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Unintended Consequences of Public Policy and Government Regulation on Supply Chain Structure, Conduct, and Performance

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Unintended Consequences of Public Policy and Government Regulation on Supply Chain Structure, Conduct, and Performance

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Abstract

Supply chains, and the firms within them, change their behaviors in response to industry conditions so they can provide efficiency, effectiveness, strategic enablement, and customer utility. Social and economic policies enacted to promote social welfare by correcting market failures can alter these conditions. While these policies may serve their intended purposes, they may also create unintended consequences that may make managing logistics, operations, and supply chains more challenging. This dissertation contributes to the nascent body of knowledge concerning the intended and unintended consequences of policy on supply chain management by examining three unique contextual settings using different methodologies and levels of analysis.

In the first essay, I examine the impacts of relationship-focused regulations on supply chain collaboration. Using a grounded theory approach, I theorize new barriers to collaboration unique to this regulatory context using data from multiple interviews with executives from suppliers and distributors in the beer industry supply chain. I find that regulations meant to promote social welfare by constraining the flow of alcohol to consumer also constrain choice in supply chain relationships that negatively affect supply chain collaboration.

In the second essay, I examine how capacity-limiting structural regulation in healthcare, specifically certificate of need (CON) laws, interacts with case complexity to affect hospital operational performance. Using a hybrid estimation approach to analyze a unique data set collected from multiple sources, I tested a conceptual model developed using the structure-conduct-performance (SCP) framework and the complex adaptive systems (CAS) perspective. I find that indicate that CON does reduce costs but also worsens quality. I also find that these relationships are intensified by case complexity.

In the third essay, I examine whether nuclear verdicts over $10 million resulting from harm caused by large truck crashes result in improved industry-level motor carrier safety performance. Drawing on institutional theory to hypothesize the effects of nuclear verdicts on safety performance and insurance spending. I test these hypotheses using autoregressive distributed lag time series econometric models. I find that nuclear verdicts may result in improvements in industry safety but may also result in increased insurance spending. Collectively, these essays demonstrate multiple perspectives of how policies can affect supply chain behaviors and performance at the individual-, firm-, and industry-level that may be undesirable or unexpected. Findings from these essays offer important insights for researchers, practitioners, and policymakers.

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I. Introduction

Supply chains and the firms within them alter their behavior in response to industry or market conditions, which impacts their performance and can lead to the development of a competitive advantage (Bain, 1956; Caves, 1992; Mason, 1939; Ralston, Blackhurst, Cantor, & Crum, 2014). Industry conditions include the size and number of rivals in the market (Mason, 1939) as well as their actions and behaviors (Caves, 1984), entry and exit conditions (Bain, 1956), and the power of buyers and suppliers (Porter, 1980). Taken together, these conditions have been packaged and popularized as forces to be analyzed and responded to through strategy formulation and execution (Porter, 1980; Porter, 1991; Porter, 2008). They also represent the persistent characteristics of the environment in which supply chains operate (Caves, 1980). In responding to these forces, firms and supply chains develop strategies (Jacquemin, 1987; Scherer, 1980) that can improve firm and supply chain performance, increase profits, achieve economies of scale, and create barriers to new competition (Bain, 1956; Ralston et al., 2014). These strategies can capitalize on existing strengths and capabilities or can involve the development of new capabilities. While developing and executing these strategies does not guarantee a competitive advantage, failure to devise strategies that consider industry conditions may reduce performance and the likelihood of survival (Porter, 1991).

An important factor that affects industry conditions is public policy and the government regulations by which public policy is exercised (Porter, 2008). While many definitions of the term "regulation" exist, for the purposes of this dissertation, we employ the definition provided by den Hertog that describes regulation as "the employment of legal instruments for the implementation of social-economic policy objectives (2010, p. 3)." Two types of regulation are discussed in the literature: social regulation and economic regulation. Social regulation is government intervention to regulate behavior that may result in externalities, that is the behavior

may result in harm to those not directly in the business activities that cause the harm (Litan, 2019). For example, drivers of large commercial motor vehicles are subject to regulations that limit the number of hours they may work during a day or week. The purpose of these rules is to prevent driver fatigue, which is a major cause of crashes that result in motorist injury or death (FMCSA, 2021).

Economic regulation is intervention by the government to govern the economic behavior of industries, markets, and firms that affect competition (Joskow & Rose, 1989). By regulating these markets, governments hope to stabilize market processes and prevent consumers from negative consequences resulting from competitive or anti-competitive behaviors of firms. These competition issues usually occur in markets where natural monopolies or hyper-competition may exist (Posner, 1974). There are two types of economic regulation: structural regulation and conduct regulation (Joskow & Rose, 1989; Kay & Vickers, 1990). Structural regulation regulates the structure of a market. It dictates who may participate in a market by restricting entry into a market or exit from a market and may limit the size of firms in an industry. For example, antitrust laws prevent firms from becoming so large that they can eliminate competition and set prices to levels that may hurt consumers (FTC, 2017).

Conduct regulation regulates the actions taken by competitors within a market. For example, while public utility companies have often been formed as “natural monopolies” under the assumption that competition would make initial capital investments into infrastructure prohibitive, regulations may require utilities to allow competing producers to access their delivery infrastructure to reduce prices (Gegax & Nowotny, 1993). In this example, conduct regulation is linked with structural regulation; however, that need not always be the case. For example, interest rate disclosure requirements are a conduct regulation that encourages

competition by providing consumers information to better choose which lender they will do business with (Litan, 2019).

A paucity of research exists concerning the effects of policy on logistics, operations, and supply chain management (SCM); however, these effects provide new and important avenues for research (Pagell, Fugate, & Flynn, 2018; Spring, Hughes, Mason, & McCaffrey, 2017; Joglekar, Davies, & Anderson, 2016). Additionally, SCM researchers are uniquely suited for researching policy and its practical effects because of their unique focus on interdependencies and their use of multiple levels of analysis in their research (Tokar & Swink, 2019). As such, scholars have begun exploring the important role that policy plays in supply chain management. For example, extant research has explored the impact of resale price maintenance regulations on the structure of and balance of power in supply chains (Gundlach, Frankel, & Krotz, 2019), the electronic logging device (ELD) mandate on truckload pricing (Miller, Scott, & Williams, 2020), government pressure on implementation of inter-organization systems across the healthcare supply chain (Bhakoo & Choi, 2013), and regulatory pressure on the relationship between trust and operational coordination (Davis, Davis-Sramek, Golicic, & McCarthy-Byrne, 2019).

In addition to the intended effects of policy, they may also create unintended consequences (Merton, 1936). Unintended consequences include unexpected benefits or drawbacks that can result from policies due to a lack of existing knowledge, failure to consult experts from all relevant fields, error in correcting the right issue or all relevant issues, or a focus on short-term interests. Scholars have begun to explore the unintended consequences of policy on SCM. For example, research has found that firms respond to economic policy uncertainty by building up inventory as a safety buffer against risk of policies being enacted that may limit access to importance resources (Darby, Ketchen, Williams, & Tokar, 2020). Also, when the

electronic logging device mandate was implemented to improve monitoring of hours-of-service (HOS) compliance, HOS compliance violations decreased as intended; however, violations for unsafe driving for drivers employed by small carriers increased (Scott, Balthrop, & Miller, 2021). Further research is needed to better understand both the intended and unintended consequences of policy in SCM.

This dissertation is comprised of three studies that use different methodologies, levels of analysis, and contexts to investigate the unintended consequences of policy in SCM. In the first essay, I examine the impacts of relationship-focused regulations on supply chain collaboration. Using a grounded theory approach, I theorize new barriers to collaboration unique to this regulatory context using data from multiple interviews with executives from suppliers and distributors in the beer industry supply chain. I find that relationship-focused regulations meant to promote social welfare by constraining the flow of alcohol to consumer also constrain choice in supply chain relationships that negatively affect supply chain collaboration. In the second essay, I examine how structural regulation that limits the building or expansion of hospital capacity, specifically certificate of need (CON) laws, affects hospital operational performance. A key determining factor of hospital operational performance is complexity, measured using case mix index (CMI), which has been found to affect resource allocation as well as patient outcomes and experience. Drawing on the structure-conduct-performance framework and the complex adaptive systems perspective, I investigate the effects of CON and CMI on hospital cost and quality performance. To test my hypotheses, I use a hybrid estimation approach to analyze a unique data set collected from multiple sources. I find that CON is associated with reduced costs but worsened quality, whereas CMI is associated with increased costs but improved quality. CMI intensifies the relationship between CON and costs but has limited impact on the relationship

between CON and quality. In the third essay, I examine the effects of nuclear verdicts on industry-level motor carrier safety and insurance spending. Verdicts over $10 million may be awarded by the courts to compensate injured parties, punish responsible parties, and deter other parties from committing similar harmful acts. Drawing on institutional theory to develop my hypotheses, I investigate the effects of nuclear verdicts on motor carrier safety and insurance expense as well as the dynamic relationship between motor carrier safety and insurance expense. I test these hypotheses using autoregressive distributed lag time series econometric models. I find that nuclear verdicts may result in improvements in industry safety but may also result in increased insurance spending.

Collectively, these essays demonstrate multiple perspectives of how policies affect behaviors and performance at the individual-, firm-, and industry-level that may be undesirable or unexpected. For research, this dissertation contributes new theory and insights to the sometimes-dire effects policy can have on SCM. In doing so, this dissertation creates a direct link between policy and SCM "problems of choice" (Pagell et al., 2018, p. 1). For logistics, operations, and supply chain managers, this dissertation offers insights into the counterproductive or harmful behaviors that can result from uncalculated responses to policy as well as recommendations of how to improve behaviors and performance. For policymakers, in addition to highlighting the unintended consequences of myopic policymaking on SCM, this dissertation provides recommendations for how to improve existing policies and reduce the likelihood of crafting future policies creating unintended consequences in SCM.

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II. Essay 1: Barriers to Supply Chain Collaboration in Relationship-focused Regulatory Environments: Lessons from the Beer Industry

Introduction

Firms collaborate to improve performance or achieve a competitive advantage (Fawcett, Magnan, & McCarter, 2008). Supply chain scholars have extensively examined many aspects of collaboration, including its dimensions (Cao & Zhang, 2011), benefits (Fawcett, Fawcett, Watson, & Magnan, 2012), and drawbacks (Villena, Choi, & Revilla, 2020). Central to the study of collaboration is the assumption that firms working together can produce outcomes that would not be possible if each firm worked alone (Daugherty, 2011). Implicit in this assumption is the choice of whether firms should partner with each other in the first place (Lambert, Emmelhainz, & Gardner, 1996).

However, in several industries, including the alcohol, tobacco, and firearms industries, firms are subject to regulations that govern their relationships with other firms (Grewal & Dharwadkar, 2002). These relationship-focused regulations can dictate how firms can interact and under what conditions, if any, they can terminate their relationship. In these situations, firms may be faced with a phenomenon known as constrained choice, whereby firms governed by relationship-focused regulations may be prohibited from leaving a relationship and pursuing relationships with alternative partners (Davis, Davis-Sramek, Golicic, & McCarthy-Byrne, 2019). Constrained choice resulting from relationship-focused regulation presents a new and as yet unexplored dynamic in the study of supply chain collaboration. Additionally, prominent theories used in the study of collaboration provide limited explanation for how firms behave in response to relationship-focused regulation that constrains choice. Resource dependence theory and agency theory assume a firm's ability to correct power imbalances and goal incongruencies (Emerson, 1962; Eisenhardt, 1989), whereas social exchange theory and transaction cost

economics assume a firm's ability to seek alternative relationships or governance mechanisms (Kelley & Thibaut, 1978; Williamson, 1981).

Further, scholars have called for more research where supply chain management and policy and regulation intersect because this area is not well-researched or well understood in the supply chain discipline (Pagell, Fugate, & Flynn, 2018). More specifically, Fawcett, Waller, & Bowersox (2011, p. 118) call for qualitative studies to explore how regulation "adds to the complexity faced by managers and the impact on the ability of supply chains to minimize costs, create value, and provide competitive advantage." Supply chain scholars are in a unique position to study regulations because both supply chain management and policy research require a systems perspective and analysis on multiple levels (Tokar & Swink, 2019). Also, scholars have called for logistics and supply chain management research that is more context-specific and managerially relevant by way of middle-range theorizing developed through interpretive or qualitative research methods (Darby, Fugate, & Murray, 2019). Finally, Daugherty (2011) calls for research that explores unique issues concerning collaboration that arise in contextual situations.

In response to these calls, our study aims to contribute to closing the gap in knowledge associated with regulation in the supply chain management literature while contextualizing the study of collaboration in ways that are meaningful for researchers, managers, and policymakers. Given the restrictive effect of relationship-focused regulation, we asked the following research question: How does relationship-focused regulation impact supply chain collaboration? We address this question using a qualitative research design, namely a grounded theory approach. Grounded theory is appropriate for exploring a phenomenon about which little is known and theorizing when existing theory is inadequate for explaining the phenomenon (Mello & Flint,

2009). We conduct our research using the U.S. beer industry as the contextual setting, which allows us to explore the effects of relationship-focused regulation in an industry where these regulations are uniquely strong. Specifically, the beer industry is regulated by the three-tier system to ensure independence between suppliers and retailers and franchise laws to protect distributors from having their contracts with suppliers terminated (Kurtz & Clements, 2014). This research provides a contextualized exploration of how relationship-focused regulations affect supply chain collaboration in the beer industry that can also be applied in the study of other industries that are subjected to similar regulations.

Our findings contribute to the literature on supply chain collaboration and offer important insights for research, practice, and policymaking. For scholars, our study conceptualizes new barriers to collaboration that are unique to relationship-focused regulatory environments. In doing so, our study builds new theory in collaboration that advances knowledge and can serve as a foundation for future research. For managers, our research highlights the opportunistic behaviors that firms engage in because of the conditions created by relationship-focused regulations. Findings from our study can provide managers with an understanding of how these behaviors can reduce opportunities for collaboration. This should drive changes in how managers leverage their power or respond to more powerful partners. Doing so could improve supply chain collaboration and enhance sales and profitability for involved firms. For policymakers, our research highlights the unintended consequences of relationship-focused regulations, which should serve as motivation for improving partner choice and flexibility in governance mechanisms to enhance supply performance.

Literature Review

Supply Chain Collaboration

Supply chain collaboration has been the subject of extensive study by supply chain management scholars. Collaboration is defined as firms working together to achieve outcomes that would not be possible for firms working alone (Daugherty, 2011). It occurs when "two or more firms voluntarily agree to integrate human, financial, or technical resources in an effort to create a new, more efficient, effective, or relevant business model" (Bowersox, Closs, & Stank, 2003, p. 22). Firms collaborate across their supply chain in response to competitive pressures to reduce costs and customer demands to provide better service (Fawcett et al., 2012). Collaboration between firms can produce a collaborative advantage that provides focal firms with improved process efficiency, customer responsiveness, business synergies, quality, and innovation (Cao & Zhang, 2011). Similarly, formalization of collaboration can enhance relationships and enable partner firms to deal with changes in service expectations (Daugherty, et al., 2006). Improving collaboration has also been linked with improved operational and relational outcomes, which in turn can result in improve business performance (Zacharia, Nix, & Lusch, 2009) and value maximization for both firms in the form of reduced transaction costs (Dyer, 1997). When organizations are compatible with each other, they can enhance their absorptive capacity, which has been found to be associated with improved operational efficiency and innovation performance (Saenz, Revilla, & Knoppen, 2014). Collaboration can improve network resilience following disruptions (Azadegan & Dooley, 2021).

