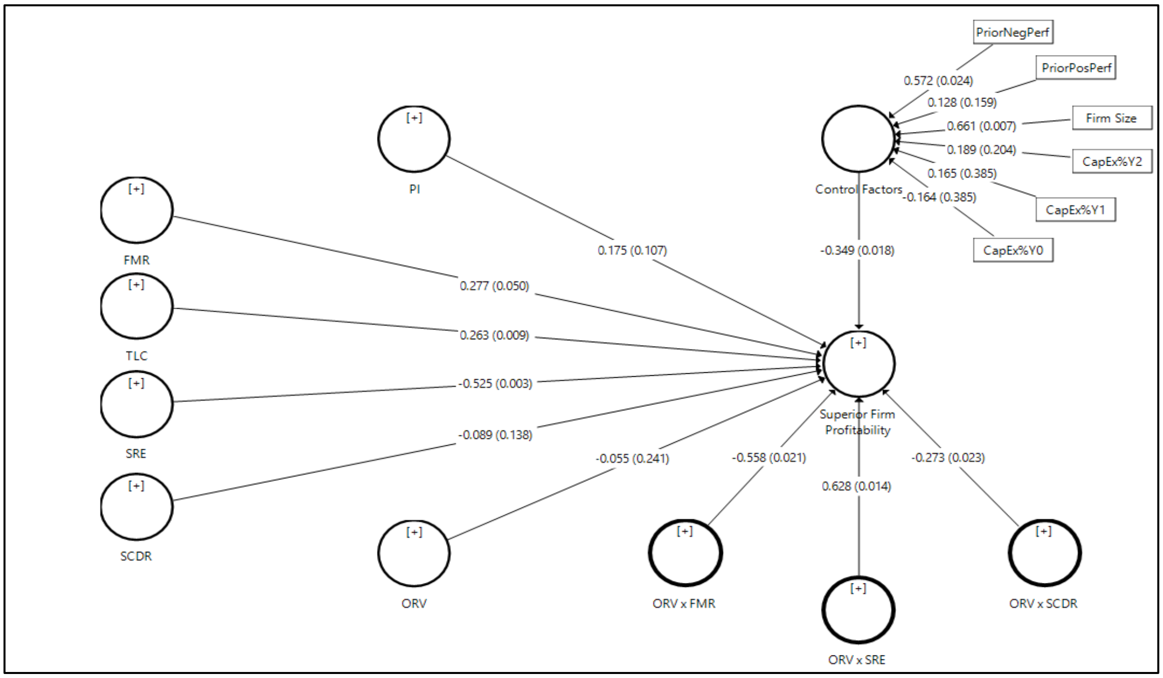
C.3 Path Modeling and Bootstrapping for Structural Model 3

Figure 27: Path Coefficients and R^2 of Model 6 for MPI Group



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

Figure 28: Path Coefficients and p-Values of Model 6 for MPI Group

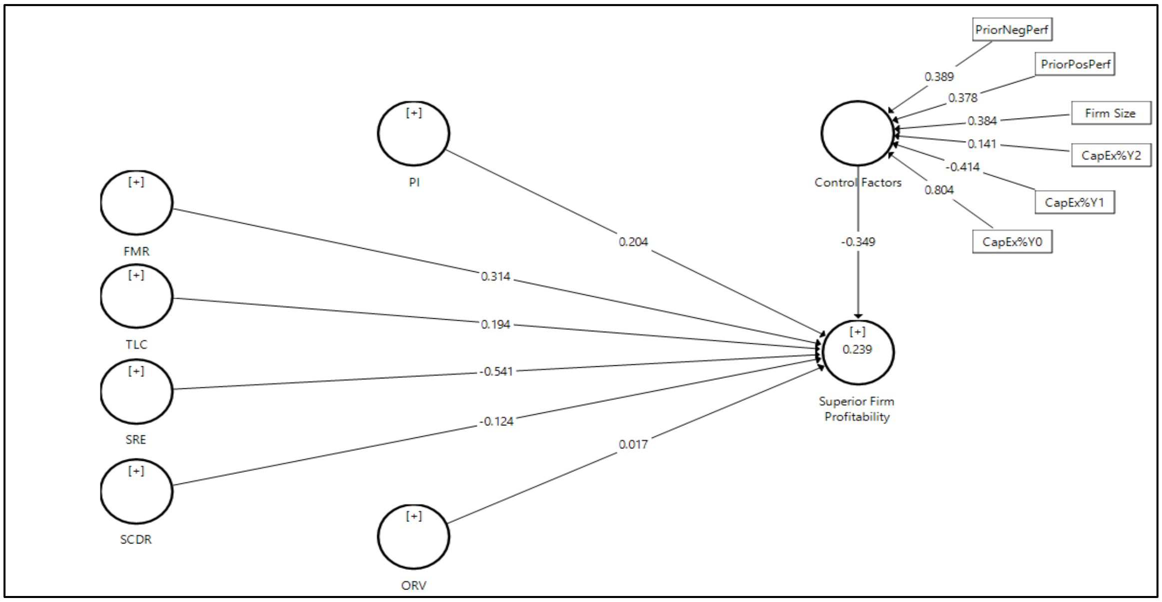


Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

APPENDIX D – SUPERIOR FIRM PROFITABILITY RELATIVE TO PI GROUP

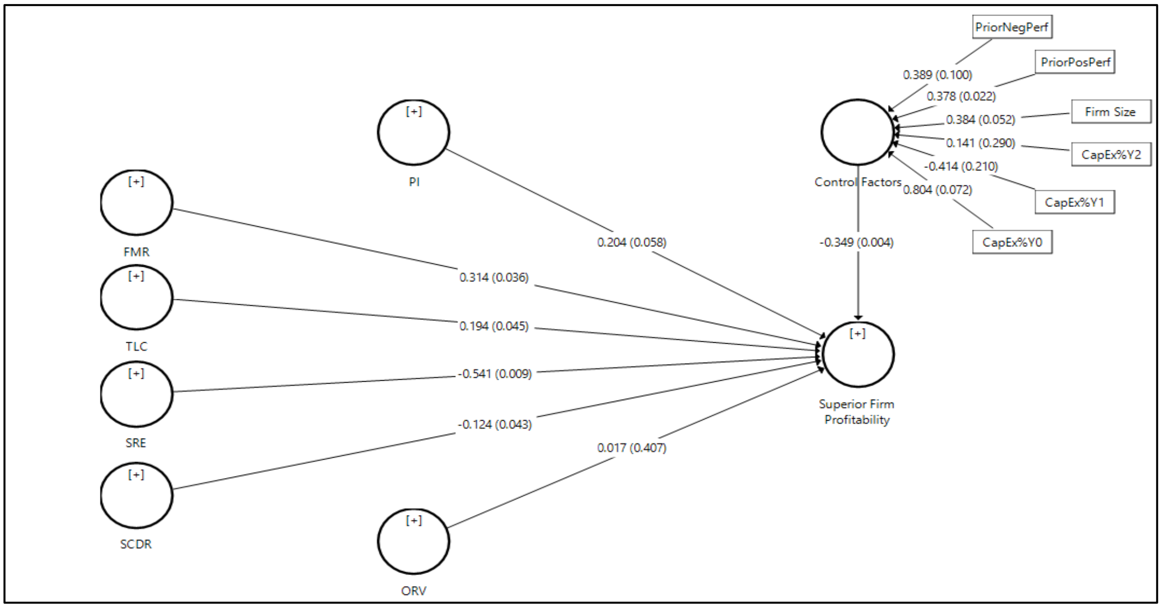
D.1 Path Modeling and Bootstrapping for Structural Model 4

Figure 29: Path Coefficients and R^2 of Model 4 for PI Group



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

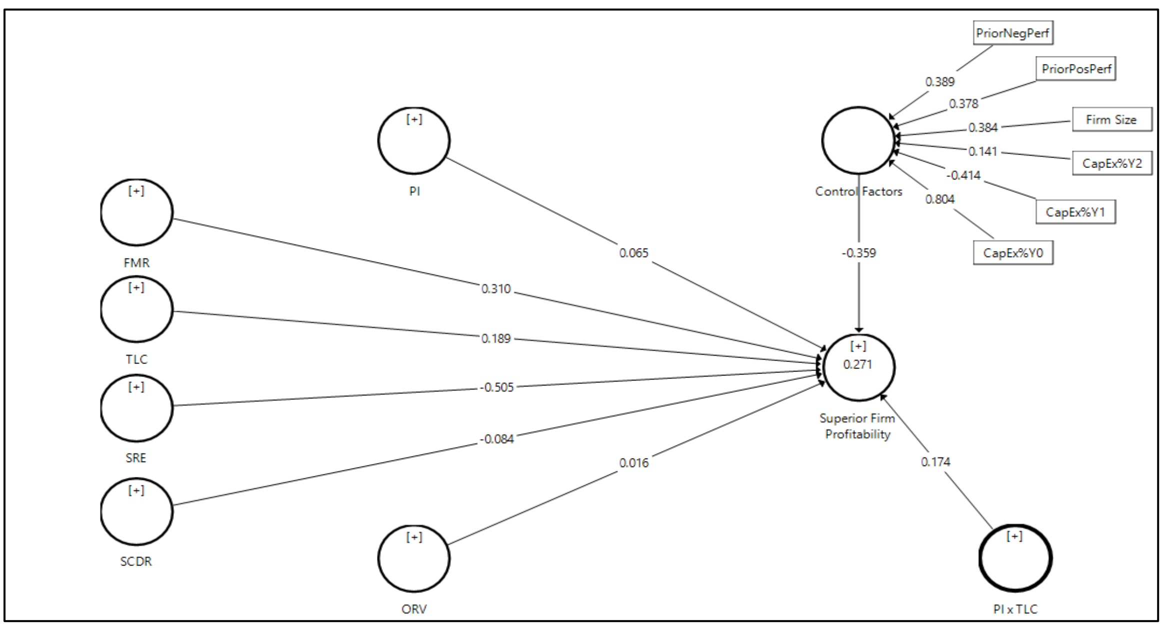
Figure 30: Path Coefficients and p-Values of Model 4 for PI Group



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

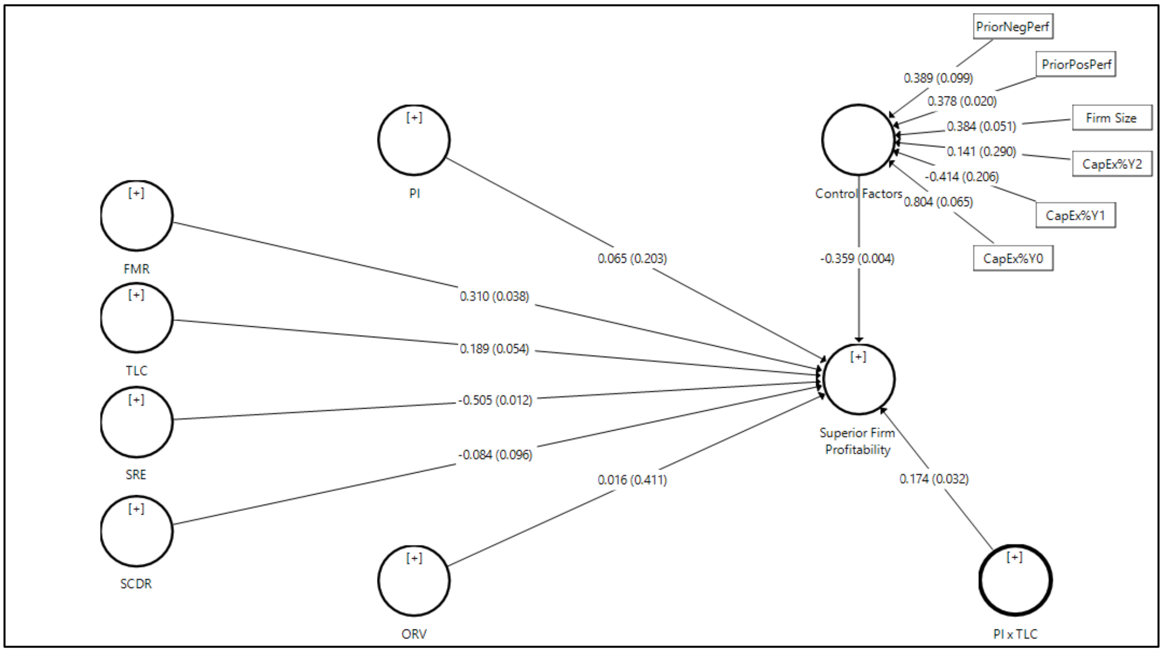
D.2 Path Modeling and Bootstrapping for Structural Model 5

Figure 31: Path Coefficients and R^2 of Model 5 for PI Group



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

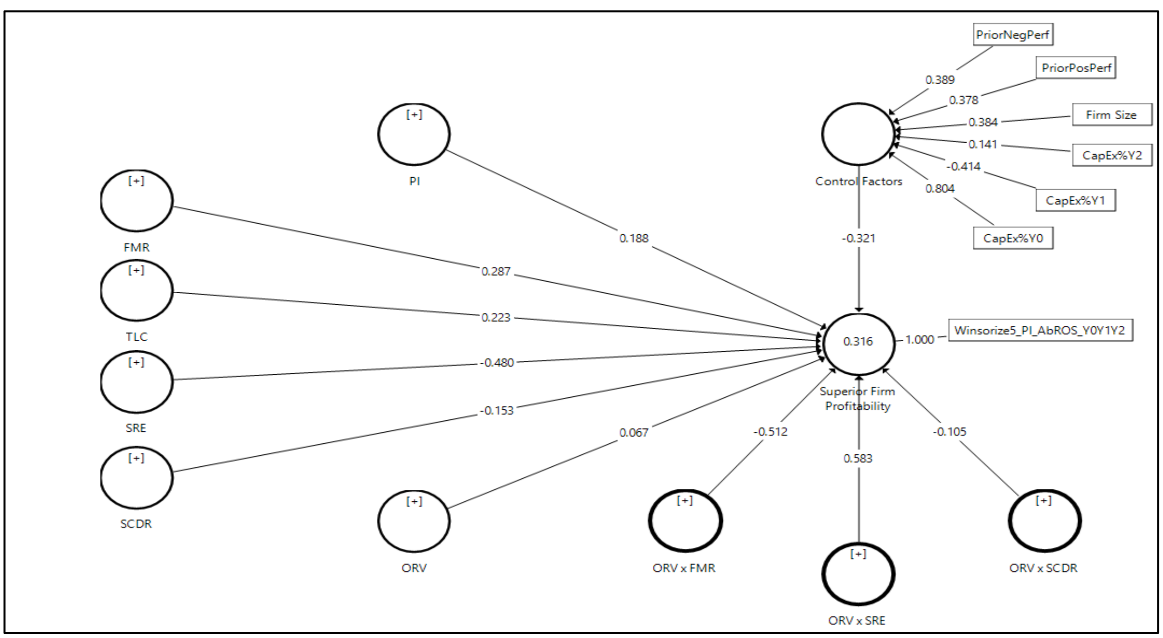
Figure 32: Path Coefficients and p-Values of Model 5 for PI Group