Key components of collaboration include the sharing of knowledge and resources, collective and aligned goals and incentives, and joint decision-making processes (Cao & Zhang, 2011; Stank, Keller, & Daugherty, 2001). Core to collaboration is information sharing, which is

defined as the sharing or forecasts, strategies, and other information with supply chain partners (Cao & Zhang, 2011). Closely related to information sharing, communication is enhanced by a long-term relationship orientation, network governance or informal social systems, and the use of information technology jointly implemented to achieve a competitive advantage (Paulraj, Lado, & Chen, 2008). In addition to information sharing, joint knowledge development can improve supply chain performance through shared meaning that aligns strategies and operations between firms (Hult, Ketchen, & Slater, 2004). It has been found that when buyers behave altruistically toward major suppliers, the propensity for collaboration increases; however, the expectation of resource scarcity can reduce altruism (Wiedmer, Whipple, Griffis, & Voorhees, 2020). The quality of collaboration can be enhanced through goal congruence as well as finding complementary capabilities and broader synergies in the relationship (Yan & Dooley, 2014). Improving goal congruence supports collaborative product development by enabling improved design quality and efficiency (Yan & Dooley, 2013). Collaboration can also be improved demonstrated commitment, information sharing, and self-governance (Dyer, 1997).

Little research has explored the barriers or challenges associated with supply chain collaboration. Richey, Roath, Whipple, and Fawcett (2010) found that unidirectionality of planning and processes, incongruency leading to lack of regard for partners, and internalization of behaviors and structures that exclude supply chain partners can act as barriers to collaboration. It has also been found that relationships experiencing decreased strength are likely to continue to spiral unless there is a decision made to correct the spiral (Autry & Golicic, 2010). Also, entrenchment in collaborative relationships can occur over time, which can reduce new idea creation, supplier monitoring, and likelihood of supplier switching even when a switch is needed. Absent mitigating mechanisms like explicit contracts, challenging goals, and expected long-term

viability of the relationship, entrenchment can result in worsened operational performance (Villena et al., 2020).

There is also limited research regarding collaboration in regulatory environments that severely limit or prohibit supply chain actors from switching relationships. Davis et al. (2019) explore how trust or calculative commitment—defined as commitment based on the expected economic benefit—can improve coordination in constrained choice situations in the wine industry brought on by regulatory constraints. The constrained choice concept is relevant to this research as the beer industry, like the wine industry, can be characterized by the regulatory constraints imposed on supply chain relationships (Davis et al., 2019; Grewal & Dharwadkar, 2002). Conceptually similar is the phenomenon known as lock-in, which occurs when "one party is heavily dependent upon the other party, with few alternatives" (Narasimhan, Nair, Griffith, Arlbjorn, & Bendoly, 2009, p. 375); however, lock-in results from power asymmetries that develop in the relationship and the existence of few alternatives. In the case of the beer industry, power asymmetries are created by regulation, which also blocks access to alternatives even though many alternatives exist. This research builds upon the nascent literature concerning constrained choice by exploring the barriers to collaboration experienced in regulatory-induced constrained choice environments. In the next section, we will explore the regulatory environment in the beer industry to set the stage for our analysis.

Regulation

Regulation is a form of government intervention. Interventions are actions taken by a governing authority to force producers and entrepreneurs to behave differently than they would absent the intervention (von Mises, 1977). Social regulations are implemented by government entities to protect the environment, workers, and consumers (den Hertog, 2010). Economic

regulation is intervention by the government to govern the economic behavior of industries, markets, and firms (Joskow & Rose, 1989). There are two types of economic regulation: structural regulation and conduct regulation (Joskow & Rose, 1989; Kay & Vickers, 1990). Structural regulation regulates the structure of a market. It dictates who may participate in a market by restricting entry into a market or exit from a market, whereas conduct regulation regulates the actions taken by producers and consumers within a market.

Two primary schools of economic theory have arisen to explain the purpose and motivations of economic regulation. First, the public interest theory of economic regulation posits that regulation is implemented in response to demands from the public to correct market failures (Posner, 1974). Second, regulatory capture theory posits that regulations are implemented by politicians and bureaucrats in response to the lobbying activities of special interest groups (Laffont & Tirole, 1991). This theory differs from the public interest theory of regulation in that the private interest theory of regulation does not assume that regulation serves the interest of the public or that a market failure exists. Although, it does assume that regulation is more likely to exist in markets where market failures do occur (den Hertog, 2010). Special interest groups are often backed by specific industries who desire to control the growth or entry of new firms or to suppress substitutable industries. These groups seek to implement, expand, or maintain regulation because the government can coerce others in a way the members of these groups are not able (Stigler, 1971).

Social and economic regulation play a prominent role in the beer industry making it the one of the most regulated industries in the United States (Kurtz & Clements, 2014). Social regulation like Prohibition in the United States banned the production, importation, and sale of beer and other alcoholic beverages to reduce the negative health, family, and economic effects

that result from drunkenness (Fosdick & Scott, 1933). When Prohibition was repealed at the federal level in 1933, the Twenty-First Amendment relegated prohibition authority to the individual states. Many states implemented economic regulations that regulate the form and function of relationships in the beer industry, namely the three-tier system and franchise laws, to continue to restrict the flow of alcohol (Kurtz & Clements, 2014). The three-tier system prevented suppliers from having a strong influence on retailers by eliminating pre-Prohibition "tied houses" whereby suppliers obtained exclusive sales rights from retailers in exchange for cash, equipment, and other considerations (Okrent, 2010). Because distributors must make large initial investments and beer suppliers were consolidated and powerful, franchise laws were enacted to protect distributors from territorial infringement, transfer of distribution rights, or termination of contracts. However, given the strength of these laws in many states, distribution contracts are, in effect, permanent, leaving suppliers unable to terminate contracts without providing evidence of fraud or criminal activity and paying substantial sums of money to distributors (Kurtz & Clements, 2014).

Theoretical Background

The purpose of this study is to develop mid-range theory related to the effects of regulation on the interactions between supply chain actors. As the study progressed, we reviewed several theories that have been used consistently in SCM literature to explain behaviors and antecedents to behaviors in these interactions. Specifically, we evaluated resource dependence theory (RDT), agency theory, social exchange theory (SET), and transaction cost economics (TCE).

RDT provides insights into the actions taken by actors when a power imbalance arises in their relationships. The theory posits that when actors are dependent on each other and a power

imbalance arises, the actor that has a power disadvantage will take action to reduce the impact of the power imbalance or will engage in balancing operations to reduce the disadvantage and restore balance (Emerson, 1962). The level of dependence between two actors is determined by three factors: resource importance, resource allocation discretion, and concentration of resource control (Pfeffer & Salancik, 1978). Resource importance is determined by the relative magnitude of the exchange between actors and the criticality of the resource. Resource allocation discretion refers to the extent of the ability of an actor to determine who can use a resource and how much of the resource to make available to the dependent actor. This discretion can result from ownership of the resource, usage rights, or regulations. Concentration of resource control refers to the number of alternative sources available (Pfeffer & Salancik, 1978). When one actor becomes more dependent on the relationship than the other is, the less dependent actor gains power, which can lead to uncertainty and instability in the relationship. In response to this power imbalance, the less powerful actor will attempt to reduce this power disadvantage and restore balance through (1) cost reduction or (2) balancing operations in order to move the relationship towards an ideal state (Emerson, 1962). Cost reduction involves changes in values that reduce the pain of meeting the demands of the more powerful actor. Balancing operations involve changing the structure of the relationship to restore the balance of power in the relationship. The first two balancing operations include withdrawing from the relationship or extending one's network to reduce the power one actor has. The less powerful actor can also balance power by giving status to the more powerful actor that creates a motivational dependence on the less powerful actor. Finally, less powerful actors can form coalitions that concentrate power that can be used to influence the more powerful actor (Emerson, 1962). However, when power imbalances arise, the more powerful actor may use its power to its own benefit and may actively

work to prevent less powerful actors from performing balancing operations (Crook, Craighead, & Autry, 2017).

Franchise laws provide powerful protections for distributors in the beer supply chain. In many states, distribution contracts are ironclad and permanent, which imbues distributors with substantial power while providing limited opportunities for suppliers to engage in balancing operations. For example, if a supplier is unhappy with the service provided by a distributor, the supplier must demonstrate egregious behaviors before a contract may be terminated. Suppliers are also prohibited from using other distributors in that same territory; thus, limiting a supplier's ability to expand their network to balance power in the relationship. Thus, RDT provides a useful explanation of behaviors actors take to correct a power imbalance in a relationship; however, the theory does not provide applicable guidance for when regulation contributes to the power imbalance and restricts an actor's ability to implement balancing operations. Next, we turn to agency theory.

Agency theory posits that principals and agents have differing goals and risk preferences which can result in goal conflict and risk aversion (Eisenhardt, 1989). To address this agency problem, principals enter contracts with agents. The type of contract used is determined by information availability. In cases of complete information availability, the principal can easily know what the agent has done and would enter a behavior-based contract. In cases of incomplete information, the principal and the agent have different goals and the principal cannot determine if the agent has behaved appropriately. This can result in a moral hazard or adverse selection. A moral hazard is a lack of effort on the part of the agent, whereas adverse selection is the misrepresentation of ability by the agent. When faced with incomplete information, principals

can invest in information systems to measure the agent's behavior more easily or can enter outcome-based contracts (Rungtusanatham, Rabinovich, Ashenbaum, & Wallin, 2007).

Agency theory provides guidance for the use of information systems and contracting to align goals and risk preferences between principals and agents. However, an implicit assumption of agency theory is that information systems and contracts provide avenues for remedy when agents do not act in the best interest of the principal. In the three-tier system, independence requirements may prohibit implementation of information systems. Also, franchise laws in many states prohibit termination of permanent distribution contracts without demonstrating egregious behaviors by the distributor or pay large sums to sever the contract. Thus, agency theory provides little guidance on how goal conflict and risk aversion can be addressed in the absence of enforceable contracts. Next, we turn to SET.

SET posits that parties enter exchange relationships with others expecting that the outcomes of repeated interactions will be rewarding. Satisfaction with the interactions, meaning that a party feels the rewards and costs of the interactions are in line with or better than what they feel they deserve, will result in continued interactions (Thibaut, 1959). Over time, each party in the relationship compares the social and economic outcomes from these interactions to those that are available from exchange alternatives (Kelley & Thibaut, 1978). Their dependence on the exchange relationship is determined based on these comparisons. Once dependence is established, continued positive interactions result in establishing trust, commitment, and norms (Lambe, Wittman, & Spekman, 2001).

Central to SET is the evaluation of the adequacy of the outcomes by comparing them to a standard and alternatives (Kelley & Thibaut, 1978). If a party feels they are not getting what they deserve from an exchange relationship, they may leave the relationship. Also, if a party feels

what they are getting from a relationship is not as good as what they believe they could get in a different relationship, they may leave the relationship. However, the three-tier system and franchise laws may prevent suppliers from breaking a distribution contract, even if the supplier does not believe they are getting what they deserve or could get in a different relationship. Thus, while SET provides an explanation of the results from positive interaction outcomes, it does not provide guidance for what happens when negative interaction outcomes cannot lead to departure from an exchange relationship because of regulatory restrictions. Next, we turn to TCE.

TCE provides insights into the considerations under which firms determine appropriate governance mechanisms (make or buy) based on economizing transaction costs, which are made up the costs of production and governance (Williamson, 1981). Governance costs are associated with the management and monitoring of the function whether outsourced or performed in-house. If performing the function in-house, a management hierarchy may need to be established, which is subject to bloating over time. Whereas governance costs when outsourcing are primarily associated with measurement and monitoring of provider performance of the contract (Williamson, 1985).

How these costs are determined are subject to three transaction dimensions: uncertainty, frequency, and asset specificity. First, uncertainty is characterized as risk that cannot be predicted or controlled. Generally, three types of uncertainty come into play here: environmental, specification, and measurement uncertainty. Environmental uncertainty arises as volatility and unpredictability in the market or of future events. Specification uncertainty arises from firms now knowing exactly what they need. Measurement uncertainty arises from difficulty measuring compliance with a contract (Ellram, Tate, & Billington, 2008). Typically, as any of these types of uncertainty increase, it is generally better to operate in-house rather than to outsource. Second,

transaction frequency measures how often a transaction is repeated. As transaction frequency increases, costs increase. Third, asset specificity concerns the size of the upfront investment along with the specialized nature of the investment (Williamson, 1981).

Human behaviors play an important role in these decisions as well. First, actors are self-interest seeking and are subject to opportunism. Self-interest seeking means actors exercise their preferences when making decisions, whereas opportunism means they may take advantage or be dishonest (Williamson, 1981). As opportunism increases transaction costs increase. Second, actors are boundedly rational, meaning actors intend to be rational but are limited by the availability of information and their ability to interpret available information (Williamson, 1981). Bounded rationality limits decision-making on the limited information available, increases bargaining costs because it is impossible to write a contract that addresses every possible issue that may arise, and reduces the ability of actors to measure the behavior of partners and outcomes of their actions.

In most states, the three-tier system prevent suppliers from choosing whether to use a distributor or to distribute their products themselves. TCE provides important insights into behavioral assumptions that impact relationships in supply chains. The theory also offers a salient explanation of the nature and determinants of transaction costs. However, the basis of TCE is that firms have a choice of whether to vertically integrate their activities or outsource to the market. This theory does not provide guidance on what actions can be taken when "make" is not an option and "buy" is the regulatory mandate.

In summary, RDT and agency theory fall short in providing guidance for actions that can be taken within a relationship to correct problems that arise in the presence of regulation that prohibits behaviors that may pressure distributors to change behaviors. Likewise, SET and TCE

fall short in providing guidance in the case of the three-tier system and franchise laws because they assume the firm can leave a costly or unrewarding relationship in favor of an alternative or performing distribution activities in house. To provide insights into how suppliers and distributors behave in the absence of the availability of corrective behaviors or alternative arrangements, we adopt a mid-range theorizing approach using a grounded theory approach. In the next section, we describe our approach and share findings that enable us to generate propositions to explain how beliefs and behaviors act as barriers to collaboration in the presence of relationship-focused regulation.

Methodology

Research approach

Investigating phenomenon in the beer industry is challenging because many of the suppliers and distributors are proprietorships or are family owned, and secondary data relating to the phenomenon of interest is not readily available. Given the gaps in the ability of prominent theories used in supply chain management research to explain phenomenon in highly regulated industries, an approach for mid-range theorizing is needed. Thus, we adopted a grounded theory approach because it enables highly contextual theorizing on substantive interactions (Corbin & Strauss, 2015). A grounded theory approach is particularly useful for analyzing problematic social processes that directly impact the people involved. It is also helpful when little is known about a emerging or obscure phenomenon, when existing theory does not (adequately) explain phenomenon, or when contextualization is needed to better understand a phenomenon (Mello & Flint, 2009).

We chose the beer industry as the setting for our study for several reasons. First, the beer industry is contextually relevant because it is one of the most regulated industries in the United

States. While other industries like food service leverage distribution contracts that are enforced by franchise laws, the beer industry is unique in the rigidity of the distributor requirements and the strength of the franchise laws (Kurtz & Clements, 2014). This provides opportunities to explore boundary conditions of existing theory and provide key insights into phenomenon that may be experienced in less regulated settings. Second, the beer industry is economically significant is in the United States, accounting for 49% of the total U.S. alcoholic beverage industry with revenues of $119 billion in 2017 (The Beer Institute, 2018). Finally, the beer industry has experienced considerable change in the past ten years with increased competition outpacing sales growth (Mathias, Huyghe, Frid, & Galloway, 2018). The number of breweries has nearly quadrupled—from 1,814 in 2010 to 6,406 in 2020—whereas production has decreased—from 195 million barrels in 2010 to 180 million barrels in 2020 (TTB, 2021).

We used a theoretical sampling approach, which entails selecting subsequent participants based on "their likelihood to contribute additional insights to existing and emergent theory" (Fugate, Mentzer, & Flint, 2008, p. 4). We identified participants using the following process. First, we attended a United States beer industry conference where we identified executives (presidents, CEOs, owners, directors, general managers, etc.) of small, medium, and large suppliers, distributors, and retailers across multiple states. Then, we asked participants for connections to additional executives within their firm or at connected suppliers, distributors, and retailers who may be willing to talk with us. We also requested connections with additional potential participants from fellow researchers and professional contacts. We reached out to and interviewed participants we thought could provide additional insights into specific themes and theorizing revealed in previous interviews (Corbin & Strauss, 2015). This approach allowed us to learn from a variety of firms across the supply chain. We conducted twenty interviews across 12

entities, including participants from four distributors, six suppliers, and two retailers (see Table 1). To ensure responses were kept confidential, we gave each firm a generic name based on the firm's position in the supply chain.