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

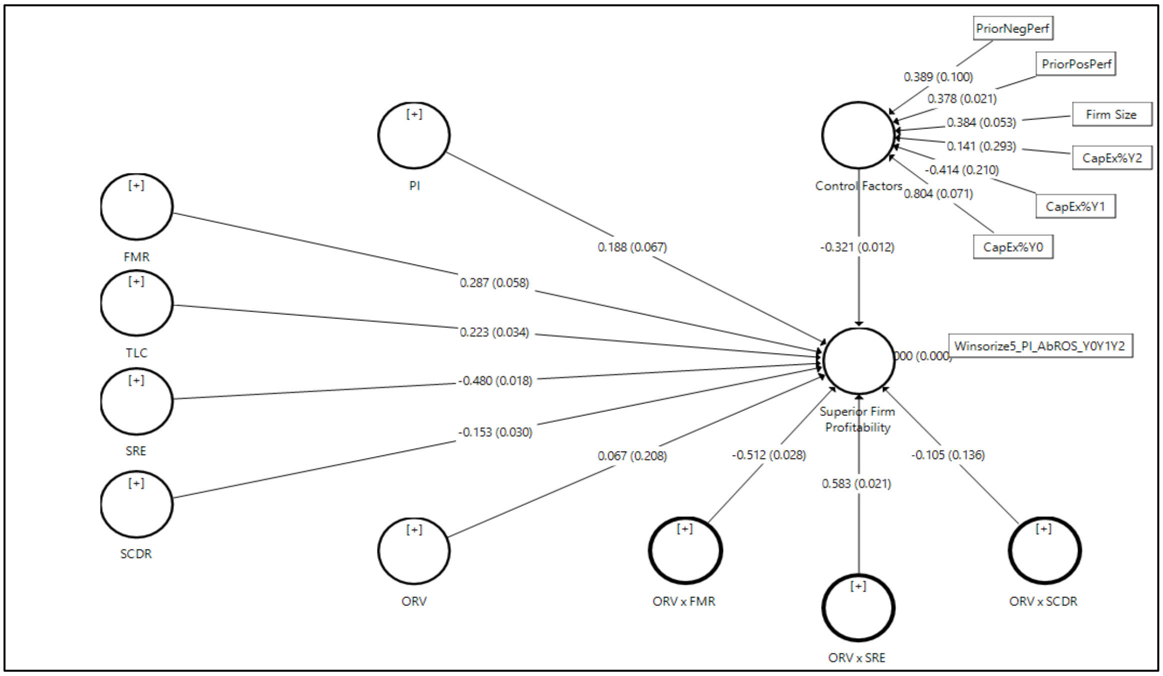
D.3 Path Modeling and Bootstrapping for Structural Model 6

Figure 33: Path Coefficients and R^2 of Model 6 for PI Group



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

Figure 34: Path Coefficients and p-Values of Model 6 for PI Group



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

APPENDIX E – ALTERNATIVE ANALYTICAL TECHNIQUE

E.1 Superior Operating Efficiency Using Hierarchical Multiple Regression

Table 30: Hierarchical Moderated Multiple Regression Results

Superior Operating Efficiency MPIS	Model 1: Control			Model 2: Direct			Model 3: Moderation		
n = 96	Std.β	t	Sig.	Std.β	t	Sig.	Std.β	t	Sig.
Constant	.044	1.854	.067*	-.078	-1.237	.220	-.754	-2.377	.020**
Ln(TEV)Y0	-.118	-1.046	.299	-.100	-.871	.387	-.067	-.600	.550
PPP	-.230	-2.127	.036**	-.186	-1.714	.091*	-.191	-1.808	.075*
NPP	-.053	-.487	.627	-.083	-.747	.457	-.055	-.498	.620
CapEx%Y0	-.103	-.530	.597	-.166	-.866	.389	-.238	-1.289	.201
CapEx%Y+1	.202	.994	.323	.179	.893	.375	.338	1.726	.089*
CapEx%Y+2	-.087	-.610	.543	-.087	-.615	.540	-.147	-1.072	.287
PI	.318	2.976	.004***	.259	2.329	.022**	-.309	-1.009	.316
ORV	-.040	-.349	.728	-.022	-.191	.849	2.724	2.304	.024**
FMR				.358	1.723	.089*	1.678	2.630	.010***
TLC				.258	1.796	.076*	.131	.834	.407
SRE				-.505	-2.327	.023**	-1.738	-3.149	.002***
SCDR				-.155	-1.272	.207	-.176	-1.444	.153
PI x TLC							.653	1.979	.052**
ORV x FMR							-2.475	-2.218	.030**
ORV x SRE							1.488	2.489	.015**
Model Predictive Capability									
F			2.045			2.027			2.559
Sig			.051			.033			.004
R^2			.168			.240			.342
Adjusted R^2			. .086			.122			.208
ΔR^2						.072			.101

Where TEV = Total Enterprise Value, PPP = Prior Positive Performance, NPP = Negative Prior Performance, PI = Product Innovativeness, ORV = Offshore Relationship Value, FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, and SCDR = Supply Chain Disruption Risk.

*Significance is two-tailed: p<.10

**Significance is two-tailed: p<.05

***Significance is two-tailed: p<.01

E.2 Superior Firm Profitability Using Hierarchical Multiple Regression

Table 31: Hierarchical Moderated Multiple Regression Results

Superior Firm Profitability MPIS n = 96	Model 1: Control			Model 2: Direct			Model 3: Moderation		
	Std.β	t	Sig.	Std.β	t	Sig.	Std.β	t	Sig.
Constant	.159	3.037	.003***	-.172	-1.276	.206	-1.576	-2.356	.021**
Ln(TEV)Y0	-.247	-2.284	.025**	-.211	-1.998	.049**	-.211	-2.205	.031**
PPP	-.118	-1.142	.257	-.063	-.632	.529	-.056	-.622	.536*
NPP	-.200	-1.923	.058*	-.248	-2.413	.018**	-.234	-2.500	.015*
CapEx%Y0	-.001	-.007	.994	-.068	-.388	.699	-.152	-.962	.339
CapEx%Y+1	.016	.083	.934	-.009	-.050	.961	.129	.772	.443
CapEx%Y+2	-.075	-.548	.585	.089	-.681	.498	-.095	-.803	.424
PI	.266	2.608	.011**	.192	1.876	.064*	-.733	-2.817	.006***
ORV	-.068	-.615	.540	-.063	-.589	.557	2.587	2.369	.020**
FMR				.391	2.043	.045**	1.369	2.481	.015*
TLC				.305	2.301	.024**	.027	.202	.841
SRE				-.648	-3.237	.002**	-1.839	-3.741	.000***
SCDR				-.140	-1.246	.216	.634	1.835	.071*
PI x TLC							1.072	3.820	.000***
ORV x FMR							-1.988	-2.028	.046**
ORV x SRE							1.520	2.806	.006***
ORV x SCDR							-.878	-2.243	.028**
Model Predictive Capability									
F			3.188			3.519			5.170
Sig			.003			.000			.000
R^2			.239			.354			.531
Adjusted R^2			.164			.254			.428
ΔR^2						.115			.177

Where TEV = Total Enterprise Value, PPP = Prior Positive Performance, NPP = Negative Prior Performance, PI = Product Innovativeness, ORV = Offshore Relationship Value, FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, and SCDR = Supply Chain Disruption Risk.

*Significance is two-tailed: p<.10
**Significance is two-tailed: p<.05
***Significance is two-tailed: p<.01

APPENDIX F – ALTERNATIVE MEASUREMENT ITEMS

F.1 Multiple Indicator Measurement Items

F.1.1 Control Index

Positive Prior Performance in matching year (Y-3)
Negative Prior Performance in matching year (Y-3)
Firm Size
Capital Expenditure Percentage in Reshoring Year (Y0)
Capital Expenditure Percentage in Y+1
Capital Expenditure Percentage in Y+2

F.1.2 Product Innovativeness

Pr_Inv 1 Research and Development Intensity in Y0

F.1.3 Offshore Relationship Value

ORV 1 Percentage of Revenue from Outside United States

F.1.4 Factor Market Rivalry

FMR 1 Global Competitive Index Country Score[a]*
FMR 2 Global Competitive Index National Rank[a]
FMR 3 Boston Consulting Group Manufacturing Cost-Competitive Index[b]
FMR 4 Boston Consulting Group Manufacturing CCI 10-year Change[b]
[a]Item obtained from World Economic Forum Global Competitive Index
[b]Item obtained from Boston Consulting Group Manufacturing Competitive Cost Index
*Reverse-scored

F.1.5 Total Logistics Costs

TLC 1 Aerial Distance Between Countries[a]
TLC 2 Ocean-borne Transit Time Between Countries[b]
TLC 3 3-Year Change in Bunker Oil Price (Y0 through Y+2)[c]
TLC 4 Average Yearly Bunker Oil Price at Y0[c]
TLC 5 Logistics Performance Index National Rank[d]
TLC 6 Logistics Performance Index Country Score[d]*
[a] Item obtained from Google Maps
[b] Item obtained from Maersk.com

[c] Item obtained from Capital IQ Commodity Index - Fuel Oil
[d] Item obtained from World Bank Data – Logistics Performance Index
*Reverse-scored

F.1.6 Strategic Risk Exposure[a]

SRE 1	Control of Corruption*
SRE 2	Regulator Quality*
SRE 3	Voice and Accountability*
SRE 4	Political Stability and Absence of Violence*
SRE 5	Government Effectiveness*
SRE 6	Rule of Law*

[a] All items obtained from Country Governance Index, all items reverse-scored
*Reverse-scored

F.1.7 Supply Chain Disruption Risk[a]

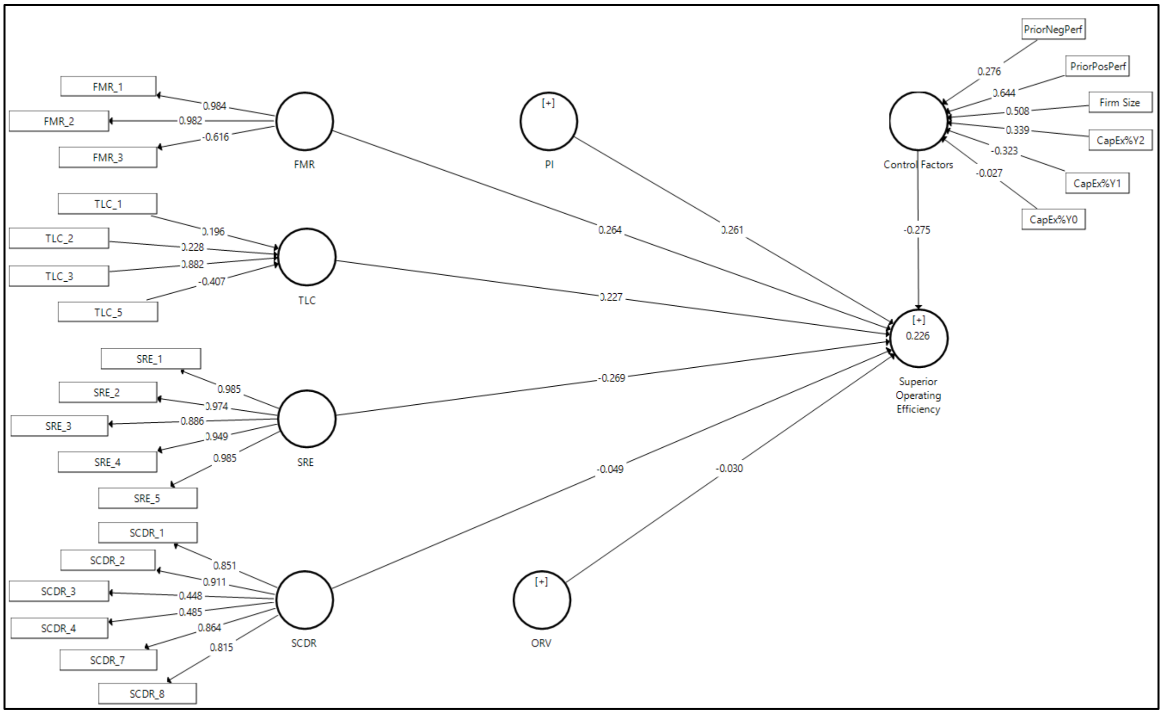
SCDR 1	Country Risk Score*
SCDR 2	Country Risk National Rank
SCDR 3	Economic Disruption Score*
SCDR 4	Economic Disruption National Rank
SCDR 5	Supply Chain Disruption Score*
SCDR 6	Supply Chain Disruption National Rank
SCDR 7	Resilience Index Global Score*
SCDR 8	Resilience Index Global Rank

[a]All items obtained from FM Global Resilience Index
*Reverse-scored

F.2 Superior Operating Efficiency Relative to MPIS Matching Group

F.2.1 Structural Model 1

Figure 35: Path Coefficients and R^2 of Model 1 with Multi-Item Measures



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SOE = Superior Operating Efficiency.

Table 32: Construct Reliability for Model 1 with Multi-Item Measures

	Composite Reliability	P Values	Average Variance Extracted (AVE)	P Values
Control Factors				
FMR	0.726	.000	0.771	.000
ORV				
PI				
SCDR	0.880	.000	0.567	.000
Superior Operating Efficiency	1.000		1.000	
SRE	0.982	.000	0.915	.000
TLC				

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Operating Efficiency.

Table 33: Outer Loadings and Weights for Model 1 with Multi-Item Measures

	Control Factors	FMR	ORV	PI	SCDR	SRE	SFP	TLC
Outer Loadings								
FMR_1		0.984						
FMR_2		0.982						
FMR_3		-0.616						
ORV_1			1					
Pr_Inv_1				1				
SCDR_1					0.851			
SCDR_2					0.911			
SCDR_3					0.448			
SCDR_4					0.485			
SCDR_7					0.864			
SCDR_8					0.815			
SRE_1						0.985		
SRE_2						0.974		
SRE_3						0.886		
SRE_4						0.949		
SRE_5						0.985		
Winsorize5_MPIS_AbROS_Y0Y1Y2							1	
Outer Weights								
CapEx%Y0	-0.027							
CapEx%Y1	-0.323							
CapEx%Y2	0.339							
Firm Size	0.508							
PriorNegPerf	0.276							
PriorPosPerf	0.644							
TLC_1								0.196
TLC_2								0.228
TLC_3								0.882
TLC_5								-0407

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Operating Efficiency.