Table 1: Participant List

Company	Type	Size	Region	Role
Dist1	Distributor	Medium	Midwest	CEO
Dist2	Distributor	Large	South	President, COO
				VP, Business Strategy
				VP, Operations
				General Manager*
				Regional Manager Sales & Operations
Dist3	Distributor	Small	West	Dir. of sales and marketing/ VP
Dist4	Distributor	Small	Midwest	Vice President
Sup1	Supplier	Medium	Northwest	President, COO
Sup2	Importer	Medium	West	Director of Operations
Sup3	Supplier	Small	South	Owner*
Sup4	Supplier	Small	South	Lead Brewer/Brewhouse Manager
Sup5	Supplier	Small	South	Marketing Director
Sup6	Supplier	Large	West	Beer strategist
Retail1	Retailer	Small	Midwest	Owner
Retail2	Retailer	Large	South	SVP, Merchandising
				VP, Merchandising

*On-site visit

Data Collection and Analysis

In conducting grounded theory research, the process of collecting and analyzing data occurs simultaneously with analysis, which takes place as data is collected and guides subsequent data collection (Gioia, Corley, & Hamilton, 2013). To prevent prematurely narrowing the focus of our research, we started with semi-structured interviews lasting between 45 and 60 minutes, which consisted of open-ended questions about innovation, including the role of innovation, drivers and barriers of innovation, and sources of innovation. These open-ended questions are listed in Table 2. Following the example of other grounded theory studies (Fugate et al., 2008; Wowak,

Craighead, & Ketchen, 2016), participants were encouraged to share examples of experiences and observations they felt were most relevant to the questions they were asked. Beyond the questions being asked, we only interacted with the participants to clarify or explore concepts further or to request additional examples of concepts being discussed. Follow-up questions were asked about the impacts of governmental policy, internal and external relationships, and decisions about equipment purchases or process improvements, if these topics were not brought up by participants.

Table 2: Initial Semi-Structured Interview Protocol

Initial Prompts
• Tell me about the role of innovation in your supply chain • Tell me about your role in innovating in your supply chain • Tell me about what motivates you to innovate • Tell me about what helps you to innovate • Tell me about what prevents you from innovating • Where do innovations come from the most in your organization?
Additional Questions for areas you want to make sure you address:
• Does governmental policy play a role in how you innovate? • What other departments/team impact your ability to innovate? • Who makes decisions on whether to invest in an innovation?

We visited some participants on-site to gain familiarity with their operational contexts; however, to reduce the possibility of natural human biases resulting from a desire to provide socially desirable responses (Alvesson, 2003), we conducted most of the interviews by phone. Most of the interviews were recorded using a voice recorder and were transcribed using a third-party service. Where recording was not an option, copious notes were taken, with special attention paid to documenting quotes relating to specific anecdotes, actions, beliefs, or processes. To improve the credibility of the data, each transcription and a summary of interpretations was provided to the participant so they could provide feedback or clarifications (Fugate et al., 2008).

If additional contacts were made with participants to collect information, those contacts were conducted as unstructured interviews guided by the participants answering of the initial request for clarification or additional information.

Following each interview, transcripts were coded using NVivo, a qualitative data analysis software application. During this process, we first employed an open coding approach, which entails a detailed coding of the interview transcripts to identify beliefs, actions, and processes described by participants (Corbin & Strauss, 1990). Following Wowak et al. (2016), we used the language and terminology for our coding that was used by the participants. Once coding categories were developed, we turned to axial coding, which entails developing second-order themes that were then tested and revised by conducting additional interviews to test the categories (Corbin & Strauss, 1990; Gioia et al., 2013). Finally, we employed selective coding, which entails unifying themes around core categories that represent the phenomenon explored during the study (Corbin & Strauss, 1990).

Findings

Our analysis resulted in a conceptual model of barriers to collaboration between suppliers and distributors in a relationship-focused regulatory environment. Table 3 outlines the second-order themes as well as representative first-order data provided in addition to the quotes used in the following narrative.

Table 3: Representative data for second-order themes

2nd order themes	**Representative 1st order data**
Perceived Unimportance	"A distributor wouldn't have seen us as having any power, or being anyone important. We wouldn't have gotten pushed, we wouldn't have been able to negotiate anything. We wouldn't have been important to the distributor." (Sup1)

Table 3 (Cont.)

2nd order themes	Representative 1st order data
Perceived Unimportance	"I got the ball happening on that, not because of our distributor. I've asked our distributor, probably for about two years now, just to say, 'Hey, how do we do this?' Eventually, I just stopped asking and figured it out myself." (Sup5) "If the bar has a beef with them, they may not just serve [a certain brand]. If we're with that distributor, then they won't serve us. That's the nature of distribution, from what I've seen." (Sup4) "[Distributors] often request [cash on delivery] and mandate it sometimes. We however, cannot request that from our distributors… Every time we've asked for that, they just say, 'Oh, no. We're not set up that way. We just can't do that.' …It's just like it doesn't matter. It is what it is to them." (Sup4)
Bypassing	"I choose not to have certain conversations with them, unfortunately, because of these types of things. It's not something that I should have to be doing, should have to be thinking about. 'Oh, I got to be careful about this, because maybe they're going to ...' It's ludicrous. It's a crazy way to do business." (Sup5) "They came to us though because we were going through the trouble to create buzz in that marketplace. We had no problem, again from the distributors... We had distributors all over the state…going, 'We want your brand.'" (Sup6)
Lack of Knowledge	"As a craft brewer, if you're not aware of that stuff, and you just start ... Because they're just happy as hell. They're happy as a pig in s***. 'I got a distributor.' They don't look at the far-reaching consequences." (Sup6) "We have to sign on as a lifelong partner, so if we sign with whatever distributor, we sign on for a lifetime. So, if they decide to let us go or if we're unhappy, which I've seen some distributors just say, 'Hey, if you don't want us we don't want you,' or 'If you don't want whatever,' you know? But it is a lifetime agreement in the state." (Sup4) "You're short on money, or you've got other pressures, and you start doing things that don't really make sense… if you don't know what the hell you're doing, then it's even worse." (Sup6)

Table 3 (Cont.)

2nd order themes	Representative 1st order data
Strength of Laws	"The supplier cannot terminate its relationship with the wholesaler unless there's a good reason, good cause. It can't just decide that it's more efficient to do somebody else." (Dist1) “The way the franchise law was written was, because it was written by wholesalers mainly, and put into law with the help of, obviously the guidance of lobbyists and those people that are in our industry. I don't think there was much, much account for the chance that a distributorship would be misbehaving.” (Dist3) “We wrote harsher legislation, and made it a felony, is what we did. So that if you ship more than X amount, in the legalese, then the…government can charge you with a felony and take you through that process.” (Dist4) “Distribution, at least in [state], is a legal mafia. What other industry can ... they have these strict territories? ‘No, no, no, you can sell here but not across the street. Can't do that. You're going to get in trouble if you do that. We're going to come after you,’ kind of mentality.” (Sup5) “They've made sure that they're not allowed by law to not pay slotting fees.” (Sup6) “Suppliers can't come in and just basically rip brands from the wholesaler if they just get sideways one day. There has to be just cause.”(Dist3) “If I was in a non-franchise protected state, that doesn't really mean the same, because I could build that brand up as big as I want it, or could and yet the supplier could come in and take that away from me without monetary compensation” (Dist2)

Perceived Unimportance

We discovered that suppliers may develop a perception that they do not matter to their distributors, which can lead to suppliers taking actions the reduce their involvement with their distributors to include only core interactions and activities. When suppliers believe they are not important to their distributors, they feel they cannot contribute to the relationship or cannot gain benefit from contributing to the relationship. This was highlighted by the owner of Sup3 who noted, "It's important for us to be important to [distributors]," continuing, "because then they're going to want to push [our beer]." Distributors can choose whether to agree to distribute a brand

provided by a supplier. If they agree to distribute a brand, the supplier is then prohibited from using another distributor for the same brand in the same territory. In some cases, a distributor may agree to distribute a brand, but then take little action to place in into retailers, leaving suppliers to pursue other routes for placing their brands with retailers. The Beer Strategist from Sup6 discussed the impact of this situation, saying,

> *They just kind of sat on it. They didn't really do much with it. So we had to spend more money to have sales reps from in that marketplace to move the needle because they were so big. We were just a blimp on their volumes. I don't think they did it intentionally. It was just because of their size alone. They just couldn't spend a whole lot of time with small brands.*

If a distributor elects not to carry a brand, this enables suppliers to pursue alternative distributors only for brands not already under contract in a given territory. The Marketing Director at Sup5 described this scenario, saying,

> *They said, "No, we don't want to carry it." We went to their direct competitor... Maybe two, three weeks after, they get a 15-case display in [the retailer]. First time we've ever had product in there. Our beer is still not in there, because they won't answer me, they deflect it.*

SET posits that when actors do not get what they feel they deserve in the relationship, they will pursue alternative relationships they believe will provide them what they deserve (Thibaut, 1959). However, given that suppliers are unable to pursue alternative relationships due to strict regulatory conditions for contract terminations, suppliers may take other actions. The extreme nature of the conditions under which a supplier could change distributors was described by the Director of Sales and Marketing at Dist3, saying,

> *[The supplier] would have to exit the state... with their brand for eight months, give up eight months' worth of sales, and then re-enter under a new distribution network. And there are a lot of suppliers that simply don't want to do that.*

RDT posits the less powerful actors may withdraw from the relationship (Emerson, 1962). While the supplier may be unable to fully withdraw from a relationship with the distributor, they may take actions to distance themselves from the distributor or seek support

from non-distributors to engage in activities the distributor would engage in with suppliers it felt were more important. Suppliers may be less likely to share information because they do not trust their supply chain partners. The President and Chief Operating Officer (COO) noted this saying that suppliers "are reluctant to give that level of detailed information to someone else because of fear that it gets into the wrong hands." In this case, the relationship persists; however, the investment the supplier makes in the relationship and thus the effort in collaboration decreases.

In combining the reasoning of SET and RDT with the insights from our analysis, we theorize that:

> *Proposition 1: A supplier's perceived unimportance to a distributor is negatively associated with supply chain collaboration in a relationship-focused regulatory environment.*

Bypassing

The three-tier system prohibits suppliers from selling their beer to retailers unless any explicit exceptions are provisioned by law. However, rules about suppliers communicating or collaborating directly with retailers are less clear. We found in our research that distributors discouraged collaborative interactions between suppliers and retailers without direct involvement of the distributor. The General Manager of a Distribution Center at Dist2 encouraged suppliers to interact directly retailers "as long as one of the distributor's sales reps was present" for the interaction. Similarly, the Marketing Director for Sup5 noted,

> *I was going to come down and just sample some accounts and just meet new people, because we were new to the market. [The distributor] said, "Oh, well you know our owner doesn't let supply reps come down on their own. You have to ride with one of us."*

We found that restrictions imposed by distributors led suppliers to bypass distributors in their interactions with retailers, which can reduce opportunities to collaborate and can have

negative effects on supply chain relationship quality. Research shows individuals may bypass institutional structures and processes if they conflict with role expectations or beliefs (Grewal & Dharwadkar, 2002). This was noted by the Marketing Director for Sup5, saying,

> *That's where it ended. I ended up going down anyway. The problem with that is I went down, and had to recap and send it to them, and nothing came of it. Who knows, at the end of the day, what actually happened. It's like there's some invisible force field that, "Oh no, you can't pass this without one of us in the car." It's just an impediment to what normal business should be.*

Thus, we theorize that:

Proposition 2: Suppliers bypassing distributors is negatively associated with supply chain collaboration in a relationship-focused regulatory environment.

Lack of Knowledge

A key component of supply chain collaboration is knowledge and information sharing (Cao & Zhang, 2011). We found that when suppliers first begin operation, they may have little knowledge about running a business or managing supply chain activities. A Beer Strategist from Sup6 noted,

> *We came out of our garage. We've got friends and so forth. We really didn't know what we're doing except for maybe brewing. That's where it really is difficult because we just didn't understand the marketplace. We didn't understand regulations.*

Similarly, the Owner of Sup3 echoed the lack of knowledge possessed by young suppliers by saying,

> *We were intellectually arrogant when we opened our first brewery. We thought we knew more than we knew. We were much more naïve than we thought we were. I think we knew money really well. We knew how to build customer experience really well. We didn't know how to do the back very well. How to make it.*

We discovered that the limited knowledge of young suppliers discourages distributors from spending important time working with suppliers to develop their brand or sales plans. The General Manager of Dist2 indicated this by saying,

> *We'll sign with these small crafts but we're not going to invest any time in them until they figure out their brand and build their customer base. Then, it's worth it for us to commit time and resources to them.*

Given that in most states young suppliers must sign with a distributor to be able to sell their brands outside of a taproom but then have little recourse when they feel they are not well-supported, distributors may act opportunistically and shirk opportunities to collaborate with young suppliers. As a result, time that could be spent early in the relationship to build trust and commitment is lost. This can leave suppliers feeling unsupported and builds resentment, which may cause them to be less invested in the relationship. The Marketing Director for Sup5 noted,

> *If I would have known six years ago, all of the different things that went into it... we may not have ever signed with any of them.*

Thus, we theorize that:

Proposition 3: A supplier's lack of knowledge is negatively associated with supply chain collaboration in a relationship-focused regulatory environment.

Strength of Laws

While the regulations enacted following the repeal of prohibition were meant to protect the health and safety of the citizens of the United States (Okrent, 2010), much of additional regulation was formed in partnership with coalitions representing subgroups of the beer industry. While both supplier and distributor groups may participate in these coalitions, in our research, only respondents from distributors discussed specific actions they took to influence regulations that favored their own benefit. For example, the Vice President of Dist4 shared an anecdote about working with a coalition of distributors to draft legislation to prevent suppliers from shipping alcohol directly to the customers' homes. In this state, this activity had been legal because no laws existed to prevent it. Once the trend had begun to gain popularity, the coalition worked to pass regulation to prevent these activities and make them criminal offences.

Distributors may also lobby to strengthen the three-tier system and franchise laws and their enforcement to increase distributors' power against suppliers. We discovered that stronger relationship-focused regulations may reduce the motivation of distributors to provide high levels of service and support to suppliers or customers. The President and COO of Dist2 noted this, saying,

> *They cannot terminate us without cause…They couldn't come in and say, 'Hey, you didn't hit your sales plan last year, I'm going to terminate you,' that's not egregious enough for them to be able to make that change.*

Given that supply chain collaboration is driven by competitive pressures (Fawcett et al., 2012), it also follows that the absence of competition can reduce collaboration. The Owner of Retail1 noted this saying, "There is no competition. Why should the service level be 110 percent? It's not." We also found that while distributors may enjoy the protections franchise laws provide them, the lack of competition can reduce the possibility of establishing or expanding relationships with suppliers. The Director of Sales and Marketing at Dist3 noted,

> *One of my competitors is selling Brand X and they're doing a horrible job. They're out-of-date. They're out of stock. It's frustrating to watch the suppliers have really no recourse because of the strength of that franchise law. It's so frustrating to see a distributor essentially disrespect, not care about the integrity of the brand they're selling, yet Brand X is something I would love to see in my house, and I'd love to get my hands on it.*

In the literature, contracts are formal governance tools to enhance trust, a key facilitator in supply chain relationships (Daugherty, 2011; Fawcett, Magnan, & Williams, 2004; Richey et al., 2010). They can also be used to correct principal-agent problems such as moral hazard or adverse selection (Eisenhardt, 1989). Further, a necessary condition of fair competition is that a party should be able to change partners when their current partner does not uphold the terms of their contract, which protects parties from unfair dealings (von Mises, 1977). However, in the beer industry, contracts may be unenforceable, as noted by the President and COO of Dist2,

In many, many states there are franchise rights that were given to distributors to give those distributors a level of independence, so they weren't bound by their contracts.

Given that strong franchise laws can reduce distributors' competitive motivation to collaborate and limit suppliers' ability to implement governance mechanisms to enable collaboration, we theorize that,

Proposition 4: The strength of laws is negatively associated with supply chain collaboration in a relationship-focused regulatory environment.