Table 34: HTMT Ratio with Bias-Corrected Confidence Interval for Model 1

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	Bias	5% BC-CI	95% BC-CI	T Statistics (|O/STDEV|)	P Values
ORV -> FMR	0.069	0.106	0.070	0.037	0.011	0.176	0.979	.164
PI -> FMR	0.044	0.097	0.059	0.053	0.003	0.078	0.750	.227
PI -> ORV	0.160	0.165	0.080	0.005	0.020	0.280	2.008	.022
SCDR -> FMR	0.894	0.903	0.034	0.010	0.845	0.948	26.221	.000
SCDR -> ORV	0.144	0.178	0.060	0.033	0.041	0.211	2.420	.008
SCDR -> PI	0.113	0.149	0.082	0.036	0.035	0.235	1.375	.085
SOE -> FMR	0.022	0.109	0.071	0.087	0.002	0.021	0.306	.380
SOE -> ORV	0.023	0.112	0.084	0.089	0.000	0.052	0.277	.391
SOE -> PI	0.272	0.257	0.150	-0.015	0.032	0.519	1.819	.034
SOE -> SCDR	0.074	0.131	0.068	0.057	0.013	0.122	1.085	.139
SRE -> FMR	0.941	0.945	0.036	0.004	0.885	1.000	25.959	.000
SRE -> ORV	0.039	0.092	0.060	0.053	0.009	0.060	0.653	.257
SRE -> PI	0.048	0.096	0.057	0.049	0.010	0.069	0.831	.203
SRE -> SCDR	0.878	0.877	0.036	-0.001	0.801	0.923	24.244	.000
SRE -> SOE	0.085	0.131	0.080	0.046	0.020	0.204	1.063	.144
SRE -> SCDR	0.878	0.877	0.036	0.000	0.798	0.923	24.094	.000
SRE -> SOE	0.085	0.131	0.080	0.046	0.021	0.202	1.068	.143

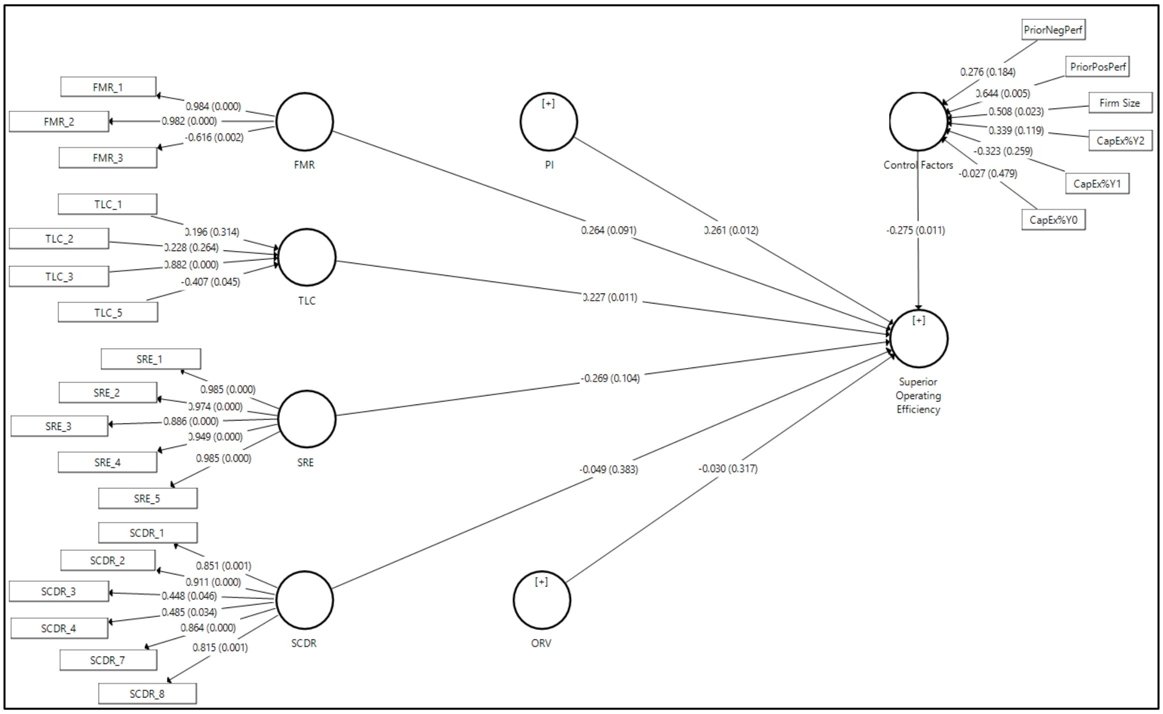
Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Operating Efficiency.

Table 35: Measures of Collinearity for Model 1 with Multi-Item Measures

	Outer VIF		Inner VIF
CapEx%Y0	3.440	Control Factors→SOE	1.067
CapEx%Y1	3.885	FMR-->SOE	4.234
CapEx%Y2	1.966	ORV-->SOE	1.096
FMR_1	12.771	PI-->SOE	1.067
FMR_2	12.238	SCDR-->SOE	1.663
FMR_3	1.395	SRE-->SOE	5.191
Firm Size	1.105	TLC-->SOE	1.106
ORV_1	1.000		
Pr_Inv_1	1.000		
PriorNegPerf	1.120		
PriorPosPerf	1.096		
SCDR_1	13.792		
SCDR_2	10.005		
SCDR_3	12.812		
SCDR_4	11.705		
SCDR_7	51.511		
SCDR_8	47.324		
SRE_1	15.932		
SRE_2	21.118		
SRE_3	6.319		
SRE_4	8.834		
SRE_5	21.107		
TLC_1	3.050		
TLC_2	3.098		
TLC_3	1.013		
TLC_5	1.084		
Winsorize5_MPIS_AbROA_Y0Y1Y2	1.000		

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Operating Efficiency.

Figure 36: Path Coefficients and p-Values of Model 1 with Multi-Item Measures



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Operating Efficiency.

Table 36: Statistical Significance of Model 1 with Multi-Item Measures

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	Bias	5% BC-CI	95% BC-CI	T Statistics (|O/STDEV|)	P Values
Coefficient of Determination (R^2)								
SOE R^2	0.226	0.345	0.105	0.119	0.063	0.277	2.152	.016**
SOE Adjusted R^2	0.165	0.293	0.114	0.128	-0.011	0.220	1.452	.073*
Path Coefficients (β)								
Control Factors -> SOE	-0.275	-0.353	0.120	-0.079	-0.385	-0.027	2.290	.011**
FMR -> SOE	0.264	0.245	0.198	-0.019	0.051	0.832	1.333	.091*
ORV -> SOE	-0.030	-0.083	0.063	-0.053	-0.078	0.000	0.476	.317
PI -> SOE	0.261	0.210	0.116	-0.052	0.085	0.471	2.261	.012**
SCDR -> SOE	-0.049	-0.181	0.164	-0.132	-0.110	0.000	0.298	.383
SRE -> SOE	-0.269	-0.271	0.213	-0.002	-0.818	-0.037	1.261	.104
TLC -> SOE	0.227	0.253	0.100	0.026	0.028	0.358	2.281	.011**
Calculated Effect Sizes (f^2)								
Control Factors -> SOE	0.091	0.192	0.148	-0.445	-0.775	-0.775	0.616	.269
FMR -> SOE	0.021	0.030	0.041	0.224	0.000	0.024	0.515	.303
ORV -> SOE	0.001	0.014	0.020	-0.084	-0.396	-0.396	0.051	.480
PI -> SOE	0.083	0.076	0.073	0.127	0.000	0.179	1.131	.129
SCDR -> SOE	0.002	0.021	0.031	-0.183	-2.091	-2.091	0.060	.476
SRE -> SOE	0.018	0.038	0.059	-0.289	-1.419	-1.419	0.308	.379
TLC -> SOE	0.060	0.080	0.060	0.193	0.000	0.039	1.007	.157

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SOE = Superior Operating Efficiency.

*Significance is one-tailed: p<.10
**Significance is one-tailed: p<.05
***Significance is one-tailed: p<.01

Table 37: Predictive Validity of Model 1 with Multi-Item Measures

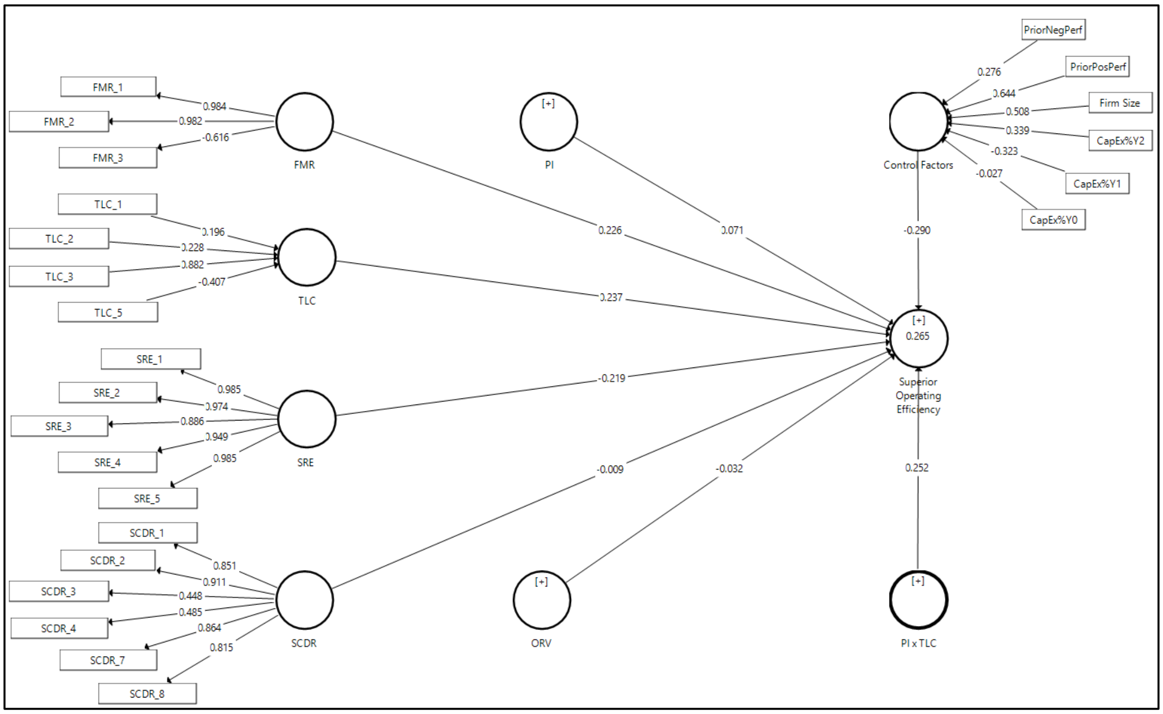
n=96	SSO	SSE	Q^2 (=1-SSE/SSO)
Construct Cross-validated Redundancy			
Control Factors	567.000	567.000	
FMR	287.000	287.000	
ORV	96.000	96.000	
PI	96.000	96.000	
SCDR	576.000	576.000	
SOE	288.000	247.192	0.142
SRE	480.000	480.000	

TLC	384.000	384.000	
Indicator Cross-validated Redundancy			
CapEx%Y0	95.000	95.000	
CapEx%Y1	95.000	95.000	
CapEx%Y2	95.000	95.000	
FMR_1	96.000	96.000	
FMR_2	96.000	96.000	
FMR_3	95.000	95.000	
Firm Size	90.000	90.000	
ORV_1	96.000	96.000	
Pr_Inv_1	96.000	96.000	
PriorNegPerf	96.000	96.000	
PriorPosPerf	96.000	96.000	
SCDR_1	96.000	96.000	
SCDR_2	96.000	96.000	
SCDR_3	96.000	96.000	
SCDR_4	96.000	96.000	
SCDR_7	96.000	96.000	
SCDR_8	96.000	96.000	
SRE_1	96.000	96.000	
SRE_2	96.000	96.000	
SRE_3	96.000	96.000	
SRE_4	96.000	96.000	
SRE_5	96.000	96.000	
TLC_1	96.000	96.000	
TLC_2	96.000	96.000	
TLC_3	96.000	96.000	
TLC_5	96.000	96.000	
Winsorize5_MPIS_AbROA_Y0Y1Y2	96.000	81.409	0.152
Winsorize5_MPI_AbROA_Y0Y1Y2	96.000	81.567	0.150
Winsorize5_PI_AbROA_Y0Y1Y2	96.000	84.216	0.123

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Operating Efficiency.

F.2.2 Structural Model 2

Figure 37: Path Coefficients and R^2 for Model 2 with Multi-Item Measures



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Operating Efficiency.

Table 38: Construct Validity for Model 2 with Multi-Item Measures

	Composite Reliability	P Values	Average Variance Extracted (AVE)	P Values
Control Factors				
FMR	0.726	.000	0.771	.000
ORV				
PI				
PI x TLC	0.396	.004	0.576	.000
SCDR	0.880	.000	0.576	.000
SOE	1		1	
SRE	0.982	.000	0.915	.000
TLC				

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Operating Efficiency.

Table 39: Outer Loadings and Weights for Model 2 with Multi-Item Measures

	Control Factors	FMR	ORV	PI	PI x TLC	SCDR	SRE	SFP	TLC
Outer Loadings									
FMR_1		0.984							
FMR_2		0.982							
FMR_3		-0.616							
ORV_1			1.000						
Pr_Inv_1				1.000					
SCDR_1						0.851			
SCDR_2						0.911			
SCDR_3						0.448			
SCDR_4						0.485			
SCDR_7						0.864			
SCDR_8						0.815			
SRE_1							0.985		
SRE_2							0.974		
SRE_3							0.886		
SRE_4							0.949		
SRE_5							0.985		
Winsorize5_MPIS_AbROA_Y0Y1Y2								1.000	
Outer Weights									
CapEx%Y0	-0.027								
CapEx%Y1	-0.323								
CapEx%Y2	0.339								
Firm Size	0.508								
PriorNegPerf	0.276								
PriorPosPerf	0.644								
Pr_Inv_1 * TLC_1					0.496				
Pr_Inv_1 * TLC_2					0.313				
Pr_Inv_1 * TLC_3					-.0.024				
Pr_Inv_1 * TLC_5					-0.324				
TLC_1									0.196
TLC_2									0.228
TLC_3									0.882
TLC_5									-0407

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Operating Efficiency.

Table 40: HTMT Ratio with Bias-Corrected Confidence Interval for Model 2

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	Bias	5% BC-CI	95% BC-CI	T Statistics (|O/STDEV|)	P Values
ORV -> FMR	0.069	0.107	0.068	0.038	0.011	0.163	1.002	.158
PI -> FMR	0.044	0.097	0.059	0.052	0.003	0.078	0.745	.228
PI -> ORV	0.160	0.164	0.080	0.004	0.021	0.284	1.998	.023
PI x TLC -> FMR	0.176	0.211	0.064	0.035	0.090	0.240	2.745	.003
PI x TLC -> ORV	0.118	0.168	0.060	0.050	0.021	0.164	1.959	.025
PI x TLC -> PI	0.826	0.734	0.185	-0.092	0.487	0.976	4.464	.000
SCDR -> FMR	0.894	0.902	0.033	0.009	0.848	0.951	26.859	.000
SCDR -> ORV	0.144	0.176	0.060	0.032	0.038	0.210	2.391	.008
SCDR -> PI	0.113	0.149	0.082	0.036	0.036	0.234	1.386	.083
SCDR -> PI x TLC	0.199	0.239	0.055	0.041	0.105	0.249	3.588	.000
SOE -> FMR	0.022	0.107	0.069	0.085	0.004	0.021	0.313	.377
SOE -> ORV	0.023	0.114	0.084	0.091	0.000	0.048	0.275	.392
SOE -> PI	0.272	0.257	0.150	-0.015	0.030	0.516	1.812	.035
SOE -> PI x TLC	0.343	0.340	0.150	-0.004	0.096	0.565	2.287	.011
SOE -> SCDR	0.074	0.132	0.068	0.058	0.012	0.122	1.074	.141
SRE -> FMR	0.941	0.944	0.036	0.003	0.886	1.001	26.334	.000
SRE -> ORV	0.039	0.092	0.059	0.053	0.012	0.059	0.657	.255
SRE -> PI	0.048	0.097	0.057	0.049	0.007	0.065	0.840	.200
SRE -> PI x TLC	0.200	0.215	0.054	0.015	0.110	0.277	3.710	.000
SRE -> SCDR	0.878	0.877	0.036	0.000	0.798	0.923	24.094	.000
SRE -> SOE	0.085	0.131	0.080	0.046	0.021	0.202	1.068	.143

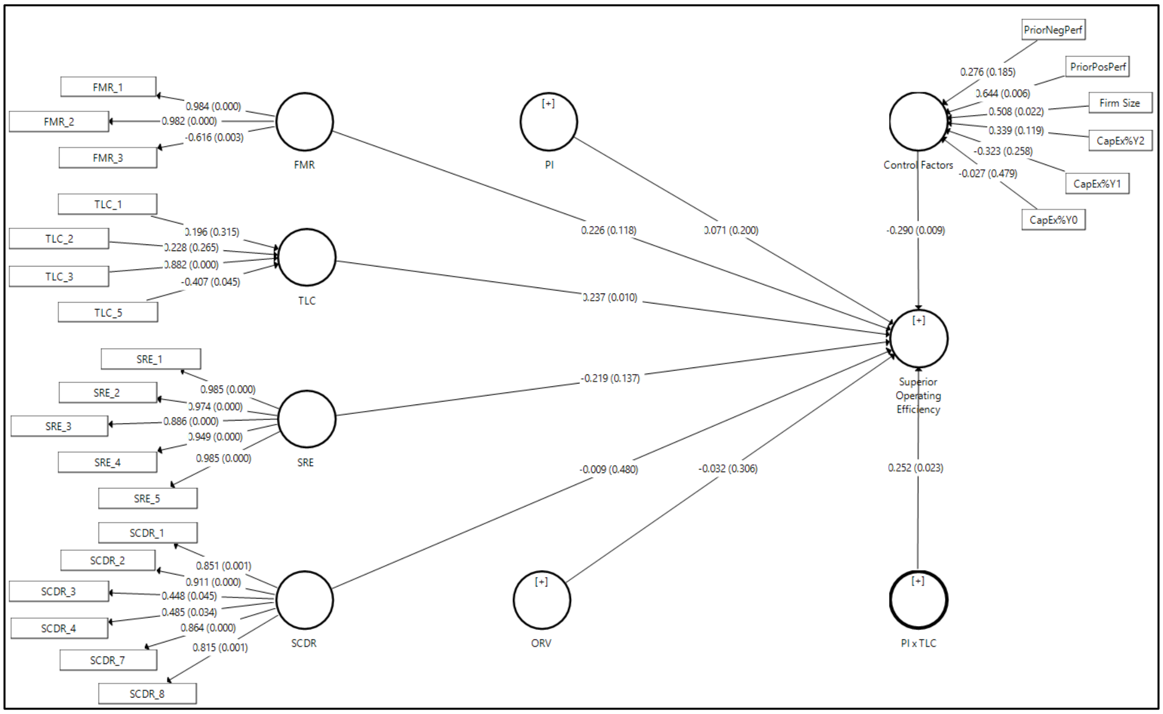
Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Operating Efficiency.

Table 41: Measures of Collinearity for Model 2 with Multi-Item Measures

	Outer VIF		Inner VIF
CapEx%Y0	3.440	Control Factors	1.074
CapEx%Y1	3.885	FMR-->SOE	4.270
CapEx%Y2	1.966	ORV-->SOE	1.096
FMR_1	12.771	PI-->SOE	2.021
FMR_2	12.238	PI x TLC-->SOE	2.005
FMR_3	1.395	SCDR-->SOE	1.704
Firm Size	1.105	SRE-->SOE	5.258
ORV_1	1.000	TLC-->SOE	1.108
Pr_Inv_1	1.000		
Pr_Inv_1 * TLC_1	7.893		
Pr_Inv_1 * TLC_2	5.759		
Pr_Inv_1 * TLC_3	1.135		
Pr_Inv_1 * TLC_5	2.101		
PriorNegPerf	1.120		
PriorPosPerf	1.096		
SCDR_1	13.792		
SCDR_2	10.005		
SCDR_3	12.812		
SCDR_4	11.705		
SCDR_7	51.511		
SCDR_8	47.324		
SRE_1	15.932		
SRE_2	21.118		
SRE_3	6.319		
SRE_4	8.834		
SRE_5	21.107		
TLC_1	3.050		
TLC_2	3.098		
TLC_3	1.013		
TLC_5	1.084		
Winsorize5_MPIS_AbROA_Y0Y1Y2	1.000		

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Operating Efficiency.

Figure 38: Path Coefficients and p-Values of Model 2 with Multi-Item Measures



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Operating Efficiency.

Table 42: Statistical Significance of Model 2 with Multi-Item Measures

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	Bias	5% BC-CI	95% BC-CI	T Statistics (|O/STDEV|)	P Values
Coefficient of Determination (R^2)								
SOE R^2	0.265	0.381	0.104	0.117	0.080	0.317	2.551	.005***
SOE Adjusted R^2	0.197	0.324	0.113	0.127	-0.005	0.255	1.739	.041**
Path Coefficients (β)								
Control Factors -> SOE	-0.290	-0.347	0.123	-0.057	-0.437	-0.041	2.358	.009***
FMR -> SOE	0.226	0.227	0.191	0.001	0.038	0.758	1.185	.118
ORV -> SOE	-0.032	-0.084	0.063	-0.052	-0.089	0.000	0.507	.306
PI -> SOE	0.071	0.112	0.084	0.041	0.002	0.192	0.842	.200
PI x TLC -> SOE	0.252	0.254	0.126	0.002	0.046	0.467	1.995	.023**
SCDR -> SOE	-0.009	-0.174	0.186	-0.164	-0.007	0.000	0.050	.480
SRE -> SOE	-0.219	-0.244	0.200	-0.025	-0.713	-0.026	1.092	.137
TLC -> SOE	0.237	0.257	0.102	0.020	0.040	0.378	2.326	.010***
Calculated Effect Sizes (f^2)								
Control Factors -> SOE	0.106	0.193	0.152	-0.453	-0.774	-0.774	0.702	.241
FMR -> SOE	0.016	0.026	0.038	0.211	0.000	0.017	0.426	.335
ORV -> SOE	0.001	0.015	0.021	-0.085	-0.393	-0.393	0.060	.476
PI -> SOE	0.003	0.016	0.023	0.108	0.000	0.001	0.146	.442
PI x TLC -> SOE	0.052	0.059	0.054	0.202	0.000	0.057	0.956	.170
SCDR -> SOE	0.000	0.016	0.025	-0.174	-2.140	-2.140	0.003	.499

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SOE = Superior Operating Efficiency.

*Significance is one-tailed: p<.10
**Significance is one-tailed: p<.05
***Significance is one-tailed: p<.01

Table 43: Predictive Validity of Model 2 with Multi-Item Measures

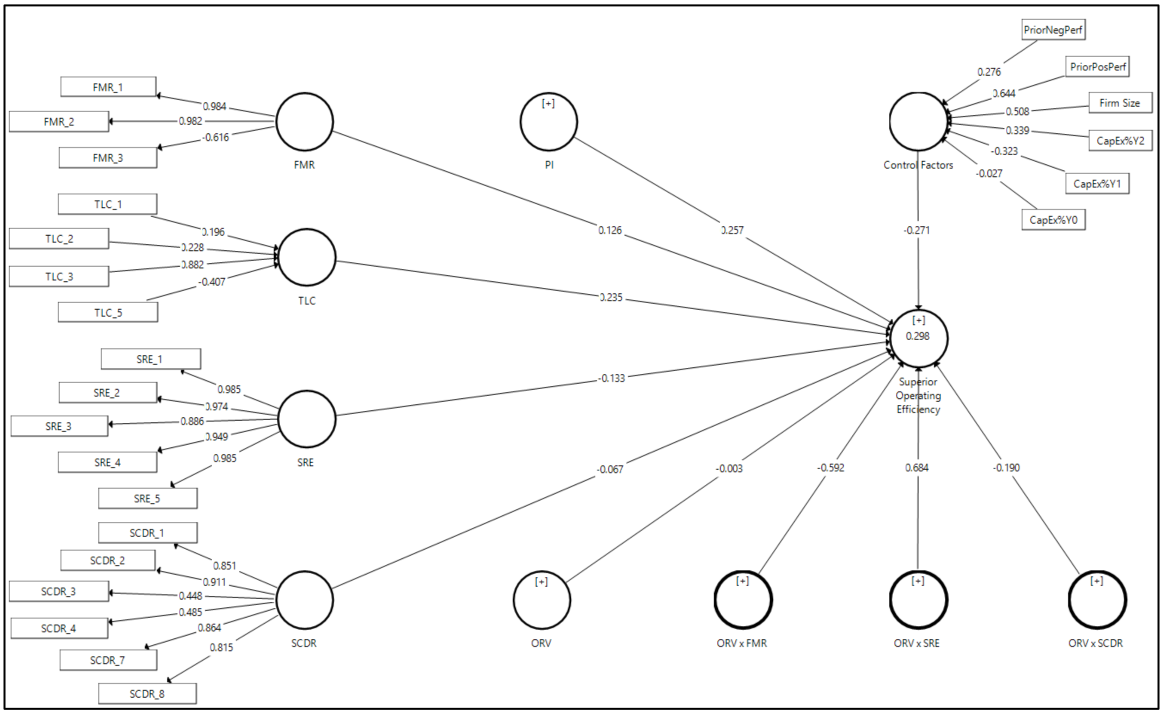
n=96	SSO	SSE	Q^2 (=1-SSE/SSO)
Construct Cross-validated Redundancy			
Control Factors	567.000	567.000	
FMR	287.000	287.000	
ORV	96.000	96.000	
PI	96.000	96.000	
PI x TLC	384.000	384.000	
SCDR	576.000	576.000	
SOE	288.000	236.555	0.179

SRE	480.000	480.000	
TLC	384.000	384.000	
Indicator Cross-validated Redundancy			
CapEx%Y0	95.000	95.000	
CapEx%Y1	95.000	95.000	
CapEx%Y2	95.000	95.000	
FMR_1	96.000	96.000	
FMR_2	96.000	96.000	
FMR_3	95.000	95.000	
Firm Size	90.000	90.000	
ORV_1	96.000	96.000	
Pr_Inv_1	96.000	96.000	
Pr_Inv_1 * TLC_1	96.000	96.000	
Pr_Inv_1 * TLC_2	96.000	96.000	
Pr_Inv_1 * TLC_3	96.000	96.000	
Pr_Inv_1 * TLC_5	96.000	96.000	
PriorNegPerf	96.000	96.000	
PriorPosPerf	96.000	96.000	
SCDR_1	96.000	96.000	
SCDR_2	96.000	96.000	
SCDR_3	96.000	96.000	
SCDR_4	96.000	96.000	
SCDR_7	96.000	96.000	
SCDR_8	96.000	96.000	
SRE_1	96.000	96.000	
SRE_2	96.000	96.000	
SRE_3	96.000	96.000	
SRE_4	96.000	96.000	
SRE_5	96.000	96.000	
TLC_1	96.000	96.000	
TLC_2	96.000	96.000	
TLC_3	96.000	96.000	
TLC_5	96.000	96.000	
Winsorize5_MPIS_AbROA_Y0Y1Y2	96.000	76.686	0.201
Winsorize5_MPI_AbROA_Y0Y1Y2	96.000	78.253	0.185
Winsorize5_PI_AbROA_Y0Y1Y2	96.000	81.616	0.150

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Operating Efficiency.

F.2.3 Structural Model 3

Figure 39: Path Coefficients and R^2 for Model 3 with Multi-Item Measures



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Operating Efficiency.

Table 44: Construct Validity for Model 3 with Multi-Item Measures

	Composite Reliability	P Values	Average Variance Extracted (AVE)	P Values
Control Factors				
FMR	0.726	.000	0.771	.000
ORV				
ORV x FMR	1.000		1.000	
ORV x SCDR	1.000		1.000	
ORV x SRE	1.000		1.000	
PI				
SCDR	0.880	.000	0.567	.000
Superior Operating Efficiency			1.000	
SRE	0.982	.000	0.915	.000
TLC				

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Operating Efficiency.

Table 45: Outer Loadings and Weights for Model 3 with Multi-Item Measures

	Control Factors	FMR	ORV	ORV x FMR	ORV x SCDR	ORV x SRE	PI	SCDR	SRE	SFP	TLC
Outer Loadings											
FMR_1		0.984									
FMR_2		0.982									
FMR_3		-0.616									
ORV_1			1								
FMR * ORV				1							
SCDR * ORV					1						
SRE * ORV						1					
Pr_Inv_1							1				
SCDR_1								0.851			
SCDR_2								0.911			
SCDR_3								0.448			
SCDR_4								0.485			
SCDR_7								0.864			
SCDR_8								0.815			
SRE_1									0.985		
SRE_2									0.974		
SRE_3									0.886		
SRE_4									0.949		
SRE_5									0.985		
MPIS_AbROS_										1	
Outer Weights											
CapEx%Y0	-0.027										
CapEx%Y1	-0.323										
CapEx%Y2	0.339										
Firm Size	0.508										
PriorNegPerf	0.276										
PriorPosPerf	0.644										
TLC_1											0.196
TLC_2											0.228
TLC_3											0.882
TLC_5											-0407

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Operating Efficiency.