Discussion

Collaboration is necessary for achieving enhanced supply chain performance and gaining a competitive advantage from supply chain activities (Daugherty, et al., 2006). Although, the importance of supply chain collaboration is well documented, how relationships are managed in relationship-focused regulatory environments is not well understood (Davis et al., 2019). As such, we investigated collaboration between suppliers and distributors in the context of this regulation.

Our grounded theory approach revealed that supply chain collaboration is hindered by relationship-focused regulations like the three-tier system and franchise laws. As our research evolved, we discovered that these regulations create situations that are counter to key components of successful supply chain collaboration. For example, goal congruence is a key facilitator of supply chain collaboration; however, strong franchise laws limit competition between distributors that would drive them to improve service to suppliers. As a result, goals held by suppliers and distributors become misaligned. We believe a quantitative approach would not have revealed key insights highlighted by findings from our qualitative approach; thus, a

grounded theory approach has provided valuable new perspectives in a well-established research area.

Implications for Theory and Research

Our research offers important implications for supply chain management theory and literature. The study of supply chain management emphasizes the efficient flow of goods and information through the supply chain (Cooper, Lambert, & Pagh, 1997; Mentzer, et al., 2001). Supply chain partners are usually studied in terms of how they can work together to achieve a shared vision to provide value to customers (Mentzer, Stank, & Esper, 2008). Additionally, scholars have long studied the importance of supply chain collaboration to improve firm performance (Daugherty, et al., 2006). Our research centers on the impact of relationship-focused regulations on supply chain collaboration. In doing so, we respond to calls for research at the interaction of government regulation and supply chain management (Pagell et al., 2018) and for exploring unique issues concerning collaboration that arise in contextual situations (Daugherty, 2011).

Our research extends the study of collaboration through the introduction of new barriers that are unique to regulatory context by defining mechanisms by which collaboration fails in these situations. A paucity of research exists the explores the role of regulatory institutions in supply chain collaboration. Information sharing, goal congruence, and joint decision-making are important elements of successful supply chain collaboration (Cao & Zhang, 2011); however, our investigation demonstrates how relationship-focused regulations can inhibit collaboration because they limit these behaviors. We find that franchise laws may reduce distributors' motivation to invest in collaborative relationships with suppliers because there is little reason or accountability to do so. In this situation, information sharing cannot take place because neither

party participates in the relationship beyond what is required to complete their transactions. Conceptually, this is similar to a barrier to integration known as unidirectionality, which refers to a one-way flow of information sharing (Richey et al., 2010); however, in our research, we found it possible that neither party engages in information sharing. Given that information sharing is necessary for establishing joint governance (Richey et al., 2010), a lack of information sharing can make goal congruence and joint decision-making nearly impossible.

By engaging in mid-range theorizing using a grounded theory approach, findings from our research also highlights boundary conditions of extant theories, which is an important means of theory contribution (Smith, 2003). Prominent theories used to explore supply chain collaboration assume the ability of supply chain actors to seek alternatives or take actions to correct or prevent issues. Findings from our research highlight the inapplicability of these assumptions in a relationship-focused regulatory environment. For example, contracting is a central to agency for aligning goals and risk in supply chain relationships (Eisenhardt, 1989); however, in the context of this research, contracts are rendered nearly useless by franchise laws. In this type of regulatory environment, these regulations may create and perpetuate power imbalances that strongly favor distributors; thus, suppliers are unable to withdraw from relationships with their distributors or hold their distributors accountable. By limiting the ability of suppliers to seek alternatives, relationship-focused regulations create a constrained choice scenario. Our research joins a nascent body of research theorizing the role of regulatory institutions in creating constrained choice in supply chain relationships (e.g., Davis et al., 2019). Our findings provide new insights into the risks of relationship-focused regulations and provide a basis for further exploration.

Implications for Practice

Our study also offers important implications for supply chain managers. Firms operating within a relationship-focused regulatory environment may behave opportunistically, just as they are assumed to do in non-regulated environments (Williamson, 1981). Our findings indicate that relationship-focused regulations create a power imbalance that if not addressed can result more powerful parties engaging in opportunistic behaviors. In response, less powerful parties may then also engage in opportunistic behaviors to offset the impact of the more powerful actor's opportunistic behaviors. Considering these findings, we make the following to recommendations to managers who operate withing a relationship-focused regulatory environment.

First, for managers working for firms that enjoy protections provided by relationship-focused regulations, it is important to acknowledge the distinct power advantage provided by these regulations and adjust accordingly. Research shows that more powerful actors are more likely to exert their power on less powerful actors (Crook et al., 2017), but this does not have to be the case. Our research highlights the negative impact on collaboration that can result from distributors' actions. Suppliers may feel unimportant in the relationship and withdraw from collaborative activities. They may also be upset by the lack of perceived support from distributors and choose to bypass them in their activities.

Research shows that firms who operate from a position of power rarely find partners willing to collaborate (Fawcett et al., 2012). These behaviors can potentially be prevented by intentionally engaging with less powerful supply chain partners. For example, distributors could consider setting up regular business reviews with suppliers to provide insights into how a supplier's brands are performing versus other brands and provide recommendations based on interactions with retailers. This process can open communication lines and provide opportunities

to engage in collaborative planning and goal setting. For young suppliers, these interactions can provide opportunities for learning that have the potential to accelerate growth and development. While increased variety in suppliers and products can introduce added complexity to the collaborative behaviors, improving information sharing and knowledge development can result in improved strategic and operational improvement (Hult, Ketchen, & Slater, 2004). Thus, even in the absence of competitive forces brought on by strong franchise laws, collaboration may help increase sales and profits for distributors, which can have a positive effect on suppliers as well.

Second, for managers working for firms that may be placed at a power disadvantage by relationship-focused regulations, it may be possible to implement informal mechanisms to reduce a power imbalance. By engaging in frequent communication and cooperative behaviors, supply chain partners can build trust, even when the ability to leave the relationship is hindered (Davis et al., 2019). For example, the President and COO of Sup1 described his process of sharing new products still in development with a panel of distributors to help build their commitment. Distributors can provide feedback on the taste and packaging of these products, which the supplier then incorporates. While this approach may not work in all scenarios, it is important to make efforts engage with more powerful partners. The Owner of Sup3 noted the importance of engaging, saying, "If you have an adversarial relationship, it's never going to work." This falls in start contrast to the sentiment of the Marketing Director at Sup5 who said, "Distribution is a legal mafia." While sharing information with supply chain partners may induce fear that shared information could fall into the wrong hands, taking the first steps of sharing information may result in positive outcomes for both supply chain partners.

Implications for Policymakers

For policymakers, our findings show that regulations meant to balance the power in a supply chain relationship have the potential instead to flip the balance of power. While the intention of the three-tier system and franchise laws was to protect social welfare by preventing undue influence, unintended consequences from these regulations may hinder supply chain function and performance. Also, scholars have shown that innovation and competition benefit consumers (Hayek, 1960). Relationship-focused regulations can alter how supply chains partners collaborate, which has the potential to introduce complexity and inefficiency into the supply chain that potentially wastes time and resources and may costs consumers money. Policymakers may want to objectively evaluate whether relationship-focused regulations achieve the intended goals, and whether the unintended consequences negate the intended benefits.

Some states have made progress in modernizing three-tier system regulations to provide flexibility to small or young suppliers. For example, in the state of Arkansas, small suppliers, defined as brewers producing fewer than 15,000 barrels a year, may choose to distribute directly to retailers without the use of a distributor (A.C.A. § 3-5-1416, 2009). This enables suppliers to choose whether to self-distribute or leverage a distributor based on their level of comfort taking on distribution tasks or giving up control over distribution activities. For example, several of the small suppliers we interviewed indicated they would use a distributor even if it were not required by law. This is because they see value and using a distributor because the suppliers did not believe they had the knowledge, resources, or desire to manage their own distribution. It should be noted that this sentiment was only expressed by suppliers that appeared to have good relationships with their distributors. Good relationships usually were associated with open communication, collaborative planning, or services that aided the supplier's growth. For

example, the distributor of one supplier had arrangement that its distributor would store its empty cans at no cost until they were ready to fill. In other industries where distributors are prevalent (e.g., food service, third-party logistics providers, etc.), suppliers have the option to self-distribute, which provides large suppliers the option to gain efficiencies by self-distributing or using distribution services provided by the retailer and large retailers have the option to operate their own warehousing and consolidation operations, if they choose to do so.

However, strong franchise laws may still hurt suppliers who sign up with a distributor that ends up being incompatible. The literature points to the importance of selective matching, which means picking a supply chain partner with shared beliefs and values (Bowersox, Daugherty, Droge, Germain, & Rogers, 1992). While even inexperienced suppliers should be expected to do due diligence before signing a contract with a distributor, it is possible that beliefs and attitudes can change over time due to the accumulation of learning and experience (Baillon, Bleichrodt, Keskin, l'Haridon, & Li, 2018) as well as changes in the operating environment (Shepherd, McMullen, & Ocasio, 2017). As supply chain partners develop and grow, it should be expected that new relationships may be needed to facilitate this growth. Policymakers may want to consider this when creating or updating relationship-focused regulations and insert provisions for growth and development.

Research shows that supply chain collaboration requires ground rules that establish expectations and remedies for when expectations are not met (Bowersox et al., 1992). When franchise laws supersede contract terms, supply chain collaboration may suffer because of the lack of important ground rules. While informal norms are important to facilitating collaboration (Daugherty, 2011), structured, firm-specific governance mechanisms like contracts are key to facilitating coordination and integration (Richey et al., 2010). While several distributors

commented on the importance of franchise laws in preventing suppliers from unjustly terminating relationships, in practice the majority of supply chain relationships are governed by contracts that are enforceable by law, hence the ongoing theme of relationship governance mechanism in supply chain collaboration literature. As such, policymakers may want to consider strengthening the role of contract terms in protecting both parties in their unique relationships rather than relying on broad-brush franchise laws to govern relationships.

Limitations and Directions for Future Research

A primary limitation of qualitative research approaches like grounded theory is that in providing precision and realism, generalizability beyond the context of the study may be sacrificed (McGrath, 1981); however, the purpose of qualitative research is not generalizability but contextual understanding of specific phenomena (Corbin & Strauss, 2015). While limited in its ability to generalize, this research provides specialized understanding of context that is important when studying the effects of policy (Joglekar, Davies, & Anderson, 2016). Consequently, our findings may serve as a platform for quantitative research that investigates the extent to which the barriers to collaboration identified in this study impact collaboration and by extension firm and supply chain performance. This also would enable further refinement of the constructs and measurements developed in this study, which would allow for extension of our theory and integration of our constructs into other theories. Also, given our focus on the beer industry as the context for the study, we acknowledge that other industries are also subject to relationship-focused regulations. Applying the constructs developed in this research to other regulatory context would improve their validity and generalizability.

Finally, we intentionally excluded "control states" from this study. In control states, the distributor and sometimes the retailer is an agency of the state government itself. While

exploring relationships between suppliers and state-run distributors would provide interesting insights into the effect of the three-tier system on collaboration, state-run distributors have different financial objectives than for-profit distributors and are not protected by explicit franchise laws. Future research could test the applicability of our findings in the context of control states.

Conclusion

Using a grounded theory research approach, this study explored the impacts of relationship-focused regulation on supply chain collaboration. This approach enabled us to theorize new barriers to collaboration that are unique to a regulatory context. Our findings suggest that while these relationship-focused regulations are meant to correct power imbalances that favor large suppliers over distributors, the result is a new power imbalance that favors distributors over suppliers. This unintended consequence constrains supplier choice and reduces supply chain collaboration. To minimize the effects of these unintended consequences, managers can re-evaluate how they comply with regulations and how they interact with each other to develop more collaborative relationships. And policymakers can revise regulations to allow small and young suppliers more flexibility in developing relationships with distributors while protecting distributors' investments.

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III. Essay 2: The Effects of Structural Regulation and Complexity in Hospital Operations

Introduction

In the United States, government entities enact regulations to curb rising healthcare costs and improve healthcare quality (Lee et al., 2016). Government regulators have a vested interest in reducing healthcare costs as federal, state, and local governments are the largest payer for healthcare, accounting for 45% of all healthcare spending in 2017 (CMS, 2020). Healthcare costs in the United States have risen at an increasing pace reaching $3.6 trillion or 17.7 percent of gross domestic product (GDP) in 2018 (NHEA, 2019). Although healthcare in the United States is the costliest in the world, it lags comparable countries in terms of quality (Kurani et al., 2020). The Institute for Healthcare Improvement (IHI) advocates for simultaneously optimizing healthcare providers' performance across three dimensions: reduced cost, improved health, and enhanced patient experience (IHI, 2020). However, few healthcare regulations address cost and quality simultaneously, which can result in unintended consequences that negatively impact patients. When regulation is implemented solely for cost reduction, hospitals may find that improvement in quality is problematic because it does not come without added cost (Senot et al., 2016b).

Many U.S. states have enacted healthcare structural regulations, namely certificate of need (CON) regulations, with the intention of reducing healthcare costs through increased utilization enabled by constraining the building of excess healthcare capacity (Langley et al., 2010). While increased utilization can reduce costs, it can also reduce healthcare quality (Roth et al., 2019). CON regulation also dictates the healthcare industry's market structure, thus altering the nature of competition in healthcare. Hospitals respond to the competitive structure of the markets in which they operate (Goldstein et al., 2002). They may alter their strategies and organizational structure to help cope with regulation, which can impact healthcare cost and

quality (Cook et al., 1983). Previous studies have examined individual dimensions or consequences of CON regulation and collectively provide mixed research findings (Conover & Bailey, 2020). While healthcare cost and quality outcomes have been studied simultaneously in the healthcare operations management literature (Ding, 2014; Roth et al., 2019), little research has comprehensively investigated the impact of regulation on healthcare cost and quality. Perhaps a more comprehensive research design that examines multiple performance dimensions would be useful in understanding the effects of CON regulation on hospital performance.

Next, it is important that research in public policy provide evidence into how regulations affect performance in specific operational contexts (Joglekar et al., 2016). Complexity has been extensively studied in the operations management literature (Nair & Reed-Tsochas, 2019) and its effects on cost and quality have been well-documented (Bozarth et al., 2009; Handley & Benton Jr, 2013). In healthcare operations management literature, complexity, often defined as the range of severity and variety of clinical conditions treated by a hospital, represents an important contextual factor that affects healthcare operational performance (McCrum et al., 2014; Peng et al., 2020). Complexity is often measured using case mix index (CMI) from the U.S. Centers for Medicaid and Medicare Services (CMS), which weights diagnosis-related groups (DRG) treated by a hospital. CMI is linked to resource intensity, meaning resources within a hospital are allocated based on case mix (Park & Shin, 2004). Typically studied in the context of changes in complexity within individual hospitals over time, complexity has been shown to increase healthcare cost (Senot et al., 2016b) and reduce healthcare quality (Peng et al., 2020). However, hospitals facing higher levels of complexity may improve the quality of care they provide through improved learning and organizational strategy (Sharma et al., 2020). Further, when complexity is controlled for in healthcare operations management research, it is often associated

with improved quality (Senot et al., 2016a; Sharma et al., 2016). As such, it appears that considering the healthcare operational context vis a vis complexity may be an important consideration in understanding the effects of CON regulation on hospital performance.

CON and complexity are intertwined factors in the battle to reduce healthcare costs and improve healthcare quality. Given that some, but not all, hospitals struggle with the trade-off between cost and quality (Roth et al., 2019), this research explores the relationship between CON regulation and complexity, and how these factors affect the tradeoff between cost and quality. Specifically, this research seeks to answer the following questions: (i) How does CON regulation affect healthcare costs and quality? (ii) How does complexity moderate the effect of CON regulation on healthcare costs and quality? Drawing on the logic of the structure-conduct-performance (SCP) framework and the complex adaptive systems (CAS) perspective, we develop a conceptual framework to inform these questions. We then test this framework by analyzing a comprehensive, longitudinal data set created by combining multiple data sets available from CMS and the American Health Planning Association (AHPA). Our data set provides detailed cost performance and quality data from 2,992 hospitals spanning eight years between 2011 and 2018 – 20,887 hospital-year observations. We measure healthcare cost performance outcomes using inpatient cost per discharge. We measure healthcare quality along two dimensions: clinical quality (CQ) and experiential quality (EQ). CQ and EQ are often studied together because of their complementarity in measuring the overall quality of care received and importance to reimbursement as part of the Patient Protection and Affordable Care Act passed in 2010 (Roth et al., 2019; Senot et al., 2016a). CQ measures the objective outcomes of the quality of care received by patients (Ding, 2014; Chandrasekaran et al., 2012). EQ

measures the patient's perception of the quality care they receive (Senot et al., 2016a; Nair et al., 2013).