Table 46: HTMT Ratio with Bias-Corrected Confidence Interval for Model 3

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	Bias	5% BC-CI	95% BC-CI	T Statistics (|O/STDEV|)	P Values
ORV -> FMR	0.069	0.105	0.068	0.037	0.012	0.173	1.006	.157
ORV x FMR -> FMR	0.092	0.145	0.088	0.054	0.013	0.206	1.037	.150
ORV x FMR -> ORV	0.261	0.232	0.121	-0.029	0.081	0.486	2.159	.015
ORV x SCDR -> FMR	0.224	0.176	0.087	-0.048	0.117	0.422	2.595	.005
ORV x SCDR -> ORV	0.228	0.215	0.130	-0.013	0.035	0.467	1.749	.040
ORV x SCDR -> ORV x FMR	0.541	0.639	0.259	0.098	0.009	0.843	2.088	.018
ORV x SRE -> FMR	0.092	0.119	0.070	0.027	0.020	0.210	1.316	.094
ORV x SRE -> ORV	0.302	0.292	0.146	-0.011	0.069	0.556	2.064	.020
ORV x SRE -> ORV x FMR	0.873	0.798	0.182	-0.075	0.508	0.927	4.801	.000
ORV x SRE -> ORV x SCDR	0.715	0.724	0.266	0.009	0.015	0.935	2.691	.004
PI -> FMR	0.044	0.097	0.060	0.052	0.005	0.079	0.742	.229
PI -> ORV	0.160	0.164	0.079	0.005	0.026	0.288	2.014	.022
PI -> ORV x FMR	0.136	0.127	0.080	-0.009	0.025	0.301	1.690	.046
PI -> ORV x SCDR	0.051	0.098	0.084	0.047	0.001	0.163	0.600	.274
PI -> ORV x SRE	0.122	0.131	0.102	0.009	0.016	0.366	1.196	.116
SCDR -> FMR	0.894	0.904	0.034	0.010	0.846	0.949	26.052	.000
SCDR -> ORV	0.144	0.176	0.060	0.032	0.042	0.210	2.420	.008
SCDR -> ORV x FMR	0.227	0.219	0.090	-0.008	0.107	0.407	2.538	.006
SCDR -> ORV x SCDR	0.217	0.228	0.081	0.011	0.068	0.333	2.689	.004
SCDR -> ORV x SRE	0.227	0.227	0.079	0.000	0.102	0.362	2.871	.002
SCDR -> PI	0.113	0.148	0.083	0.035	0.036	0.236	1.369	.085
SRE -> FMR	0.022	0.107	0.070	0.085	0.003	0.021	0.310	.378
SRE -> ORV	0.023	0.114	0.084	0.091	0.000	0.048	0.277	.391
SRE -> ORV x FMR	0.000	0.105	0.077	0.105	0.000	0.000	0.001	.500
SRE -> ORV x SCDR	0.008	0.164	0.114	0.156	0.000	0.005	0.071	.472
SRE -> ORV x SRE	0.121	0.166	0.117	0.046	0.005	0.326	1.029	.152
SRE -> PI	0.272	0.260	0.149	-0.012	0.026	0.511	1.823	.034
SRE -> SCDR	0.074	0.132	0.067	0.058	0.013	0.121	1.093	.137
SOE-> FMR	0.941	0.945	0.037	0.004	0.877	0.999	25.207	.000
SOE -> ORV	0.039	0.092	0.058	0.053	0.011	0.057	0.671	.251
SOE -> ORV x FMR	0.089	0.121	0.063	0.032	0.032	0.189	1.403	.080
SOE -> ORV x SCDR	0.242	0.190	0.085	-0.052	0.139	0.421	2.837	.002
SOE -> ORV x SRE	0.145	0.155	0.077	0.010	0.045	0.286	1.887	.030
SOE -> PI	0.048	0.096	0.057	0.048	0.003	0.069	0.835	.202
SOE -> SCDR	0.878	0.877	0.036	0.000	0.803	0.923	24.281	.000
SOE -> SRE	0.085	0.131	0.079	0.046	0.021	0.199	1.077	.141

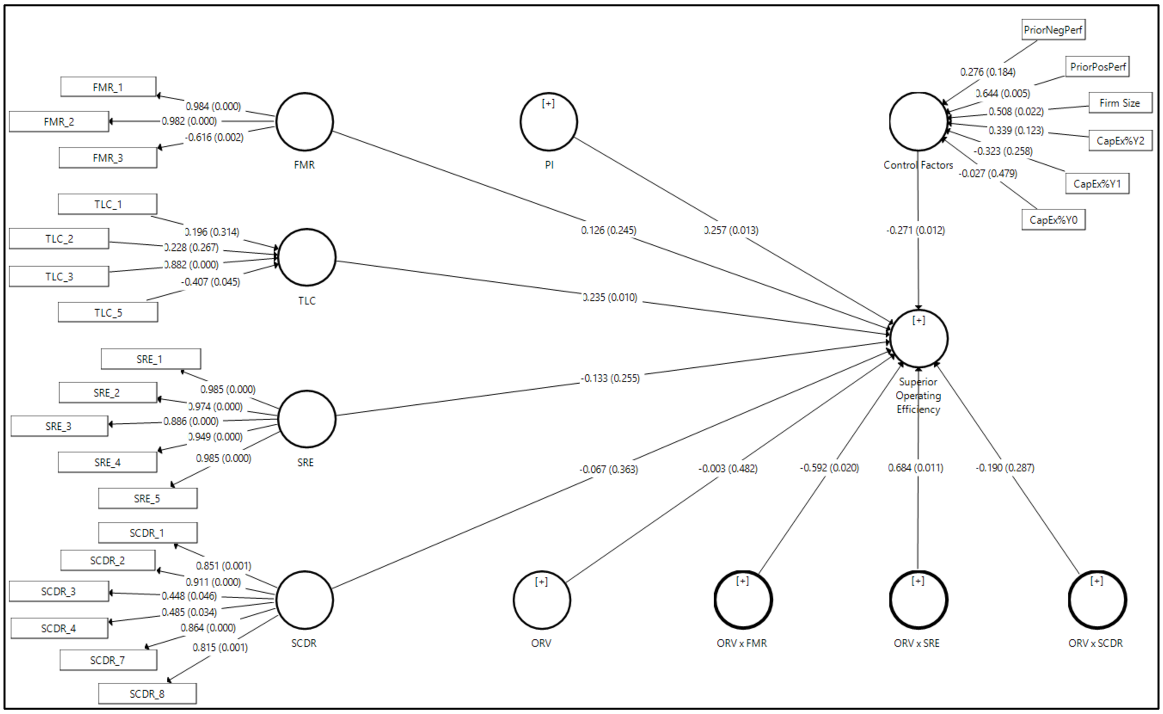
Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Operating Efficiency.

Table 47: Measures of Collinearity for Model 3 with Multi-Item Measures

	Outer VIF		Inner VIF
CapEx%Y0	3.440	Control Factors	1.073
CapEx%Y1	3.885	FMR-->SOE	4.536
CapEx%Y2	1.966	ORV-->SOE	1.187
FMR * ORV	1.000	ORV x FMR-->SOE	4.925
FMR_1	12.771	ORV x SCDR-->SOE	2.636
FMR_2	12.238	ORV x SRE-->SOE	7.077
FMR_3	1.395	PI-->SOE	1.083
Firm Size	1.105	SCDR-->SOE	1.96
ORV_1	1.000	SRE-->SOE	5.616
Pr_Inv_1	1.000	TLC-->SOE	1.163
PriorNegPerf	1.120		
PriorPosPerf	1.096		
SCDR * ORV	1.000		
SCDR_1	13.792		
SCDR_2	10.005		
SCDR_3	12.812		
SCDR_4	11.705		
SCDR_7	51.511		
SCDR_8	47.324		
SRE * ORV	1.000		
SRE_1	15.932		
SRE_2	21.118		
SRE_3	6.319		
SRE_4	8.834		
SRE_5	21.107		
TLC_1	3.050		
TLC_2	3.098		
TLC_3	1.013		
TLC_5	1.084		
Winsorize5_MPIS_AbROS_Y0Y1Y2	1.000		

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Operating Efficiency.

Figure 40: Path Coefficients and p-Values of Model 3 with Multi-Item Measures



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Operating Efficiency.

Table 48: Statistical Significance of Model 3 with Multi-Item Measures

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	Bias	5% BC-CI	95% BC-CI	T Statistics (|O/STDEV|)	P Values
Coefficient of Determination (R^2)								
SOE R^2	0.298	0.412	0.102	0.215	0.343	0.114	2.919	.002***
SOE Adjusted R^2	0.215	0.343	0.114	0.128	-0.015	0.281	1.887	.030**
Path Coefficients (β)								
Control Factors -> SOE	-0.271	-0.330	0.119	-0.060	-0.408	-0.038	2.267	.012**
FMR -> SOE	0.126	0.230	0.183	0.104	0.003	0.366	0.691	.245
ORV -> SOE	-0.003	-0.088	0.067	-0.085	-0.001	0.000	0.045	.482
ORV x FMR -> SOE	-0.592	-0.446	0.287	0.146	-1.591	-0.292	2.062	.020**
ORV x SCDR -> SOE	-0.190	-0.298	0.338	-0.108	-0.950	-0.015	0.561	.287
ORV x SRE -> SOE	0.684	0.439	0.300	-0.245	0.412	1.787	2.278	.011**
PI -> SOE	0.257	0.203	0.115	-0.054	0.094	0.468	2.228	.013**
SCDR -> SOE	-0.067	-0.193	0.191	-0.126	-0.177	0.000	0.349	.363
SRE -> SOE	-0.133	-0.253	0.202	-0.120	-0.374	-0.002	0.660	.255
TLC -> SOE	0.235	0.241	0.101	0.006	0.058	0.394	2.335	.010***
Calculated Effect Sizes (f^2)								
Control Factors -> SOE	0.097	0.167	0.123	-0.428	-0.776	-0.776	0.790	.215
FMR -> SOE	0.005	0.026	0.037	0.225	0.000	0.001	0.137	.446
ORV -> SOE	0.000	0.015	0.021	-0.088	-0.495	-0.495	0.001	.500
ORV x FMR -> SOE	0.080	0.063	0.068	-0.526	-2.126	-2.126	1.183	.118
ORV x SCDR -> SOE	0.019	0.030	0.046	-0.317	-4.348	-4.348	0.419	.338
ORV x SRE -> SOE	0.098	0.054	0.064	0.341	0.000	0.202	1.543	.061*
PI -> SOE	0.087	0.075	0.076	0.116	0.000	0.189	1.135	.128
SCDR -> SOE	0.003	0.020	0.030	-0.196	-3.248	-3.248	0.106	.458
SRE -> SOE	0.004	0.032	0.051	-0.258	-2.229	-2.229	0.089	.465
TLC -> SOE	0.068	0.073	0.056	0.173	0.000	0.062	1.205	.114

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SOE = Superior Operating Efficiency.

*Significance is one-tailed: p<.10

**Significance is one-tailed: p<.05

***Significance is one-tailed: p<.01

Table 49: Predictive Validity of Model 3 with Multi-Item Measures

n=96	SSO	SSE	Q^2 (=1-SSE/SSO)
Construct Cross-validated Redundancy			
Control Factors	567.000	567.000	
FMR	287.000	287.000	
ORV	96.000	96.000	
ORV x FMR	96.000	96.000	
ORV x SCDR	96.000	96.000	
ORV x SRE	96.000	96.000	
PI	96.000	96.000	
SCDR	576.000	576.000	
SOE	288.000	237.651	0.175
SRE	480.000	480.000	
TLC	384.000	384.000	
Indicator Cross-validated Redundancy			
CapEx%Y0	95.000	95.000	
CapEx%Y1	95.000	95.000	
CapEx%Y2	95.000	95.000	
FMR * ORV	96.000	96.000	
FMR_1	96.000	96.000	
FMR_2	96.000	96.000	
FMR_3	95.000	95.000	
Firm Size	90.000	90.000	
ORV_1	96.000	96.000	
Pr_Inv_1	96.000	96.000	
PriorNegPerf	96.000	96.000	
PriorPosPerf	96.000	96.000	
SCDR * ORV	96.000	96.000	
SCDR_1	96.000	96.000	
SCDR_2	96.000	96.000	
SCDR_3	96.000	96.000	
SCDR_4	96.000	96.000	
SCDR_7	96.000	96.000	
SCDR_8	96.000	96.000	
SRE * ORV	96.000	96.000	
SRE_1	96.000	96.000	
SRE_2	96.000	96.000	
SRE_3	96.000	96.000	
SRE_4	96.000	96.000	
SRE_5	96.000	96.000	

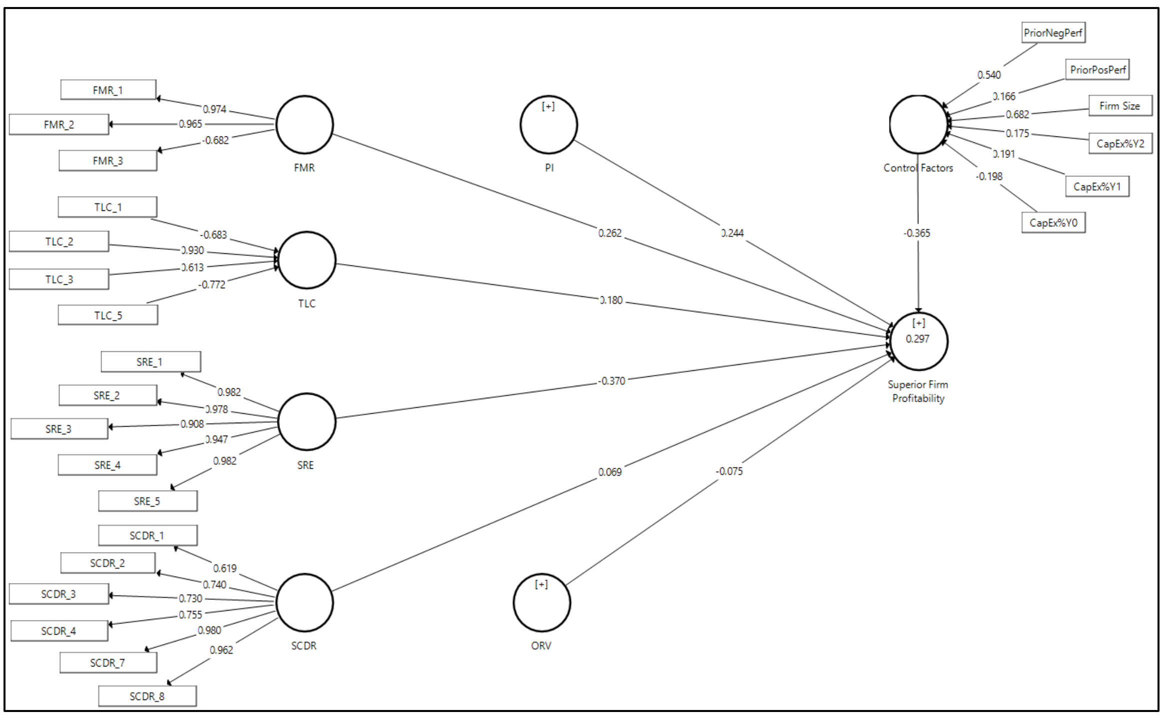
TLC_1	96.000	96.000	
TLC_2	96.000	96.000	
TLC_3	96.000	96.000	
TLC_5	96.000	96.000	
Winsorize5_MPIS_AbROA_Y0Y1Y2	96.000	79.508	0.172
Winsorize5_MPI_AbROA_Y0Y1Y2	96.000	78.600	0.181
Winsorize5_PI_AbROA_Y0Y1Y2	96.000	79.543	0.171

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Operating Efficiency.