Results from our econometric analysis produce multiple important findings. First, we find that CON regulation is associated with reduced costs but worsened quality. We also find the CMI is associated with increased costs but improved quality. Finally taken together, we find that CMI intensifies the relationship between CON and costs but has limited impact on the relationship between CON and quality. This finding is important because we find that CON reduces costs in hospitals with higher CMI, where treatment of more complex conditions is expected to be more resource intensive, while hospitals with lower CMI see increased costs in CON states. Further, results from our post hoc analyses provide additional important insights. First, our findings reveal a curvilinear relationship between CMI and healthcare cost and quality. Second, by deconstructing our CQ measurement, we highlight interesting counteracting effects that provide a more granular understanding of the effects of CON and CMI on CQ.

Our research has several managerial and policy implications. From a health policy perspective, myopic regulations with a sole focus on reducing costs can have wide-ranging unintended consequences that may put patients' health, the primary responsibility of healthcare, at risk. Further, failing to consider how hospital-level variables like complexity may interact with various regulation currently being considered by policymakers may result in a disparate impact on hospitals that defeats the purpose of the regulation. For instance, CON is aimed at reducing healthcare costs by constraining access to resources. Our research shows this goal is accomplished in hospitals with high CMI but not in hospitals with low CMI. Hospitals that would be expected to use more resources use less, while hospitals that should use fewer resources use more. From a hospital management perspective, hospitals that differentiate to

obtain a competitive advantage in the market may be at a disadvantage if they are in states with CON regulation. Our results show that hospitals with high CMI will fare less well on cost performance than hospitals with low CMI will in states with CON regulations. This may imply that a differentiation strategy will be less effective in states with CON regulations in place.

In the next section, we review the literature concerning the role of regulation and complexity in healthcare.

Literature Review

Structural Regulation and Healthcare

Hospitals face over 340 regulatory requirements that are primarily administered by four federal agencies as well as other federal and state entities. The number of regulations introduced and the frequency of updates to existing regulations change rapidly (AHA, 2017). Healthcare regulation generally has two main aims: cost control and improving quality of care (Lee et al., 2016). With healthcare costs growing as a main expense for citizens and the U.S. government being the single largest payer for healthcare services (CMS, 2016), the federal government has implemented several regulations to help curb the rising cost of healthcare. Regulations dealing with the cost and quality of providing healthcare have been enacted to encourage modernization and integration of technology, govern financial relationships and kickbacks, link government payments to healthcare quality using federal reimbursement models like the value-based purchasing program and expand access to healthcare through programs like the Affordable Care Act (Dobrzykowski, 2019). These regulations are examples of conduct regulation that regulate the actions of players in the healthcare industry by setting standards that hospitals must meet, restricting undesirable behaviors, or encouraging desirable behaviors. Another type of regulation is structural regulation, which regulates the structure of the market by governing the

concentration of competition and barriers to entry into a market (Kay et al., 1988). In the United States, the Antitrust Division of the U.S. Department of Justice, and the Federal Trade Commission (FTC) enforce structural regulations, namely the Sherman Antitrust Act and the Clayton Act, which are aimed at preventing the concentration of competition in markets. These regulations are meant to facilitate competitive activity in markets which should result in lower prices as well as increased quality, choice, and innovation (Gundlach et al., 2019). In the healthcare industry, hospital system mergers and acquisitions are often subject to this type of regulation. For example, in 2012, the FTC ordered ProMedica Health System to sell St. Luke's Hospital, which it had purchased in 2011, because the acquisition was likely to reduce competition in the Toledo, OH area, thus increasing the price of healthcare services (FTC, 2012).

Structural regulations concerned with market entry are typically enacted when regulators believe that a single firm would provide lower prices to customers than would be possible in a competitive market (Joskow & Rose, 1989). In the United States, this justification was used to limit entry into several major industries such as energy and communications utilities as well as air, rail, ocean, and trucking transportation (Joskow & Rose, 1989). However, beginning in the 1970s, many of these industries were deregulated because it was believed that regulatory agencies were under the control of producers and thus benefitted from higher prices provided by this regulatory capture (Stigler, 1971; Peltzman, 1989). During the same period in the healthcare industry, certificate of need (CON) regulation gained popularity among states as a way of controlling increasing healthcare costs by restricting the construction of excess healthcare capacity (NCSL, 2019). Excess capacity, seen by lawmakers as inefficiency, was thought to result from healthcare firms prioritizing growth because they were protected from the financial consequences of their decisions (Madden, 1999). CON was implemented first at the state level

beginning with New York in 1964. In 1974, CON became federally mandated and by 1982 every state but Louisiana had implemented a form of CON (NCSL, 2019).

CON has been met with mixed support in industry. Proponents of CON regulation cite improved planning and access as benefits of the regulation (AHPA, 2004). Opponents, including the FTC, cite lack of competition in the healthcare marketplace and lack of evidence that CON regulations accomplish their intended goals of cost reduction (Ohlhausen, 2015). In fact, once supported at the federal level, the U.S. Congress repealed its version of CON in 1987 after only 12 years, citing failure to contain costs (DOJ, 2008). Still 35 states have active CON regulations or similar programs in place (NCSL, 2019). CON has also been cited as a barrier for healthcare providers to respond to changing market demand—notably CON has been cited as a reason for insufficient bed capacity in response to the COVID-19 pandemic of 2020-21 (Wilson & Phillips, 2020). Research also finds mixed support for CON regulations. In a longitudinal study of hospitals in Michigan, it was found that limitations on expanding bed supply increased utilization (Langley et al., 2010). In a cross-sectional analysis of imaging service providers, CON regulation was found to have no effect on hospitals financial performance but did help to increase their market share (Stratmann & Baker, 2016). CON regulation has also been found to constrain improvement efforts in a cross-sectional study of Medicaid-certified nursing homes (Grabowski & Angelelli, 2004). More broadly, in a literature review of articles investigating the effects of CON regulation, Conover and Bailey (2020) found that CON regulations increased healthcare costs and had mixed effects on patient mortality. In summary, existing studies provide uncertain evidence of the financial impact of CON regulation while highlighting the possibility that CON can also negatively affect the quality of provider facilities and healthcare outcomes. Our study

investigates both longitudinal and cross-sectional effects of CON regulation on hospital costs as well a multi-dimensional view of the effects of CON on healthcare quality.

Complexity and Healthcare

Complexity refers to the number and variety of interrelated activities within a system (Anderson, 1999; Bode & Wagner, 2015). In the operations management literature, many sources of complexity have been studied along the supply chain as well as the internal operations of the firm (Bozarth et al., 2009). A key source of complexity resulting from the heterogeneity of customer demand is product complexity, which refers to the number of products or services a firm produces or provides (Chong et al., 2001). Product complexity is associated with increased capital and materials requirements (Bozarth et al., 2009), limits a firm's ability to batch work (Thonemann & Bradley, 2002), can result in decreased fill rate (Closs et al., 2010), and can lead to diseconomies of scale (Salvador et al., 2002). Product complexity also increases task complexity, another key type of complexity found in the operations management literature. Task complexity is made up of the steps, information, and interdependence required to accomplish the goal of producing a product or providing a service (Haerem et al., 2015; Wood, 1986). As task complexity increases, workers must be able to cognitively process more steps and information to complete the task. Complexity also increases when completion of tasks requires exchanging information or transferring steps with other workers, teams, and organizations. Thus, as complexity increases, knowledge transfer activities become harder and can lead to lower performance (Lang et al., 2014).

In the healthcare operations management literature, complexity is often defined in terms of case mix, which reflects the severity and heterogeneity of the conditions of patients treated by a hospital (McCrum et al., 2014; Peng et al., 2020). Case mix also represents how resources are

allocated in a hospital to treat conditions (CMS, 2020b). Complexity has consistently been found in empirical studies to be positively associated with hospital cost. As hospitals increase the complexity of tasks performed in a facility, the amount and cost of administrative work has been shown to increase (Anderson & Warkov, 1961). Increased case mix has been shown to be associated with high resource intensity (Park & Shin, 2004). In a study of the effects of utilization on "triple aim performance", CMI is used as a control and estimation results show it to be negatively associated with technical efficiency, meaning the processes that should be associated with improved cost performance are negatively affected by CMI (Roth et al., 2019). Finally, in a study of the effects of conformance quality and EQ on readmission rate and cost per discharge, CMI was used as a control variable that was associated with higher cost per discharge (Senot et al., 2016b).

Extant research has provided mixed rationales concerning the relationship between hospital complexity and healthcare quality. Higher complexity has been associated with higher levels of uncertainty, which can lead to more process variation (Donabedian, 1988). However, higher complexity has also been associated with lower mortality, a key dimension of CQ (McCrum et al., 2014). In terms of EQ, hospital CMI has been found to negatively impact patient-level outcomes (Peng et al., 2020); however, it is important to note that this relationship is tested using within-hospital CMI variation meaning hospitals EQ suffers when CMI increases over time. Specifically, CMI can negatively impact EQ because treating complex conditions can result in communication challenges (McFarland et al., 2017), and patients suffering from more complex conditions may be harder to satisfy (Hall et al., 1998). However, CMI has consistently been positively correlated with both CQ and EQ. In a study of the effects of hospitals' implementation of an office of patient experience, CMI is shown to positively moderate the

relationship between the length of operation of an Office of Patient Experience and EQ. Although not explicitly hypothesized, CMI is shown in this study to have a significant positive direct effect on EQ (Sharma et al., 2020). In a study of the effect of magnet status, CMI is used as a control variable and shown to have a significant positive effect on simultaneous improvement of CQ and EQ. In fact, the CMI odds ratio showed an effect size of nearly double that of the independent variable of interest, magnet status (Senot et al., 2016a). CMI has also been shown to positively affect CQ and EQ, even though the opposite effect was expected. For example, while using CMI as a control variable in their study of the effect of health information technology on hospital performance, Sharma et al (2016) state that increased complexity is expected to result in lower CQ and EQ scores, their results indicate a significant positive relationship between CMI and both CQ and EQ.

In summary, extant healthcare operations management research is aligned on the costly effects of complexity but provides a mixed view of the effects of complexity on quality. Further, while cost and quality have been investigated together as outcomes (Roth et al., 2019), they have not been studied together in response complexity as an independent variable of interest. Given the important role of complexity in determining resource allocation in hospitals and mixed findings regarding the effects of complexity on hospital quality, this research contributes to this literature stream by simultaneously investigating the effects of complexity on hospital costs and quality.

Figure 1 represents our conceptualization of the effects of structural regulation and complexity on hospital costs and quality, which we will use to develop our hypotheses in the next section.

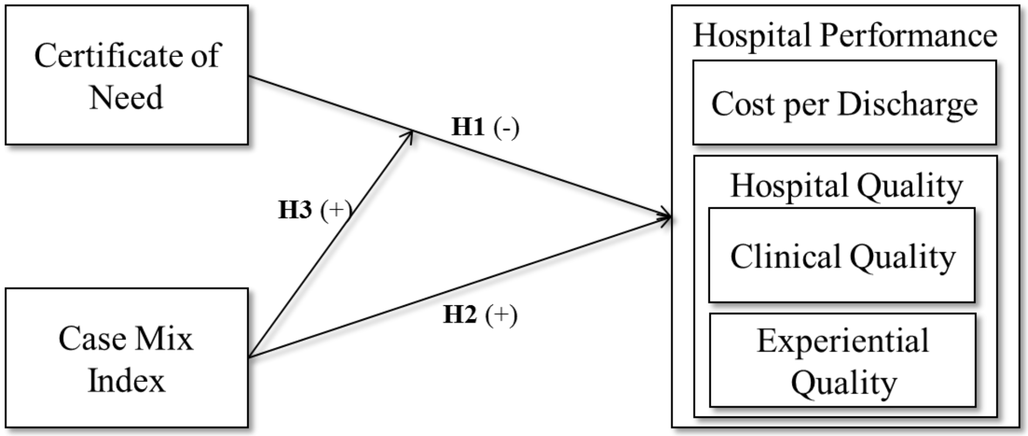

Figure 1: Conceptual framework

Theory and Hypothesis Development

Influence of Regulation

The structure-conduct-performance (SCP) framework posits that firm behaviors in response to market structure or other market conditions can lead to the creation of competitive advantages (Bain, 1956; Caves, 1992; Mason, 1939). Market structure describes the state of competition in a market, including the number of firms competing in a market, the concentration of firms in a market, the conditions under which firms may enter or exit a market, and the differentiation of products offered within a market. Conduct is the behavior a firm exhibits in response to its market structure, and includes a firm's strategy, internal procedures, and interactions with other firms. Performance represents the outcomes of the firm, which result from its conduct within the market (Jacquemin, 1987; Scherer, 1980). Firms develop strategies that capitalize on existing firm strengths and capabilities and new capabilities that consider market structure, learnings from competitors, and applicable operating standards. Failure to do so may reduce firm performance and the likelihood of firm survival (Porter, 1991).

Firms alter their strategies to exploit opportunities in the market or to mitigate the impact of threats in the market. Doing so can improve their opportunities to earn profits, which

ultimately increases their likelihood of survival (Bain, 1956). These strategies are generally aimed at capturing the largest portion of market share possible. When few firms in a market possess a large portion of the share of profits, market concentration increases (Weiss, 1979). As market concentration increases, dominant firms can control their own prices in the market because demand for their production comprises much of the market demand. When the market consists of a few dominant firms, they can tacitly collude to keep prices high (1979). Dominant firms may also be able to leverage their capacity more fully because they can achieve economies of scale not possible for small or entrant firms (Mason, 1939). Firms with economies of scale can fluctuate pricing to levels that make a market unappealing to new entrants and thus create barriers to entry. These economies of scale also make entry into a market less appealing because new entrants must make large upfront investments to be competitive in the market (Bain, 1956).

However, decreasing industry profits may not be a direct result of increased concentration solely. Even in highly concentrated markets, if dominant firms do not respond to new entrants, their profit can decrease (Cool & Dierickx, 1993). Firms in highly competitive industries develop diverse strategies for product differentiation and perform better than firms in less competitive industries that did not diversify their strategies (Bettis, 1981). Firms that diversify and become highly successful can develop consumer goodwill that results in supranormal performance that new entrants would not easily replicate (Demsetz, 1973). Even in markets where they are dominant, firms must adjust their conduct to maintain performance (Joglekar et al., 2016; Schmalensee, 1988). Further, highly competitive industries requiring higher upfront investments may see higher levels of market entry and exit without reaching high concentration levels or lower profitably (Dunne et al., 2013).

Following the SCP framework, we posit that hospitals will take actions to respond to regulation to achieve desirable performance. Response behaviors to regulation can take one of two complementary forms: adaptation and selection. Adaptation is defined as the changes made by organizations to cope with changing environmental conditions caused by changes in the regulatory environment (Cook et al., 1983; Lawrence & Lorsch, 1967; Thompson, 1967). Selection is defined as the market exit or dramatic transformation of non-dominant firms due to their inability to adapt to changes in the regulatory environment (Aldrich, 1979; Cook et al., 1983; Hannan & Freeman, 1978). To avoid selection and enhance performance, hospitals may partner with other hospitals or consolidate to create economies of scale (Cook et al., 1983).

Structural regulations that restrict market entry may motivate hospitals to make adaptations that improve financial performance. Firms make adaptations to become dominant. Once dominant, they can take advantage of economies of scale and set their own prices. These advantages then allow dominant firms to create barriers to entry that make it harder for small firms to compete and for new entrants to succeed. Over time the market is made up of fewer competitors who enjoy a greater portion of industry profits. Structurally regulated markets will likely have reductions in excess bed capacity, which should allow hospitals to utilize existing bed capacity more fully The resulting utilization can help hospitals better cover fixed costs, thus lowering fixed costs per discharge (Litvak & Bisognano, 2011). Research shows that revising routines and increasing coordination when faced with increased patient volumes can lead to performance improvements (Johnson et al., 2020). As patient volumes increase hospitals find new ways to reduce operating costs, which increases efficiency (Ding, 2014). Increased utilization has also been shown to improve technical efficiency, which may result in lower hospital costs (Roth et al., 2019). Given that structural regulation limits competition and thus

increases the ability for hospitals to achieve efficiency through economies of scale and increased utilization, we hypothesize,

H1a. *Structural regulation that restricts market entry is negatively associated with healthcare costs, such that, when structural regulation is present, healthcare costs will be lower than when they are not present.*

Market structure regulation that limits entry can accelerate the process of firms becoming dominant due to the artificial limitations on competition. These limitations can reduce the likelihood that dominant firms would develop strategies and routines to create a competitive advantage that they would have otherwise worked to create in a naturally competitive environment. The effect is the creation of monopolistic competition without the benefit of the competition needed to create the dominant firm. As a result, firms operating in regulated environments that restrict competition may have a harder time learning how to become effective. For example, healthcare organizations were previously seen as IT laggards (Leidner et al., 2010), which may be explainable by the fact that a lack of competition has reduced the likelihood of innovative behavior. A lack of external pressure to develop strategies to create a competitive advantage means that quality may be lower for hospitals in less competitive markets than hospitals that face more competition. In addition, hospitals that are subject to market structure regulation are more likely to have larger administrative overhead to ensure compliance with regulatory requirements. Increase administrative overhead may reduce physician autonomy and inhibit medical decision making in caring for patients, which can lead to worsened patient outcomes (Cook et al., 1983).

As markets become more competitive, the number of higher quality services increases, and overall quality improves (Berry & Waldfogel, 2010). In the absence of competition, higher

quality may be unneeded because profits are protected. Thus, when competition is reduced due to high levels of market concentration brought on by structural regulation, motivation to provide high levels of quality is reduced. Although investments in staffing and technology can improve the quality of care (Wani et al., 2018), investing in improvement programs aimed at clinical quality and EQ can be more complex, time consuming and costly (Senot et al., 2016b) and is unlikely to be undertaken. Empirical studies have shown reduced competition has been found to be associated with worse clinical outcomes (Kessler & McClellan, 1999). Low competition also creates information asymmetries regarding healthcare quality, leaving patients in the dark when choosing their healthcare provider (Madden, 1999). This further reduces the motivation for hospitals to invest in improving healthcare quality.

Increased utilization, resulting from structural regulation restricting market entry, can also result in lower quality. Empirical studies show that increased bed utilization can result in worse CQ (Roth et al., 2019). While higher concentrated hospital markets may result in lower inpatient costs, the overall risk of failure-to-rescue after complication increases (Cerullo et al., 2018). Bed constraints caused by increased volumes have been shown to reduce patient outcomes (Grabowski & Angelelli, 2004). When faced with high utilization, healthcare staff begin to cut corners and make more frequent errors due to stress (Kuntz et al., 2015). High utilization may lead to the temptation to expedite discharges, which can result in increased readmissions (Anderson et al., 2011). High utilization can also result in delayed patient admission to the correct hospital unit (KC & Terwiesch, 2009) and increased errors due to increased multi-taking (KC, 2014). Also, high volume hospitals may be less likely to undertake process quality efforts due to increased bureaucracy and communication challenges (Theokary & Ren, 2011). Empirical research has shown that EQ decreases when hospitals become more

consolidated (Hanson et al., 2019), and can be worsened by increased utilization (Roth et al., 2019) due to decreased caregiver responsiveness and increased interruptions (Halbesleben et al., 2010). Further, patients perceive that larger hospitals are not as clean, are less responsive, and provide poorer communication (McFarland et al., 2017). Structural regulation aims to decrease costs by forcing hospitals to be larger and more concentrated; however, size and concentration do not directly translate to improved quality. Therefore, we hypothesize,

H1b. *CON regulation is negatively associated with clinical quality, such that, when CON regulation is present, clinical quality will be worse than when it is not present.*

H1c. *CON regulation is negatively associated with experiential quality, such that, when CON regulation is present, experiential quality will be worse than when it is not present.*

Influence of Complexity

A complex adaptive system (CAS) is a system of numerous independent but related actors that organize and adapt over time to environmental factors (Cilliers, 1998). Actors in a CAS have agency to act within a broad set of behavioral rules and often interact with other actors who also have varying levels of agency within their own set of behavioral rules. Through these interactions, actors self-organize into feedback loops that impact the autonomy of the actors affected by the patterns. Changes in the environment with which actors in a CAS interact affects how actors act and how they interact with other actors. However, the system itself can also affect the environment in which it operates. When actors in a CAS interact with changes in the environment, their patterns of behavior will co-evolve to create new unpredictable, non-linear patterns of behavior and interactions (Choi et al., 2001).

Though the application of the CAS perspective in the operations management literature can be seen predominantly in the study of supply networks (Choi et al., 2001; Pathak et al.,

2007), the underlying mechanisms of CAS have motivated or have been the subject of extensive management and operations management research (Nair & Reed-Tsochas, 2019). For example, studies of task complexity are often conducted in the context of coordination (Handley & Benton Jr, 2013). This is because increases in difficulty or variability of tasks result in greater coordination via better planning and adjusting through feedback loops, whereas increases in interdependence of tasks result in greater coordination through better planning and adjusting as well as establishing clear cut processes (Van De Ven et al., 1976). As the CAS perspective would predict, as task complexity increases (the result of environmental changes), the actors who interact with each other develop new means of coordination (self-organize feedback loops) to deal with the changes in complexity.

In healthcare operations research, hospitals (among other healthcare organizations) have been conceptualized as complex adaptive systems because they are made up of many autonomous actors (doctors and nurses) with varying goals and rules who must interact across multiple departments in constantly changing environments (Begun et al., 2003; McDaniel et al., 2013). While treatment of conditions is administered to produce a desired, foreseeable outcome, the actual actions, decisions, and interactions required to administer treatment are often non-linear and unpredictable due to the heterogeneity of conditions that patients present with. These actions and decisions can affect admission and throughput, meaning that as complexity increases, utilization decreases (Nugus, et al., 2010). Further, when medical staff from different departments interact during treatment of complex conditions, they identify novel ways of preventing hospital-acquired infections and improving treatment outcomes (Holden, 2005). This is supported by research that shows that when doctors and nurses frequently interact with each

other, their coordination activities and information exchange relationships improve (Dobrzykowski & Tarafdar, 2015).

The CAS perspective is useful for understanding how changes in case mix complexity affect hospital costs. When faced with complex patient conditions, doctors and nurses must interact across departments to coordinate treatment (Faraj & Xiao, 2006). While increasing coordination in response to increased complexity can improve the quality of task performance, introducing coordination activities adds administrative costs (Van De Ven et al., 1976) and can decrease utilization (Nugus, et al., 2010). Further, to enable coordination, hospitals invest in health information technology (AHRQ, 2013; Angst et al., 2011); however, adopting these technologies has been shown to increase costs (Dranove et al., 2012). Therefore, logic based on the CAS perspective paired with prior findings suggesting that increased complexity is associated with higher resource intensity, we hypothesize,

H2a. *Hospital complexity is positively associated with healthcare costs, such that higher hospital complexity will be associated with higher healthcare costs.*

Following the logic of the CAS perspective, we theorize that increased complexity can lead to improved quality. Changes in case mix complexity represent a changing operating environment that must be addressed by doctors and nurses across interdependent departments. While treating complex patients, doctors and nurses from different departments establish informal relationships that enable improved diagnosis and treatment planning, joint sensemaking to problem-solve unexpected patient events, and interventions to prevent accidents or unsafe practices (Faraj & Xiao, 2006). Further, although more complex cases present communication challenges (McFarland et al., 2017) making it harder to satisfy patients (Hall et al., 1998), coordination through social interaction ties has been shown to improve information exchange

between medical staff. This coordination improves communication between healthcare providers and patients (Dobrzykowski & Tarafdar, 2015). Thus, rapidly changing case complexity requires the emergence of coordination mechanisms that can improve patient outcomes and experience.

Also, according to the SCP framework, firms will alter their strategies in response to market forces. Hospitals seek opportunities to differentiate to increase profitability (Bettis, 1981; Demsetz, 1973). One way that hospitals may choose to differentiate their strategy is to treat more complex cases. Hospital systems may designate hospitals within local markets that will specialize in providing treatment for highly complex conditions (Kash et al., 2014; Shay & Mick, 2017). For example, in systems deploying this type of differentiation strategy, specialty hospitals like heart or surgical hospitals will exclusively treat highly complex conditions while community hospitals will treat a wider variety of less complex conditions. While higher case mix is associated with higher costs, higher case mix is also associated with increased hospital revenue (Lee et al., 2020). Seeking a more complex case mix to improve profitability allows hospitals to repeat complex procedures, enabling them to improve processes (Ding et al., 2020). These hospitals are also more likely to make investments in revealed quality, like reducing wait time resulting in better patient experience (Wani et al., 2018) and improved process quality resulting in better patient outcomes (Kessler & McClellan, 1999). Conversely, hospitals that are not strategically differentiated to focus on only highly complex conditions but consistently deal with a more complex case mix will increase the variety of services they provide. These hospitals are more effective at providing comprehensive care which can improve patient outcomes and can reduce the likelihood of patients having to be transferred and delay care (McCrum et al., 2014). Given that delayed care can increase safety risks (Tucker & Spear, 2006), minimizing delays by

expanding service offerings to treat a more complex case mix can also improve patient outcomes.

By applying the logic of the CAS perspective and the SCP framework, we argue that increases in CMI will be associated with improved healthcare quality and that hospitals may pursue a more complex case mix, enabling them to focus on improving patient outcomes and experience. Thus, we hypothesize,

H2b. *CMI is positively associated with clinical quality, such that higher CMI will be associated with higher clinical quality.*

H2c. *CMI is positively associated with experiential quality, such that higher CMI will be associated with higher experiential quality.*

Interaction between Structural Regulation and Complexity

Structural regulation that restricts entry is hypothesized to reduce cost due to increased utilization resulting from consolidated capacity. Increased utilization can lead hospitals to implement lean practices to improve patient flow (Johnson et al., 2020). Lean practices enable improved cost performance through increased coordination (Dobrzykowski et al., 2016). Lean practices also provide effective tools for diagnosing and improving problems, which have been shown to provide greater benefit in more complex environments (Azadegan et al., 2013). More complex environments provide more opportunities for improvement and thus more opportunities for cost savings. As a result of focusing on process efficiency, hospitals with lean practices are positioned to see greater cost reductions when facing higher levels of hospital complexity. Therefore, we hypothesize,

H3a. *CMI moderates the negative relationship between CON and healthcare costs such that the relationship becomes stronger as CMI increases.*

In markets with structural regulation that restricts entry, competition is low due to high hospital concentration. As such, hospitals are less likely to invest in equipment and processes to improve patient outcomes (Kessler & McClellan, 1999). Managing high case mix complexity requires investment in costly and highly specialized equipment—the type of equipment investments governed by regulations like CON (Park & Shin, 2004). Hospitals with high case mix complexity operating in markets with structural regulation that restricts capital investment may encounter resource scarcity and be unable to provide the best care for more complex diagnoses. As a result, CQ will suffer because patients at these hospitals will have worse outcomes. Hospitals that differentiate or build specialized departments to treat highly complex conditions are typically located in states that do not have regulations in place that restrict building or expanding capacity (Guterman, 2006; Tiwari & Heese, 2009). Patients perceive hospitals that provide a wider array of services as being able to provide a higher level of care (McCrum et al., 2014). Further, while high volume has been shown to improve the service quality for routine patients, this relationship is weakened when treating more complex patients (Kuntz et al., 2019). Therefore, hospitals with high case mix complexity operating in CON-regulated markets will find that restrictions on building or expanding specialized capacity will result in lower EQ. Thus, we hypothesize,

H3b. *CMI moderates the negative relationship between CON and clinical quality such that the relationship becomes stronger as CMI increases.*

H3b. *CMI moderates the negative relationship between CON and experiential quality such that the relationship becomes stronger as CMI increases.*

Research Methods

Data Collection

We tested our hypotheses using a unique dataset containing aggregated patient healthcare outcomes and experience, hospital characteristics and performance, and state-level CON regulations compiled from multiple data sources for eight years between 2011 and 2018. This study uses secondary data from sources including CMS HCAHPS data for EQ measures, CMS outcome measures for CQ measures, as well as CMS impact files, CMS case mix index, and Medicare Cost Reports for hospital characteristics and controls. In addition to the secondary data sources, we collected CON regulatory data from the American Health Planning Association (AHPA) and the National Conference of State Legislatures (NCSL) to create our independent variable of interest.

To collect CON regulatory data, we began by collecting data from the AHPA CON coverage summary matrices (AHPA, 2016a), which provides CON regulation coverage information across 26 major categories in the 35 U.S. states and Washington, D.C. that have some CON regulation in place. This information is provided for the years 2012 and 2016. CON regulation coverage categories include restrictions on the addition of bed capacity like acute care beds, facilities like cardiac catheterization laboratories, services like open heart surgery, and equipment like CT scanners. For states where CON coverage was different between those two years and for the years before and after, we collected data from the AHPA CON map books (AHPA, 2016b), the NCSL list of CON state laws (NCSL, 2019), and various state CON websites. The resulting comprehensive data set contained CON regulatory data for all major categories for eight years between 2011 and 2018. Finally, since government hospitals like

veterans' affairs and public hospitals are not subject to CON regulations in many states, we retained only for-profit hospitals and nonprofit, non-government hospitals.

We combined the CON regulatory data we collected with our other secondary data sources to create an unbalanced panel data set of 20,887 hospital-year observations across 2,992 acute care hospitals in all 50 U.S. states and Washington, D.C. Based on data availability, our final sample contains 20,242 observations across 2,893 hospitals for our cost analyses, 18,739 observations across 2,660 hospitals for our CQ analyses, and 19,459 observations across 2,809 hospitals for our cost analyses.

Dependent Variables

Cost per Discharge is used to operationalize healthcare cost performance in this study. We follow the approach used by Senot et al. (2016b) in calculating this variable by first inflation-adjusting each hospital's total inpatient operating charges by multiplying the charges to 2011 U.S. dollars using the consumer price index for inpatient hospital services. We then divide these inflation-adjusted inpatient charges by the total number of inpatient discharges. Next, we impute inpatient operating costs per discharge by multiplying the inflation-adjusted inpatient charges to discharge ratio by a hospital-specific operating cost-to-charge ratio. This cost-to-charge ratio is calculated by taking total costs divided by total charges. Inpatient operating charges, inpatient discharges, total charges, and total costs are extracted from Medicare cost reports. Finally, to ensure normality and homoscedasticity, we took the natural logarithm transformation to the final *Cost per Discharge* ratio.

Clinical Quality (CQ) is measured by creating a weighted average of 30-day risk-standardized mortality rates and readmission rates contained in CMS outcome measures reporting across three different categories: heart attack, heart failure, and pneumonia (Ding,

2014). These categories are consistently reported at the hospital level by CMS for all years included in this study. CMS outcome measures reflect the result of care provided by hospitals and are appropriate proxies for hospital quality (Roth et al., 2019). To calculate this variable, we average the 30-day risk-standardized mortality rates and readmission rates for each of the three medical conditions, weighted by the number of patients for those three conditions. Following guidelines provided by CMS as well as prior studies (Roth et al., 2019; Senot et al. 2016b), we only include measurements that have a sample of at least 25 patients for a given condition in our computation.