F.3 Superior Firm Performance Relative to MPIS Matching Group

F.3.1 Structural Model 4

Figure 41: Path Coefficients and R^2 for Model 4 with Multi-Item Measures



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

Table 50: Construct Reliability for Model 4 with Multi-Item Measures

	Composite Reliability	P Values	Average Variance Extracted (AVE)	P Values
Control Factors				
FMR	0.707	.000	0.782	.000
ORV				
PI				
SCDR	0.917	.000	0.653	.000
SRE	0.983	.000	0.921	.000
Superior Firm Profitability	1		1	
TLC				

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

Table 51: Outer Loadings and Weights for Model 4 with Multi-Item Measures

	Control Factors	FMR	ORV	PI	SCDR	SRE	SFP	TLC
Outer Loadings								
FMR_1		0.974						
FMR_2		0.965						
FMR_3		-0.682						
ORV_1			1					
Pr_Inv_1				1				
SCDR_1					0.740			
SCDR_2					0.619			
SCDR_3					0.730			
SCDR_4					0.755			
SCDR_7					0.980			
SCDR_8					0.962			
SRE_1						0.982		
SRE_2						0.978		
SRE_3						0.908		
SRE_4						0.947		
SRE_5						0.982		
Winsorize5_MPIS_AbROS_Y0Y1Y2							1	
Outer Weights								
CapEx%Y0	-0.198							
CapEx%Y1	0.191							

CapEx%Y2	0.175	
Firm Size	0.682	
PriorNegPerf	0.540	
PriorPosPerf	0.166	
TLC_1		-0.683
TLC_2		0.930
TLC_3		0.613
TLC_5		-0.772

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

Table 52: HTMT Ratio with Bias-Corrected Confidence Interval for Model 4

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	Bias	5% BC-CI	95% BC-CI	T Statistics (|O/STDEV|)	P Values
ORV -> FMR	0.069	0.106	0.070	0.038	0.010	0.173	0.980	.164
PI -> FMR	0.044	0.097	0.059	0.052	0.005	0.077	0.756	.225
PI -> ORV	0.160	0.163	0.080	0.003	0.025	0.287	1.990	.023
SCDR -> FMR	0.894	0.903	0.034	0.010	0.846	0.946	26.666	.000
SCDR -> ORV	0.144	0.177	0.060	0.032	0.038	0.209	2.422	.008
SCDR -> PI	0.113	0.149	0.082	0.036	0.036	0.234	1.378	.084
SRE -> FMR	0.941	0.945	0.036	0.004	0.883	1.000	25.969	.000
SRE -> ORV	0.039	0.093	0.061	0.054	0.008	0.056	0.646	.259
SRE -> PI	0.048	0.097	0.057	0.050	0.007	0.066	0.834	.202
SRE -> SCDR	0.878	0.877	0.036	-0.001	0.798	0.923	24.082	.000
SFP -> FMR	0.098	0.128	0.075	0.030	0.015	0.221	1.306	.096
SFP -> ORV	0.144	0.178	0.121	0.034	0.010	0.364	1.187	.118
SFP -> PI	0.253	0.261	0.176	0.008	0.027	0.603	1.442	.075
SFP -> SCDR	0.146	0.171	0.071	0.025	0.040	0.253	2.059	.002
SFP -> SRE	0.192	0.198	0.090	0.006	0.044	0.337	2.132	.017

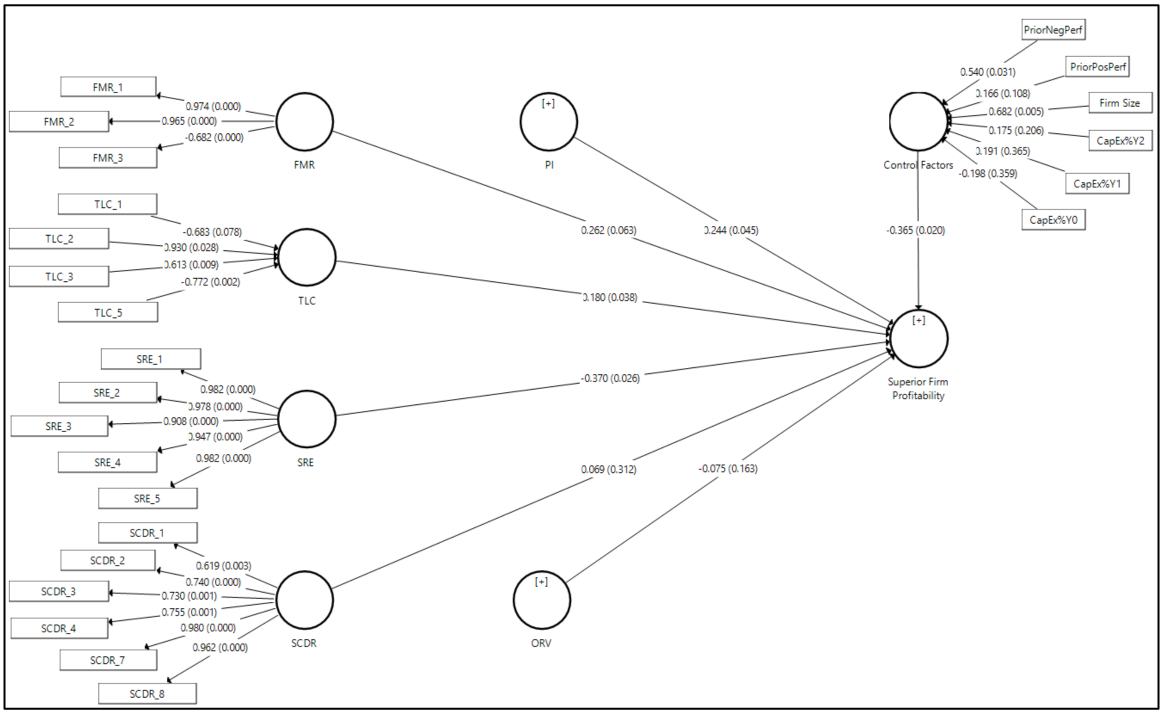
Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

Table 53: Measures of Collinearity for Model 4 with Multi-Item Measures

	Outer VIF		Inner VIF
CapEx%Y0	3.440	Control Factors →SFP	1.175
CapEx%Y1	3.885	FMR →SFP	4.201
CapEx%Y2	1.966	ORV →SFP	1.180
FMR_1	12.771	PI →SFP	1.071
FMR_2	12.238	SCDR →SFP	3.095
FMR_3	1.395	SRE →SFP	5.768
Firm Size	1.105	TLC →SFP	1.534
ORV_1	1.000		
Pr_Inv_1	1.000		
PriorNegPerf	1.120		
PriorPosPerf	1.096		
SCDR_1	13.792		
SCDR_2	10.005		
SCDR_3	12.812		
SCDR_4	11.705		
SCDR_7	51.511		
SCDR_8	47.324		
SRE_1	15.932		
SRE_2	21.118		
SRE_3	6.319		
SRE_4	8.834		
SRE_5	21.107		
TLC_1	3.050		
TLC_2	3.098		
TLC_3	1.013		
TLC_5	1.084		
Winsorize5_MPIS_AbROS_Y0Y1Y2	1.000		

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

Figure 42: Path Coefficients and p-Values of Model 4 with Multi-Item Measures



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

Table 54: Statistical Significance of Model 4 with Multi-Item Measures

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	Bias	5% BC-CI	95% BC-CI	T Statistics (|O/STDEV|)	P Values
Coefficient of Determination (R^2)								
SFP R^2	0.297	0.467	0.144	0.171	0.101	0.359	2.062	.020**
SFP Adjusted R^2	0.241	0.425	0.155	0.184	0.030	0.308	1.550	.061*
Path Coefficients (β)								
Control Factors -> SFP	-0.365	-0.471	0.179	-0.105	-0.578	-0.057	2.045	.020**
FMR -> SFP	0.262	0.221	0.171	-0.041	0.070	0.793	1.534	.063*
ORV -> SFP	-0.075	-0.104	0.077	-0.028	-0.213	-0.004	0.983	.163
PI -> SFP	0.244	0.213	0.143	-0.030	0.025	0.491	1.700	.045**
SCDR -> SFP	0.069	0.162	0.141	0.093	0.000	0.194	0.489	.312
SRE -> SFP	-0.370	-0.295	0.191	0.074	-0.960	-0.144	1.936	.026**
TLC -> SFP	0.180	0.206	0.101	0.026	0.013	0.319	1.776	.038**
Calculated Effect Sizes (f^2)								
Control Factors -> SFP	0.162	0.463	0.462	-0.632	-0.961	-0.961	0.350	.363
FMR -> SFP	0.023	0.029	0.038	0.198	0.000	0.033	0.614	.270
ORV -> SFP	0.007	0.026	0.036	-0.110	-0.439	-0.439	0.188	.426
PI -> SFP	0.079	0.110	0.124	0.135	0.001	0.266	0.634	.263
SCDR -> SFP	0.002	0.022	0.038	0.159	0.000	0.000	0.058	.477
SRE -> SFP	0.034	0.042	0.052	-0.329	-1.197	-1.197	0.651	.258
TLC -> SFP	0.030	0.057	0.051	0.176	0.000	0.020	0.589	.278

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

*Significance is one-tailed: p<.10
**Significance is one-tailed: p<.05
***Significance is one-tailed: p<.01

Table 55: Predictive Validity of Model 4 with Multi-Item Measures

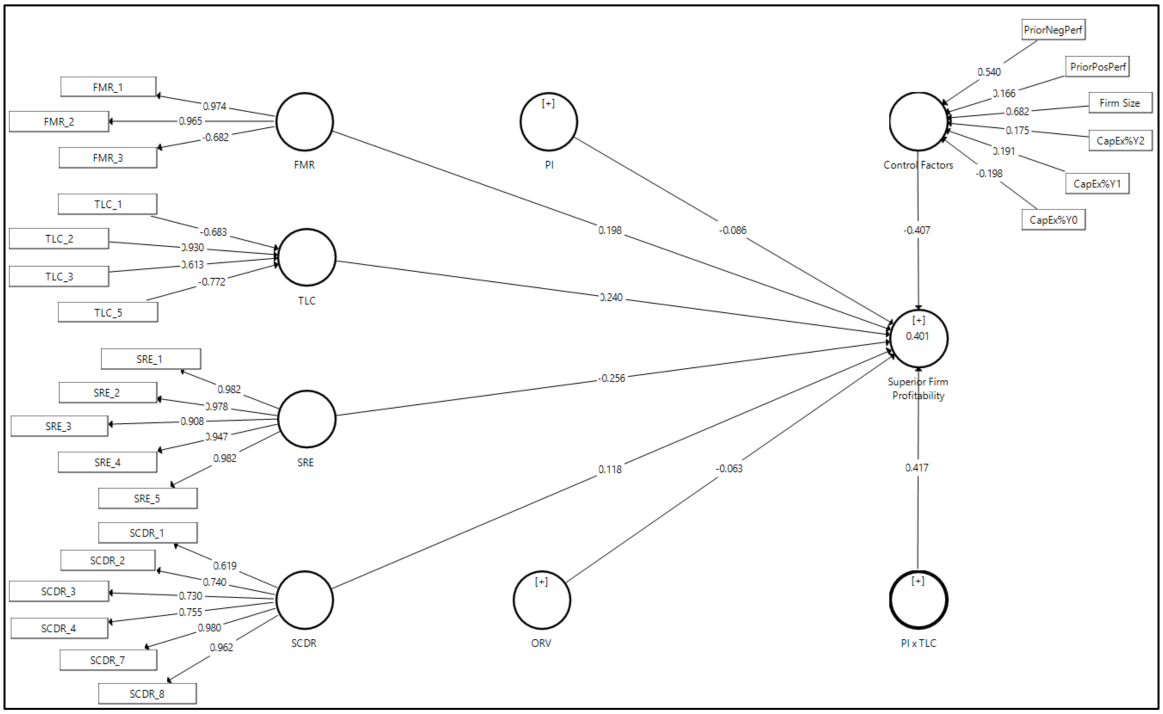
n=96	SSO	SSE	Q^2 (=1-SSE/SSO)
Construct Cross-validated Redundancy			
Control Factors	567.000	567.000	
FMR	287.000	287.000	
ORV	96.000	96.000	
PI	96.000	96.000	
SCDR	576.000	576.000	
SRE	480.000	480.000	
Superior Firm Profitability	288.000	243.885	0.153

TLC	384.000	384.000	
Indicator Cross-validated Redundancy			
CapEx%Y0	95.000	95.000	
CapEx%Y1	95.000	95.000	
CapEx%Y2	95.000	95.000	
FMR_1	96.000	96.000	
FMR_2	96.000	96.000	
FMR_3	95.000	95.000	
Firm Size	90.000	90.000	
ORV_1	96.000	96.000	
Pr_Inv_1	96.000	96.000	
PriorNegPerf	96.000	96.000	
PriorPosPerf	96.000	96.000	
SCDR_1	96.000	96.000	
SCDR_2	96.000	96.000	
SCDR_3	96.000	96.000	
SCDR_4	96.000	96.000	
SCDR_7	96.000	96.000	
SCDR_8	96.000	96.000	
SRE_1	96.000	96.000	
SRE_2	96.000	96.000	
SRE_3	96.000	96.000	
SRE_4	96.000	96.000	
SRE_5	96.000	96.000	
TLC_1	96.000	96.000	
TLC_2	96.000	96.000	
TLC_3	96.000	96.000	
TLC_5	96.000	96.000	
Winsorize5_MPIS_AbROS_Y0Y1Y2	96.000	77.949	0.188
Winsorize5_MPI_AbROS_Y0Y1Y2	96.000	80.803	0.158
Winsorize5_PI_AbROS_Y0Y1Y2	96.000	85.133	0.113

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

F.3.2 Structural Model 5

Figure 43: Path Coefficients and R^2 of Model 5 with Multi-Item Measures



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

Table 56: Construct Reliability for Model 5 with Multi-Item Measures

	Composite Reliability	P Values	Average Variance Extracted (AVE)	P Values
Control Factors				
FMR	0.707	.000	0.782	.000
ORV				
PI				
PI x TLC	0.412	.004	0.565	.000
SCDR	0.917	.000	0.653	.000
SFP	1		1	
SRE	0.983	.000	0.921	.000
TLC				