When analyzing mortality and readmission rates, and by extension our measure of *CQ*, increases in values would normally be interpreted as worsened outcomes. For example, Hypothesis 1b posits that CON is negatively associated with clinical quality. A positive coefficient for this relationship would confirm this hypothesis. To simplify our discussion of estimation results concerning *CQ* as the outcome variable, we have subtracted the calculated variable from 1; thus, interpretation of coefficient signs in our analyses is straightforward, i.e., a negative coefficient confirms a hypothesized negative relationship. Because mortality and readmission rates are cumulative percentages of binary outcomes (e.g., survival=1 whereas death=0), we transform our measure of *CQ* into its normally distributed logit form to satisfy normality and heteroskedastic requirements (Collett, 2003). This approach is also used in prior healthcare research (Senot et al., 2016b). As such, CQ_{it} for hospital *i* in year *t* of the weighted average of survival and non-readmission rates C_{it} is calculated as

$$CQ_{it} = \ln\left(\frac{C_{it}}{1 - C_{it}}\right).$$

Experiential Quality (EQ) is measured by creating a weighted average of five items measuring physician and nursing communication and responsiveness from the Hospital

Consumer Assessment of Healthcare Providers and Systems (HCAHPS) surveys published by CMS (Senot et al., 2016b; Sharma et al., 2020). Prior studies utilize six measures of communication and responsiveness; however, reporting of the fourth measurement regarding pain management responsiveness was discontinued in 2017 (HCAHPS, 2018) and is therefore excluded from our analysis. These measures were developed in partnership between CMS and the U.S. Agency for Health care Research and Quality (AHRQ). Starting in 2008, hospital-level results were reported on the CMS Hospital Compare website to allow standardized comparison of hospitals. Following guidelines provided by CMS as well as prior studies (Roth et al., 2019; Senot et al., 2016b), we only include survey results for hospital samples with at least 100 patient responses. As with *CQ*, we transform this percentage score to its normally distributed logit form such that EQ_{it} for hospital *i* in year *t* of the weighted average of the five communication and responsiveness scores E_{it} is calculated as

$$EQ_{it} = \ln\left(\frac{E_{it}}{1 - E_{it}}\right).$$

Independent Variables

Certificate of need (CON) Regulation is measured as a dichotomous variable denoting whether at least one appropriate CON regulatory coverage was in place in a given U.S. state or Washington, D.C. during a given year included in our study. Our data set included 26 CON regulation coverage categories; however, given this study's focus on severe acute conditions typically treated on an inpatient basis, we limited the focus of the variable to inpatient bed capacity restrictions. Thus, if any of the following ten inpatient coverages are present in a given state, the variable takes a value of "1": acute care beds, long-term acute care beds, inpatient obstetrics beds, psychiatric services or beds, inpatient rehabilitation beds, subacute services, substance abuse services or beds, swing beds, burn care services or beds, and NICU services or

beds. Otherwise, the variable takes a value of "0". We calculated this value using the data we assembled from reports provided by AHPA and NCSL.

Case Mix Index (CMI) is measured using the weighted average of diagnosis-related groups (DRG) treated by a hospital during a given year. A higher CMI means a hospital treats patients with more severe and heterogenous conditions. Treating patients within complex DRGs requires intensive resources, communication, and coordination, potentially increasing cost, process variability, and the likelihood of error (McCrum et al., 2014; Peng et al., 2020; Sharma et al., 2020). We retrieved this variable in its already-calculated form from the CMS CMI data files. We then adjust the variable in terms of teaching intensity to account for the added cost and complexity incurred by teaching hospitals (Senot et al., 2016b; Koenig et al. 2003).

Control Variables

We control for several variables that may impact hospital performance on cost and quality. We control for hospital-level *Average Length of Stay (LOS)*, log transformed to satisfy normality concerns, because longer hospital stay durations can negatively impact *EQ* (Sharma et al., 2020). We control for *Outpatient Mix*, calculated as outpatient charges divided by total charges, to account for pressure from insurance companies to reduce costs by prioritizing outpatient procedures over inpatient procedures (Ding, 2014). *LOS* and *Outpatient Mix* were derived from the Medicare cost reports. We control for the effect of hospital size and utilization using the natural logarithm of a hospital's *Number of Beds (Beds)* and *Full-time Employees (FTEs)*. *Beds* was retrieved from the Medicare cost reports, while *FTEs* was retrieved from the CMS impact files. We control for *Teaching Intensity*, calculated by dividing the number of residents by the number of beds, because teaching hospitals tend to incur higher costs due to training and research (Ding, 2014). We also control wages' effect on healthcare costs using *Wage*

Index, adjusting for teaching intensity because teaching hospitals tend to pay higher wages (Senot et al., 2016b; Koenig et al., 2003). To account for the treatment of usually costly cases and patients, we control for the *Operating Disproportionate Share Hospital Payment (OPDSH) Adjustment Factor*, which measures the proportion of treating more costly Medicare and Medicaid patients, and the *Outlier Adjustment Factor*, which measures the proportion of treating more extraordinarily costly cases (Senot et al., 2016b). *Teaching Intensity, Wage Index,* the *OPDSH Adjustment Factor,* and the *Outlier Adjustment Factor* were all derived from the CMS impact files. We also control for hospital *Ownership*, as reported in the HCAHPS survey results, to account for differing strategic objectives pursued by hospital ownership types (i.e., proprietary and nonprofit) (Ding, 2014). Finally, we control for unobserved time-effects by including year dummy variables.

Model Estimation and Results

Table 1 gives descriptive statistics and Table 2 gives correlations on the key variables used in the analysis.

Table 1: Descriptive statistics

Variable	Mean	Std. Dev.
Cost per Discharge (ln)	10.65	0.72
Clinical Quality (ln)	0.84	0.01
Experiential Quality (ln)	1.08	0.26
Teaching Intensity	0.07	0.18
Wage Index (teaching adjusted)	0.01	0.18
OPDSH Adj. Factor	1.27	0.17
Outlier Adj. Factor	1.04	0.10
Beds (ln)	4.93	0.93
FTE (ln)	6.63	1.04
LOS (ln)	1.42	0.26
Outpatient Mix	0.53	0.15
Proprietary	0.26	0.44
CON	0.60	0.49
CMI (teaching adjusted)	0.07	0.32

Table 2: Correlation matrix

Variable	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.
1. Cost per Discharge (ln)													
2. Clinical Quality (ln)	**0.04**												
3. Experiential Quality (ln)	**-0.13**	**0.17**											
4. Teaching Intensity	**0.14**	**-0.04**	**-0.15**										
5. Wage Index (teaching adjusted)	**0.17**	**0.09**	**-0.24**	**0.13**									
6. OPDSH Adj. Factor	**0.05**	**-0.10**	**-0.37**	**0.22**	**0.10**								
7. Outlier Adj. Factor	**0.22**	**0.09**	**0.03**	**0.10**	**0.09**	**-0.02**							
8. Beds (ln)	**0.21**	-0.01	**-0.49**	**0.36**	**0.18**	**0.23**	**0.07**						
9. FTE (ln)	**0.17**	**0.06**	**-0.36**	**0.46**	**0.23**	**0.14**	**0.11**	**0.89**					
10. LOS (ln)	**0.18**	**-0.03**	**-0.47**	**0.27**	**0.12**	**0.30**	**0.13**	**0.59**	**0.51**				
11. Outpatient Mix	**-0.48**	**0.04**	**0.46**	**-0.18**	**-0.32**	**-0.23**	**-0.08**	**-0.55**	**-0.40**	**-0.42**			
12. Proprietary	**0.23**	**-0.08**	**0.04**	**-0.12**	**-0.12**	**0.04**	0.01	**-0.21**	**-0.35**	**-0.19**	**-0.08**		
13. CON	**-0.14**	**-0.17**	**-0.06**	**0.07**	**-0.15**	**-0.02**	**-0.05**	**0.09**	**0.11**	**0.14**	**0.06**	**-0.13**	
14. CMI (teaching adjusted)	**0.39**	**0.17**	**0.16**	**0.20**	**0.14**	**-0.17**	**0.18**	**0.29**	**0.35**	**-0.04**	**-0.33**	**0.08**	**-0.18**

The data used in this study is includes hospital-level information measured over eight years, so panel model estimation techniques are required (Greene, 2012). Previous hospital performance studies have used fixed effects models to observe within-hospital variation (Lee et al., 2020; Sharma et al., 2020). The purpose of this study is to assess variation in response to both hospital- and policy-level variables, the latter of which has very little variation over time. Therefore, fixed effects models are inappropriate for this study because they discard between-hospital variation and thus are unable to estimate variables that do not vary over time (Certo et al., 2017). Random effects models enable modelling of both within- and between-hospital variation; however, these models provide a single coefficient to represent both types of variation, which makes interpretation challenging (Certo et al., 2017). In such an application, a hybrid estimation approach is appropriate because it enables estimation of both within- and between-hospital variation individually in the same model, thus allowing the full modelling of both time-variant and -invariant variables (Allison, 2009). This is accomplished by splitting variables into within- and between-hospital effects and simultaneously estimating their effects on the outcome variables using a generalized linear mixed model (GLMM). Within-hospital effects are calculated by subtracting the within-hospital variable mean from the variable. Between-hospital effects are calculated by taking the mean of the within-hospital variable. Time-invariant variables are treated as random effects that only vary between hospitals (Schunck, 2013).

With respect to endogeneity, two primary concerns arise in and are addressed in this research: omitted variables and reverse causality. To account for the potential for endogeneity resulting from omitted variables, we first included a comprehensive set of control variables in our models that effect the dependent variables while also correlating with the independent variables (Lu et al., 2018). For example, teaching intensity has been found to be positively

associated with process quality (Theokary & Ren, 2011) but has also been found to be positively associated with increased costs and case mix complexity (Koenig et al., 2003). Second, our hybrid estimation approach uses fixed effects to account for heterogeneity caused by omitted variables that are correlated with explanatory variables (Lu et al., 2018; Wooldridge, 2010).

In terms of endogeneity resulting from reverse causality, prior literature provides evidence that changes in quality could lead to changes in case mix index. For example, case mix should be naturally exogenous to patient outcomes or experience (Peng et al., 2020). Yet under VBP, hospitals that receive financial penalties for poor CQ and EQ performance may seek to increase the complexity of cases they treat because they provide additional revenue opportunities (Lee et al., 2020). Therefore, it is possible that our data structure may also introduce endogeneity. For example, *Cost per Discharge*, *EQ*, and *CMI* are based on the preceding 12-month period, while *CQ* is based on the previous 36-month period. It is therefore possible that changes in *CQ* during the reporting period could lead to changes in case mix. To account for this issue, we estimate our model using a lag of *CMI.* Following the example of Ding (2014) in selecting an appropriate lag length, we determined the optimal lag length using the Akaike's Information Criterion (AIC) (Greene, 2012). AIC aids in selecting the optimal lag length by measuring the amount of information that is lost when variables are not included in the model. As appropriate variables are added to the model, the amount of information lost decreases. Thus, the model specification with the lowest AIC should be selected. We tested our specifications up to a maximum of four lags because there is no theoretical rationale for using additional lags. Based on our analysis, we chose a *CMI* lag length of one for the *EQ* specification. For both the *Cost per Discharge* and *EQ* specifications, a lag length of zero was most appropriate indicating our concern over reverse causality was unfounded.

The hybrid regression equation model for the *Cost per Discharge* and *CQ* specifications for hospital *i* in time period *t* is

$$Y_{it} = \alpha + \beta_1\overline{CON}_i + \beta_2\overline{CMI}_i + \beta_3(CMI_{it} - \overline{CMI}_i) + \beta_4\overline{CON}_i * \overline{CMI}_i +$$
$$\beta_5(CON_{it} * CMI_{it} - \overline{CON}_i * \overline{CMI}_i) + \vartheta_6\overline{H}_i + \vartheta_7(H_{it} - \overline{H}_i) + \mu_i + \varepsilon_{it}$$

and the hybrid regression equation model for the *EQ* specification for hospital *i* in time period *t* is

$$EQ_{it} = \alpha + \beta_1\overline{CON}_i + \beta_2\overline{CMI}_{it-1} + \beta_3(CMI_{it-1} - \overline{CMI}_{it-1}) + \beta_4\overline{CON}_i * \overline{CMI}_{i-1} +$$
$$\beta_5(CON_{it} * CMI_{it-1} - \overline{CON}_i * \overline{CMI}_{it-1}) + \vartheta_6\overline{H}_i + \vartheta_7(H_{it} - \overline{H}_i) + \mu_i + \varepsilon_{it}$$

where Y_{it} is the outcome measure (*Cost per Discharge* or *CQ*); β_1, β_2, and β_4 represent exogenous between-hospital effects; β_3, and β_5 represent exogenous within-hospital effects; ϑ_6 represents a vector of between-hospital controls and time dummies; ϑ_7 represents a vector of within-hospital controls and time dummies; μ_i represents the within-hospital effects error term; and ε_{it} represents the random effects error term.

We performed our econometric analysis in Stata 16.1 MP by estimating our hybrid model using the xthybrid command. For each outcome variable (*Cost per Discharge*, *CQ*, and *EQ*), we ran four regression models. The first model includes our control variables. The second and third models examine the main effects of *CON* and *CMI* respectively. The fourth model adds the interaction effects between *CON* and *CMI*. Models 1 through 4 in Table 3 summarizes the results for the *Cost per Discharge* estimations. Models 5 through 8 in Table 4 summarizes the results for the *CQ* estimations. Models 9 through 12 in Table 5 summarizes the results for the *EQ* estimations.

Effect of CON and CMI on Cost

Hypothesis 1a posits that the presence of CON will result in lower costs than if CON were not present. Model 2 shows a significant negative relationship between *CON* and *Cost per Discharge* (β = -0.080, $p < 0.01$), providing support for Hypothesis 1a. Hypothesis 2a posits that higher CMI will be associated with higher costs. Model 3 shows a significant positive relationship between *CMI* and *Cost per Discharge* for both within-hospital effects (β = 0.099, $p < 0.01$) and between-hospital effects (β = 0.428, $p < 0.01$), providing support for Hypothesis 2a. It should be noted that the between-hospital effect coefficient is more than four times larger than the within-hospital coefficient. This indicates that while increases in CMI over time increase healthcare costs, it appears that CMI is a more important predictor of differences in costs between hospitals than within hospitals. Hypothesis 3a posits that with increased *CMI*, the negative relationship between *CON* and *Cost per Discharge* will intensify. Model 4 shows a significant negative relationship between the *CON-CMI* interaction term and *Cost per Discharge* for within-hospital effects (β = -0.390, $p < 0.01$); however, the between-hospital effects are negative but not significant (β = -0.023, $p > 0.10$), providing partial support for Hypothesis 3a. Figure 2A plots the within-hospital interaction based on Model 4, which aids in understanding the effect of the *CON-CMI* interaction on *Cost per Discharge.* On average, hospitals subject to CON regulations with high CMI (one standard deviation (SD) above the mean) will have 1.1% lower costs than hospitals with low CMI (one SD below the mean). In contrast, hospitals *not* subject to CON regulations with high CMI will have 1.2% higher costs than low-CMI hospitals.