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

Table 57: Outer Loadings and Weights for Model 5 with Multi-Item Measures

	Control Factors	FMR	ORV	PI	PI x TLC	SCDR	SRE	SFP	TLC
Outer Loadings									
FMR_1		0.974							
FMR_2		0.965							
FMR_3		-0.682							
ORV_1			1.000						
Pr_Inv_1				1.000					
SCDR_1						0.740			
SCDR_2						0.619			
SCDR_3						0.755			
SCDR_4						0.730			
SCDR_7						0.980			
SCDR_8						0.962			
SRE_1							0.982		
SRE_2							0.978		
SRE_3							0.908		
SRE_4							0.947		
SRE_5							0.982		
MPIS_AbROS_								1.000	
Outer Weights									
CapEx%Y0	-0.198								
CapEx%Y1	0.191								
CapEx%Y2	0.175								
Firm Size	0.682								
PriorNegPerf	0.540								
PriorPosPerf	0.166								
Pr_Inv_1 * TLC_1					0.519				
Pr_Inv_1 * TLC_2					0.293				
Pr_Inv_1 * TLC_3					0.054				
Pr_Inv_1 * TLC_5					-0.314				
TLC_1									-0.683
TLC_2									0.930
TLC_3									0.613
TLC_5									-0.772

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

Table 58: HTMT Ratio with Bias-Corrected Confidence Interval for Model 5

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	Bias	5% BC-CI	95% BC-CI	T Statistics (|O/STDEV|)	P Values
ORV -> FMR	0.069	0.105	0.069	0.036	0.012	0.174	0.998	.159
PI -> FMR	0.044	0.097	0.061	0.052	0.003	0.076	0.733	.232
PI -> ORV	0.160	0.164	0.080	0.004	0.020	0.286	1.988	.023
PI x TLC -> FMR	0.176	0.209	0.066	0.034	0.088	0.247	2.657	.004
PI x TLC -> ORV	0.118	0.167	0.060	0.049	0.031	0.162	1.959	.025
PI x TLC -> PI	0.826	0.734	0.180	-0.091	0.503	0.977	4.595	.000
SCDR -> FMR	0.894	0.903	0.035	0.009	0.847	0.950	25.878	.000
SCDR -> ORV	0.144	0.177	0.061	0.033	0.035	0.211	2.387	.009
SCDR -> PI	0.113	0.151	0.084	0.037	0.036	0.236	1.340	.090
SCDR -> PI x TLC	0.199	0.240	0.058	0.041	0.112	0.254	3.448	.000
SFP -> FMR	0.098	0.127	0.075	0.029	0.017	0.225	1.308	.096
SFP -> ORV	0.144	0.178	0.120	0.034	0.008	0.363	1.194	.116
SFP -> PI	0.253	0.266	0.175	0.013	0.028	0.591	1.449	.074
SFP -> PI x TLC	0.415	0.413	0.187	-0.002	0.130	0.720	2.219	.013
SFP -> SCDR	0.146	0.170	0.072	0.024	0.041	0.253	2.033	.021
SRE -> FMR	0.941	0.945	0.037	0.004	0.883	1.003	25.634	.000
SRE -> ORV	0.039	0.093	0.060	0.054	0.010	0.059	0.647	.259
SRE -> PI	0.048	0.097	0.059	0.050	0.006	0.067	0.807	.210
SRE -> PI x TLC	0.200	0.215	0.054	0.015	0.110	0.279	3.688	.000
SRE -> SCDR	0.878	0.878	0.036	0.000	0.799	0.922	24.529	.000
SRE -> SFP	0.192	0.197	0.090	0.005	0.050	0.340	2.134	.016

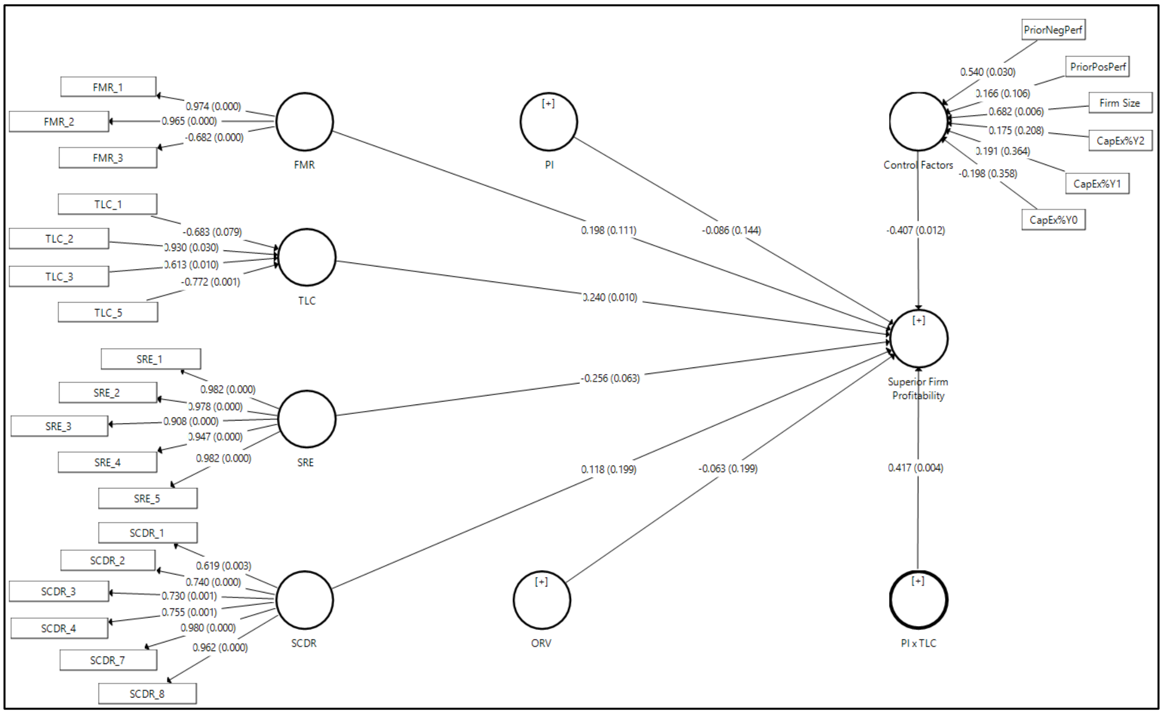
Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

Table 59: Measures of Collinearity for Model 5 with Multi-Item Measures

	Outer VIF		Inner VIF
CapEx%Y0	3.440	Control Factors-->SFP	1.191
CapEx%Y1	3.885	FMR-->SFP	4.24
CapEx%Y2	1.966	ORV-->SFP	1.181
FMR_1	12.771	PI-->SFP	2.111
FMR_2	12.238	PI x TLC-->SFP	2.048
FMR_3	1.395	SCDR-->SFP	3.118
Firm Size	1.105	SRE-->SFP	5.892
ORV_1	1.000	TLC-->SFP	1.568
Pr_Inv_1	1.000		
Pr_Inv_1 * TLC_1	7.893		
Pr_Inv_1 * TLC_2	5.759		
Pr_Inv_1 * TLC_3	1.135		
Pr_Inv_1 * TLC_5	2.101		
PriorNegPerf	1.120		
PriorPosPerf	1.096		
SCDR_1	13.792		
SCDR_2	10.005		
SCDR_3	12.812		
SCDR_4	11.705		
SCDR_7	51.511		
SCDR_8	47.324		
SRE_1	15.932		
SRE_2	21.118		
SRE_3	6.319		
SRE_4	8.834		
SRE_5	21.107		
TLC_1	3.050		
TLC_2	3.098		
TLC_3	1.013		
TLC_5	1.084		
Winsorize5_MPIS_AbROA_Y0Y1Y2	1.000		

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

Figure 44: Path Coefficients and p-Values of Model 5 with Multi-Item Measures



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

Table 60: Statistical Significance of Model 5 with Multi-Item Measures

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	Bias	5% BC-CI	95% BC-CI	T Statistics (|O/STDEV|)	P Values
Coefficient of Determination (R^2)								
SFP R^2	0.401	0.533	0.138	0.132	0.127	0.494	2.904	.002***
SFP Adjusted R^2	0.346	0.491	0.151	0.144	0.047	0.448	2.294	.011**
Path Coefficients (β)								
Control Factors -> SFP	-0.407	-0.451	0.180	-0.044	-0.721	-0.112	2.266	.012**
FMR -> SFP	0.198	0.203	0.162	0.005	0.028	0.612	1.221	.111
ORV -> SFP	-0.063	-0.102	0.075	-0.039	-0.179	-0.002	0.845	.199
PI -> SFP	-0.086	-0.104	0.081	-0.017	-0.259	-0.008	1.060	.144
PI x TLC -> SFP	0.417	0.352	0.156	-0.065	0.203	0.690	2.675	.004***
SCDR -> SFP	0.118	0.143	0.140	0.025	0.015	0.455	0.847	.199
SRE -> SFP	-0.256	-0.241	0.167	0.015	-0.647	-0.048	1.532	.063*
TLC -> SFP	0.240	0.223	0.104	-0.017	0.082	0.431	2.317	.010***
Calculated Effect Sizes (f^2)								
Control Factors -> SFP	0.232	0.477	0.484	-0.683	-0.930	-0.930	0.479	.316
FMR -> SFP	0.015	0.027	0.036	0.188	0.000	0.017	0.433	.332
ORV -> SFP	0.006	0.028	0.038	-0.107	-0.459	-0.459	0.148	.441
PI -> SFP	0.006	0.017	0.025	-0.109	-0.666	-0.666	0.240	.405
PI x TLC -> SFP	0.175	0.160	0.134	0.177	0.000	0.296	1.299	.097*
SCDR -> SFP	0.007	0.015	0.022	0.135	0.000	0.005	0.345	.365

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

*Significance is one-tailed: p<.10
**Significance is one-tailed: p<.05
***Significance is one-tailed: p<.01

Table 61: Predictive Validity of Model 5 with Multi-Item Measures

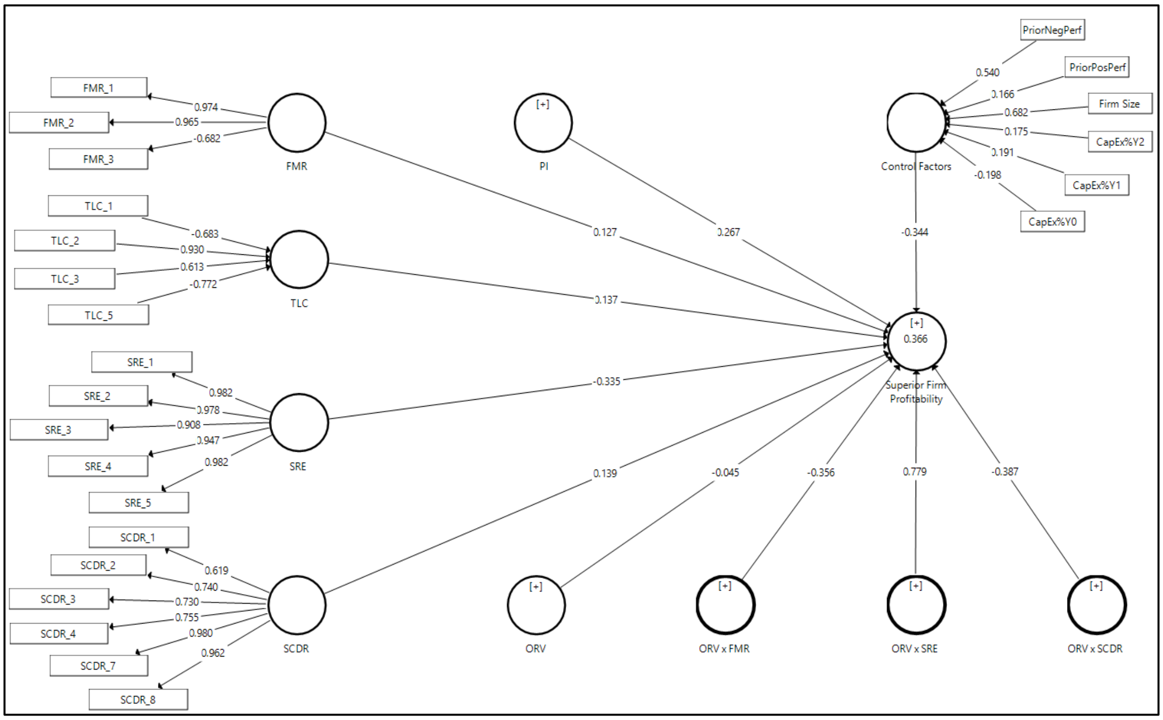
n=96	SSO	SSE	Q^2 (=1-SSE/SSO)
Construct Cross-validated Redundancy			
Control Factors	567.000	567.000	
FMR	287.000	287.000	
ORV	96.000	96.000	
PI	96.000	96.000	
PI x TLC	384.000	384.000	

SCDR	576.000	576.000	
SRE	480.000	480.000	
Superior Firm Profitability	288.000	217.356	0.245
TLC	384.000	384.000	
Indicator Cross-validated Redundancy			
CapEx%Y0	95.000	95.000	
CapEx%Y1	95.000	95.000	
CapEx%Y2	95.000	95.000	
FMR_1	96.000	96.000	
FMR_2	95.000	95.000	
FMR_3	96.000	96.000	
Firm Size	90.000	90.000	
ORV_1	96.000	96.000	
Pr_Inv_1	96.000	96.000	
Pr_Inv_1 * TLC_1	96.000	96.000	
Pr_Inv_1 * TLC_2	96.000	96.000	
Pr_Inv_1 * TLC_3	96.000	96.000	
Pr_Inv_1 * TLC_5	96.000	96.000	
PriorNegPerf	96.000	96.000	
PriorPosPerf	96.000	96.000	
SCDR_1	96.000	96.000	
SCDR_2	96.000	96.000	
SCDR_3	96.000	96.000	
SCDR_4	96.000	96.000	
SCDR_7	96.000	96.000	
SCDR_8	96.000	96.000	
SRE_1	96.000	96.000	
SRE_2	96.000	96.000	
SRE_3	96.000	96.000	
SRE_4	96.000	96.000	
SRE_5	96.000	96.000	
TLC_1	96.000	96.000	
TLC_2	96.000	96.000	
TLC_3	96.000	96.000	
TLC_5	96.000	96.000	
Winsorize5_MPIS_AbROS_Y0Y1Y2	96.000	67.398	0.298
Winsorize5_MPI_AbROS_Y0Y1Y2	96.000	69.124	0.280
Winsorize5_PI_AbROS_Y0Y1Y2	96.000	80.834	0.158

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

F.3.3 Structural Model 6

Figure 45: Path Coefficients and R^2 of Model 6 with Multi-Item Measures



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

Table 62: Construct Reliability for Model 6 with Multi-Item Measures

	Composite Reliability	P Values	Average Variance Extracted (AVE)	P Values
Control Factors				
FMR	0.707	.000	0.782	.000
ORV				
ORV x FMR	1		1	
ORV x SCDR	1		1	
ORV x SRE	1		1	
PI				
SCDR	0.917	.000	0.653	.000
SRE	0.983	.000	0.921	.000
Superior Firm Profitability	1		1	
TLC				

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

Table 63: Outer Loadings and Outer Weights for Model 6 with Multi-Item Measures

	Control Factors	FMR	ORV	ORV x FMR	ORV x SCDR	ORV x SRE	PI	SCDR	SRE	SFP	TLC
Outer Loadings											
FMR_1		0.974									
FMR_2		0.965									
FMR_3		-0.682									
ORV_1			1								
FMR * ORV				1							
SCDR * ORV					1						
SRE * ORV						1					
Pr_Inv_1							1				
SCDR_1								0.740			
SCDR_2								0.619			
SCDR_3								0.755			
SCDR_4								0.730			
SCDR_7								0.980			
SCDR_8								0.962			
SRE_1									0.982		
SRE_2									0.978		
SRE_3									0.908		
SRE_4									0.947		
SRE_5									0.982		
MPIS_AbROS_										1	
Outer Weights											
CapEx%Y0	-0.198										
CapEx%Y1	0.191										
CapEx%Y2	0.175										
Firm Size	0.682										
PriorNegPerf	0.540										
PriorPosPerf	0.166										
TLC_1											-0.683
TLC_2											0.930
TLC_3											0.613
TLC_5											-0.772

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

Table 64: HTMT Ratio with Bias-Corrected Confidence Interval for Model 6

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	Bias	5% BC-CI	95% BC-CI	T Statistics (|O/STDEV|)	P Values
ORV -> FMR	0.069	0.105	0.071	0.036	0.012	0.185	0.968	.167
ORV x FMR -> FMR	0.095	0.140	0.086	0.044	0.017	0.217	1.114	.133
ORV x FMR -> ORV	0.250	0.241	0.122	-0.009	0.052	0.461	2.048	.020
ORV x SCDR -> FMR	0.196	0.183	0.085	-0.013	0.068	0.360	2.312	.010
ORV x SCDR -> ORV	0.254	0.239	0.132	-0.015	0.053	0.499	1.917	.028
ORV x SCDR -> ORV x FMR	0.755	0.678	0.231	-0.077	0.124	0.904	3.269	.001
ORV x SRE -> FMR	0.097	0.111	0.064	0.013	0.025	0.223	1.531	.063
ORV x SRE -> ORV	0.294	0.296	0.147	0.002	0.051	0.540	2.008	.022
ORV x SRE -> ORV x FMR	0.876	0.837	0.135	-0.039	0.648	0.921	6.512	.000
ORV x SRE -> ORV x SCDR	0.881	0.791	0.225	-0.090	0.214	0.967	3.913	.000
PI -> FMR	0.044	0.097	0.059	0.053	0.003	0.077	0.752	.226
PI -> ORV	0.160	0.163	0.080	0.004	0.020	0.281	2.000	.023
PI -> ORV x FMR	0.123	0.130	0.081	0.007	0.013	0.275	1.513	.065
PI -> ORV x SCDR	0.019	0.090	0.079	0.070	0.000	0.047	0.244	.404
PI -> ORV x SRE	0.106	0.124	0.087	0.018	0.009	0.268	1.222	.111
SCDR -> FMR	0.894	0.904	0.033	0.010	0.844	0.943	26.792	.000
SCDR -> ORV	0.144	0.177	0.059	0.033	0.041	0.208	2.440	.007
SCDR -> ORV x FMR	0.220	0.225	0.087	0.005	0.100	0.386	2.519	.006
SCDR -> ORV x SCDR	0.195	0.222	0.084	0.027	0.044	0.309	2.325	.010
SCDR -> ORV x SRE	0.231	0.228	0.077	-0.002	0.109	0.365	2.985	.001
SCDR -> PI	0.113	0.149	0.082	0.036	0.036	0.231	1.381	.084
SRE -> FMR	0.941	0.946	0.036	0.005	0.883	0.998	26.172	.000
SRE -> ORV	0.039	0.092	0.060	0.053	0.012	0.060	0.648	.258
SRE -> ORV x FMR	0.095	0.117	0.059	0.022	0.041	0.206	1.609	.054
SRE -> ORV x SCDR	0.228	0.205	0.080	-0.023	0.111	0.375	2.851	.002
SRE -> ORV x SRE	0.152	0.152	0.072	0.000	0.055	0.299	2.100	.018
SRE -> PI	0.048	0.097	0.057	0.049	0.006	0.070	0.831	.203
SRE -> SCDR	0.878	0.877	0.036	0.000	0.801	0.923	24.466	.000
SFP -> FMR	0.098	0.129	0.074	0.031	0.015	0.221	1.324	.093
SFP -> ORV	0.144	0.179	0.121	0.036	0.007	0.358	1.193	.116
SFP -> ORV x FMR	0.110	0.154	0.107	0.044	0.005	0.300	1.025	.153
SFP -> ORV x SCDR	0.167	0.229	0.144	0.063	0.005	0.395	1.161	.123
SFP -> ORV x SRE	0.241	0.249	0.152	0.008	0.026	0.512	1.589	.056
SFP -> PI	0.253	0.266	0.176	0.013	0.029	0.597	1.440	.075
SFP -> SCDR	0.146	0.172	0.071	0.026	0.040	0.254	2.049	.020
SFP -> SRE	0.192	0.198	0.090	0.007	0.046	0.335	2.141	.016

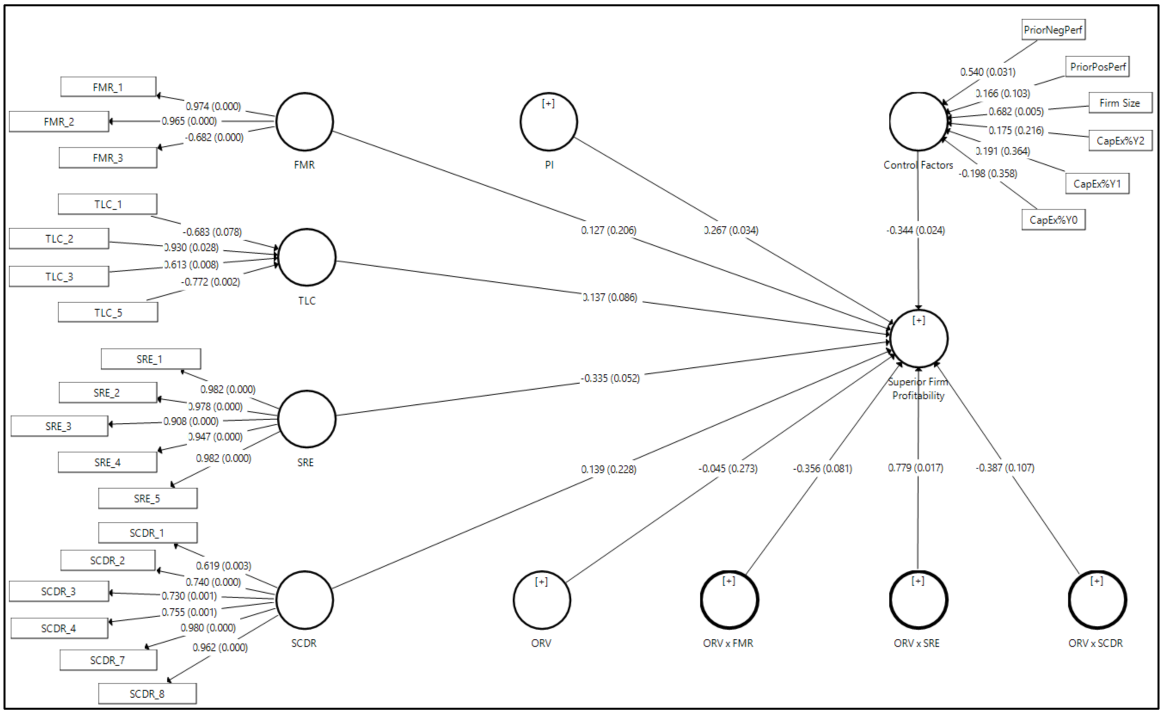
Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

Table 65: Measures of Collinearity for Model 6 with Multi-Item Measures

	Outer VIF		Inner VIF
CapEx%Y0	3.440	Control Factors	1.194
CapEx%Y1	3.885	FMR-->SFP	4.513
CapEx%Y2	1.966	ORV-->SFP	1.245
FMR * ORV	1.000	ORV x FMR-->SFP	4.641
FMR_1	12.771	ORV x SCDR-->SFP	5.673
FMR_2	12.238	ORV x SRE-->SFP	9.412
FMR_3	1.395	PI-->SFP	1.096
Firm Size	1.105	SCDR-->SFP	3.473
ORV_1	1.000	SRE-->SFP	6.231
Pr_Inv_1	1.000	TLC-->SFP	0.616
PriorNegPerf	1.120		
PriorPosPerf	1.096		
SCDR * ORV	1.000		
SCDR_1	13.792		
SCDR_2	10.005		
SCDR_3	12.812		
SCDR_4	11.705		
SCDR_7	51.511		
SCDR_8	47.324		
SRE * ORV	1.000		
SRE_1	15.932		
SRE_2	21.118		
SRE_3	6.319		
SRE_4	8.834		
SRE_5	21.107		
TLC_1	3.050		
TLC_2	3.098		
TLC_3	1.013		
TLC_5	1.084		
Winsorize5_MPIS_AbROS_Y0Y1Y2	1.000		

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

Figure 46: Path Coefficients and p-Values of Model 6 with Multi-Item Measures



Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

Table 66: Statistical Significance of Model 6 with Multi-Item Measures

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	Bias	5% BC-CI	95% BC-CI	T Statistics (|O/STDEV|)	P Values
Coefficient of Determination (R^2)								
SFP R^2	0.366	0.540	0.131	0.174	0.114	0.414	2.800	.003***
SFP Adjusted R^2	0.291	0.486	0.146	0.194	0.009	0.345	1.995	.023**
Path Coefficients (β)								
Control Factors -> SFP	-0.344	-0.441	0.174	-0.097	-0.566	-0.071	1.976	.024**
FMR -> SFP	0.127	0.193	0.154	0.066	0.005	0.380	0.822	.206
ORV -> SFP	-0.045	-0.100	0.074	-0.055	-0.119	0.000	0.602	.273
ORV x FMR -> SFP	-0.356	-0.318	0.255	0.038	-1.135	-0.082	1.398	.081*
ORV x SCDR -> SFP	-0.387	-0.382	0.311	0.006	-1.430	-0.099	1.244	.107
ORV x SRE -> SFP	0.779	0.553	0.367	-0.226	0.356	1.811	2.122	.017**
PI -> SFP	0.267	0.219	0.146	-0.048	0.033	0.509	1.824	.034**
SCDR -> SFP	0.139	0.194	0.186	0.054	0.012	0.554	0.747	.228
SRE -> SFP	-0.335	-0.310	0.206	0.024	-0.825	-0.076	1.628	.052*
TLC -> SFP	0.137	0.178	0.100	0.042	0.004	0.272	1.368	.086*
Calculated Effect Sizes (f^2)								
Control Factors -> SFP	0.157	0.403	0.387	-0.598	-0.979	-0.979	0.404	.343
FMR -> SFP	0.006	0.025	0.035	0.187	0.000	0.002	0.162	.436
ORV -> SFP	0.003	0.024	0.033	-0.102	-0.467	-0.467	0.076	.470
ORV x FMR -> SFP	0.035	0.050	0.076	-0.353	-2.267	-2.267	0.456	.324
ORV x SCDR -> SFP	0.043	0.070	0.094	-0.425	-2.932	-2.932	0.459	.323
ORV x SRE -> SFP	0.104	0.087	0.101	0.448	0.000	0.200	1.037	.150
PI -> SFP	0.103	0.128	0.149	0.117	0.001	0.327	0.688	.246
SCDR -> SFP	0.009	0.023	0.035	0.185	0.000	0.006	0.248	.402
SRE -> SFP	0.028	0.047	0.054	-0.339	-1.293	-1.293	0.521	.301
TLC -> SFP	0.018	0.048	0.049	0.160	0.000	0.012	0.373	.354

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

*Significance is one-tailed: p<.10

**Significance is one-tailed: p<.05

***Significance is one-tailed: p<.01

Table 67: Predictive Validity of Model 6 with Multi-Item Measures

n=96	SSO	SSE	Q^2 (=1-SSE/SSO)
Construct Cross-validated Redundancy			
Control Factors	567.000	567.000	
FMR	287.000	287.000	
ORV	96.000	96.000	
ORV x FMR	96.000	96.000	
ORV x SCDR	96.000	96.000	
ORV x SRE	96.000	96.000	
PI	96.000	96.000	
SCDR	576.000	576.000	
SRE	480.000	480.000	
Superior Firm Profitability	288.000	235.259	0.183
TLC	384.000	384.000	
Indicator Cross-validated Redundancy			
CapEx%Y0	95.000	95.000	
CapEx%Y1	95.000	95.000	
CapEx%Y2	95.000	95.000	
FMR * ORV	96.000	96.000	
FMR_1	96.000	96.000	
FMR_2	95.000	95.000	
FMR_3	96.000	96.000	
Firm Size	90.000	90.000	
ORV_1	96.000	96.000	
Pr_Inv_1	96.000	96.000	
PriorNegPerf	96.000	96.000	
PriorPosPerf	96.000	96.000	
SCDR * ORV	96.000	96.000	
SCDR_1	96.000	96.000	
SCDR_2	96.000	96.000	
SCDR_3	96.000	96.000	
SCDR_4	96.000	96.000	
SCDR_7	96.000	96.000	
SCDR_8	96.000	96.000	
SRE * ORV	96.000	96.000	
SRE_1	96.000	96.000	
SRE_2	96.000	96.000	
SRE_3	96.000	96.000	
SRE_4	96.000	96.000	
SRE_5	96.000	96.000	

TLC_1	96.000	96.000	
TLC_2	96.000	96.000	
TLC_3	96.000	96.000	
TLC_5	96.000	96.000	
Winsorize5_MPIS_AbROS_Y0Y1Y2	96.000	74.677	0.222
Winsorize5_MPI_AbROS_Y0Y1Y2	96.000	77.914	0.188
Winsorize5_PI_AbROS_Y0Y1Y2	96.000	82.668	0.139

Where FMR = Factor Market Rivalry, TLC = Total Logistics Costs, SRE = Strategic Risk Exposure, SCDR = Supply Chain Disruption Risk, PI = Product Innovativeness, ORV = Offshore Relationship Value, and SFP = Superior Firm Profitability.

*Significance is one-tailed: p<.10
**Significance is one-tailed: p<.05
***Significance is one-tailed: p<.01