Table 3: Hybrid estimation results for Cost per Discharge

	Model 1	Model 2	Model 3	Model 4
Within-hospital effects				
Teaching Intensity	-0.011 (0.044)	-0.011 (0.044)	-0.002 (0.044)	-0.023 (0.044)
Wage Index (adjusting for teaching)	1.038*** (0.071)	1.039*** (0.071)	1.034*** (0.071)	1.003*** (0.071)
OPDSH Adj. Factor	-0.310*** (0.056)	-0.309*** (0.056)	-0.307*** (0.056)	-0.298*** (0.056)
Outlier Adj. Factor	0.131*** (0.043)	0.131*** (0.043)	0.121*** (0.043)	0.106** (0.043)
Beds (ln)	-0.089*** (0.018)	-0.089*** (0.018)	-0.090*** (0.018)	-0.090*** (0.018)
FTE (ln)	-0.090*** (0.013)	-0.091*** (0.013)	-0.093*** (0.013)	-0.094*** (0.013)
LOS (ln)	0.547*** (0.023)	0.547*** (0.023)	0.548*** (0.023)	0.554*** (0.023)
Outpatient Mix	-3.119*** (0.068)	-3.117*** (0.068)	-3.102*** (0.068)	-3.073*** (0.068)
Proprietary	0.016 (0.019)	0.016 (0.019)	0.016 (0.019)	0.015 (0.019)
CMI (adjusting for teaching)			0.099*** (0.026)	0.243*** (0.031)
CON x CMI				-0.390*** (0.045)
Between-hospital effects				
Teaching Intensity	0.212*** (0.062)	0.223*** (0.061)	0.159*** (0.060)	0.159*** (0.060)
Wage Index (adjusting for teaching)	0.080 (0.056)	0.046 (0.056)	0.090* (0.055)	0.091* (0.055)
OPDSH Adj. Factor	-0.374*** (0.060)	-0.385*** (0.060)	-0.181*** (0.062)	-0.181*** (0.062)
Outlier Adj. Factor	1.064*** (0.085)	1.039*** (0.085)	0.931*** (0.084)	0.933*** (0.084)
Beds (ln)	-0.214*** (0.028)	-0.214*** (0.028)	-0.175*** (0.028)	-0.175*** (0.028)
FTE (ln)	0.186*** (0.025)	0.188*** (0.024)	0.096*** (0.025)	0.096*** (0.025)
LOS (ln)	0.057 (0.047)	0.084* (0.048)	0.273*** (0.050)	0.273*** (0.050)
Outpatient Mix	-2.389*** (0.084)	-2.359*** (0.084)	-1.986*** (0.088)	-1.986*** (0.088)
Proprietary	0.360*** (0.024)	0.354*** (0.024)	0.303*** (0.024)	0.304*** (0.024)
CMI (adjusting for teaching)			0.428*** (0.037)	0.440*** (0.045)
CON x CMI				-0.023 (0.057)
CON		-0.080*** (0.018)	-0.047** (0.018)	-0.043** (0.018)
Constant	11.029*** (0.190)	11.043*** (0.189)	10.786*** (0.187)	10.777*** (0.188)
Year dummies	Yes	Yes	Yes	Yes
Observations	20,244	20,244	20,242	20,242
Number of groups	2,893	2,893	2,893	2,893
χ^2	5,939	5,977	6,217	6,309
P-value	0.00	0.00	0.00	0.00
Δ AIC (base: Model 1)	-	-16,208.0	-16,208.0	-16,208.0
Δ BIC (base: Model 1)	-	-16,485.0	-16,485.0	-16,485.0

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Effect of CON and CMI on Clinical Quality

Hypothesis 1b posits that the presence of CON will result in worsened clinical quality than if CON were not present. Model 6 shows a significant negative relationship between *CON* and *CQ* (β = -0.023, $p < 0.01$), providing support for Hypothesis 1b. Hypothesis 2b posits that higher CMI is associated with better clinical quality. Model 7 shows a significant positive relationship between *CMI* and *CQ* for both within-hospital effects (β = 0.077, $p < 0.01$) and between-hospital effects (β = 0.038, $p < 0.01$), providing support for Hypothesis 2b. Hypothesis 3b posits that with increased *CMI*, the negative relationship between *CON* and *CQ* will intensify.

Model 8 shows a marginally significant negative relationship between the *CON-CMI* interaction term and *CQ* for within-hospital effects (β = -0.015, $p < 0.10$); however, the between-hospital effects are positive and not significant (β = 0.003, $p > 0.10$), providing partial support for Hypothesis 3b. Figure 2B plots the between-hospital interaction based on Model 12, which aids in understanding the effect of the *CON-CMI* interaction on *EQ*. On average, hospitals subject to CON regulations with high CMI (one SD above the mean) will have 2.4% higher CQ than hospitals with low CMI (one SD below the mean). In contrast, hospitals *not* subject to CON regulations with high CMI will have 2.9% higher CQ than low-CMI hospitals.

Table 4: Hybrid estimation results for Clinical Quality

	Model 5	Model 6	Model 7	Model 8
Within-hospital effects				
Teaching Intensity	0.037*** (0.009)	0.037*** (0.009)	0.042*** (0.009)	0.042*** (0.009)
Wage Index (adjusting for teaching)	0.033*** (0.011)	0.034*** (0.011)	0.029** (0.011)	0.027** (0.011)
OPDSH Adj. Factor	0.008 (0.009)	0.008 (0.009)	0.007 (0.009)	0.007 (0.009)
Outlier Adj. Factor	-0.011 (0.012)	-0.011 (0.012)	-0.018 (0.012)	-0.018 (0.012)
Beds (ln)	0.005* (0.003)	0.006* (0.003)	0.004 (0.003)	0.004 (0.003)
FTE (ln)	-0.004* (0.002)	-0.004* (0.002)	-0.005** (0.002)	-0.005** (0.002)
LOS (ln)	0.029*** (0.004)	0.029*** (0.004)	0.029*** (0.004)	0.029*** (0.004)
Outpatient Mix	0.011 (0.012)	0.012 (0.012)	0.016 (0.012)	0.016 (0.012)
Proprietary	0.006** (0.003)	0.006** (0.003)	0.007** (0.003)	0.007** (0.003)
CMI (adjusting for teaching)			0.077*** (0.005)	0.085*** (0.007)
CON x CMI				-0.015* (0.008)
Between-hospital effects				
Teaching Intensity	-0.044*** (0.008)	-0.040*** (0.007)	-0.040*** (0.007)	-0.041*** (0.007)
Wage Index (adjusting for teaching)	0.024*** (0.007)	0.017** (0.007)	0.020*** (0.007)	0.020*** (0.007)
OPDSH Adj. Factor	-0.037*** (0.008)	-0.042*** (0.007)	-0.031*** (0.008)	-0.031*** (0.008)
Outlier Adj. Factor	0.181*** (0.029)	0.152*** (0.028)	0.102*** (0.029)	0.102*** (0.029)
Beds (ln)	-0.024*** (0.004)	-0.024*** (0.004)	-0.024*** (0.004)	-0.024*** (0.004)
FTE (ln)	0.023*** (0.003)	0.024*** (0.003)	0.018*** (0.003)	0.018*** (0.003)
LOS (ln)	-0.022*** (0.008)	-0.014* (0.007)	-0.009 (0.007)	-0.009 (0.007)
Outpatient Mix	-0.014 (0.012)	-0.005 (0.012)	0.016 (0.012)	0.016 (0.012)
Proprietary	-0.004 (0.003)	-0.005 (0.003)	-0.007** (0.003)	-0.007** (0.003)
CMI (adjusting for teaching)			0.038*** (0.006)	0.037*** (0.007)
CON x CMI				0.003 (0.008)
CON		-0.023*** (0.002)	-0.020*** (0.002)	-0.020*** (0.002)
Constant	1.497*** (0.038)	1.527*** (0.037)	1.580*** (0.038)	1.580*** (0.038)
Year dummies	Yes	Yes	Yes	Yes
Observations	18,740	18,740	18,739	18,739
Number of groups	2,660	2,660	2,660	2,660
χ^2	7,244	7,351	7,713	7,718
P-value	0.00	0.00	0.00	0.00
Δ AIC (base: Model 1)	-	57,137.0	57,137.0	57,137.0
Δ BIC (base: Model 1)	-	56,863.0	56,863.0	56,863.0

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Effect of CON and CMI on Experiential Quality

Hypothesis 1c posits that the presence of CON will result in worsened experiential quality than if CON were not present. Model 10 shows that the relationship between *CON* and *EQ* is negative, but only marginally significant (β = -0.013, p < 0.10). Thus, we find weak support for Hypothesis 1c. Hypothesis 2c posits that higher CMI is associated with better experiential quality. Model 11 shows a significant positive relationship between *CMI* and *CQ* for between-hospital effects (β = 0.264, p < 0.01); however, the within-hospital effects are negative and not significant (β = -0.008, p > 0.10), providing partial support for Hypothesis 2c. Hypothesis 3c posits that with increased *CMI*, the negative relationship between *CON* and E*Q* will intensify. Model 12 shows a significant and negative relationship between the *CON-CMI* interaction term and E*Q* for between-hospital effects (β = -0.066, p < 0.01), but the within-hospital effects are positive and non-significant (β = 0.012, p > 0.10). Thus, we find partial support for Hypothesis 3c. Figure 2C plots the between-hospital interaction based on Model 12, which aids in understanding the effect of the *CON-CMI* interaction on *EQ*. On average, hospitals subject to CON regulations with high CMI (one SD above the mean) will have 9.3% higher EQ than hospitals with low CMI (one SD below the mean). On the other hand, hospitals *not* subject to CON regulations with high CMI will have 12.3% higher EQ than low-CMI hospitals.

Table 5: Hybrid estimation results for Experiential Quality

	Model 9	Model 10	Model 11	Model 12
Within-hospital effects				
Teaching Intensity	0.044*** (0.015)	0.044*** (0.015)	0.044*** (0.015)	0.044*** (0.015)
Wage Index (adjusting for teaching)	0.073*** (0.024)	0.073*** (0.024)	0.074*** (0.024)	0.074*** (0.024)
OPDSH Adj. Factor	0.046** (0.021)	0.046** (0.021)	0.045** (0.021)	0.045** (0.021)
Outlier Adj. Factor	0.038** (0.018)	0.038** (0.018)	0.038** (0.018)	0.038** (0.018)
Beds (ln)	-0.009 (0.006)	-0.009 (0.006)	-0.009 (0.006)	-0.009 (0.006)
FTE (ln)	-0.006 (0.005)	-0.006 (0.005)	-0.005 (0.005)	-0.005 (0.005)
LOS (ln)	-0.048*** (0.008)	-0.048*** (0.008)	-0.048*** (0.008)	-0.048*** (0.008)
Outpatient Mix	0.184*** (0.024)	0.184*** (0.024)	0.182*** (0.024)	0.181*** (0.024)
Proprietary	-0.026*** (0.006)	-0.026*** (0.006)	-0.026*** (0.006)	-0.026*** (0.006)
CMI (adjusting for teaching)			-0.008 (0.009)	-0.012 (0.011)
CON x CMI lag 1				0.012 (0.016)
Between-hospital effects				
Teaching Intensity	0.057** (0.023)	0.059** (0.023)	0.020 (0.022)	0.020 (0.022)
Wage Index (adjusting for teaching)	-0.235*** (0.021)	-0.240*** (0.021)	-0.205*** (0.020)	-0.207*** (0.020)
OPDSH Adj. Factor	-0.325*** (0.023)	-0.326*** (0.023)	-0.203*** (0.023)	-0.207*** (0.023)
Outlier Adj. Factor	0.402*** (0.047)	0.396*** (0.047)	0.241*** (0.046)	0.243*** (0.046)
Beds (ln)	-0.127*** (0.011)	-0.127*** (0.011)	-0.100*** (0.011)	-0.100*** (0.011)
FTE (ln)	0.060*** (0.010)	0.060*** (0.010)	0.007 (0.010)	0.009 (0.010)
LOS (ln)	-0.274*** (0.020)	-0.270*** (0.020)	-0.159*** (0.020)	-0.158*** (0.020)
Outpatient Mix	0.179*** (0.034)	0.185*** (0.034)	0.455*** (0.036)	0.454*** (0.035)
Proprietary	-0.009 (0.009)	-0.010 (0.009)	-0.035*** (0.009)	-0.036*** (0.009)
CMI_{t-1} (adjusting for teaching)			0.264*** (0.015)	0.293*** (0.018)
$CON \times CMI_{t-1}$				-0.066*** (0.022)
CON		-0.013* (0.007)	0.006 (0.006)	0.008 (0.007)
Constant	1.643*** (0.084)	1.645*** (0.083)	1.548*** (0.079)	1.534*** (0.079)
Year dummies	Yes	Yes	Yes	Yes
Observations	19,459	19,459	19,459	19,459
Number of groups	2,809	2,809	2,809	2,809
χ^2	8,485	8,495	9,121	9,141
P-value	0.00	0.00	0.00	0.00
Δ AIC (base: Model 1)	-	26,705.0	26,705.0	26,705.0
Δ BIC (base: Model 1)	-	26,429.0	26,429.0	26,429.0

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

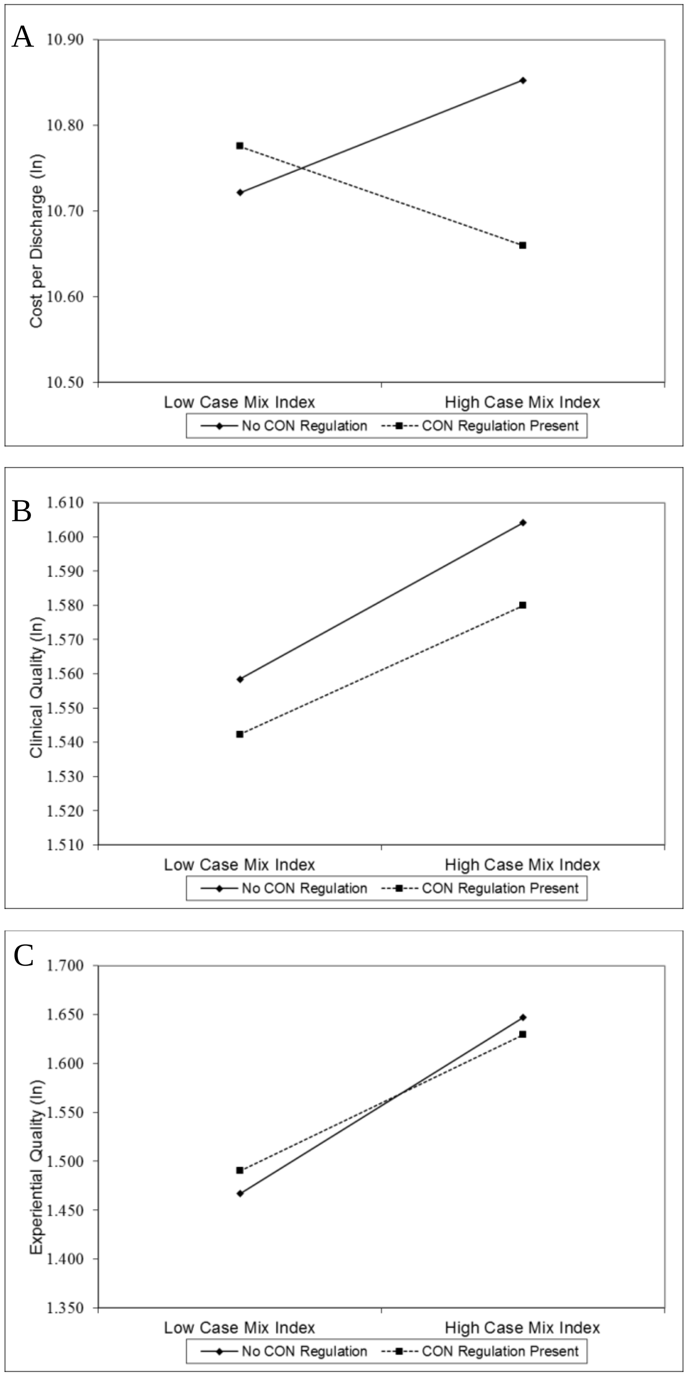

Figure 2: Interaction plots for (A) Cost per Discharge, (B) Clinical Quality, and (C) Experiential Quality

Robustness Checks

We conducted several additional analyses to test the robustness of our results. First, we test whether our models using the normally distributed logit forms of *CQ* and *EQ* are robust by

rerunning our models using the raw values instead. Tables 1A and 2A show the results of these runs that are consistent with our main analyses. The relationship between *CON* and *CQ* is negative and significant (β = -0.003, p < 0.01) whereas the relationship between *CON* and *EQ* is negative and marginally significant (β = -0.002, p < 0.10). The relationship between *CMI* and *CQ* is positive and significant for both within-hospital effects (β = 0.010, p < 0.01) and between-hospital effects (β = 0.005, p < 0.01), whereas the relationship between *CMI* and *EQ* is negative and not significant for within-hospital effects (β = -0.002, p > 0.10) and positive and significant for between-hospital effects (β = 0.043, p < 0.01). The relationship between the *CON-CMI* interaction and *CQ* loses significance for within-hospital effects (β = -0.002, p > 0.10) and continues to be non-significant for between-hospital effects (β = 0.003, p > 0.10). The relationship between the *CON-CMI* interaction and *EQ* continues to be non-significant for within-hospital effects (β = 0.002, p > 0.10) and significant and negative for between-hospital effects (β = -0.011, p < 0.01). While the relationship between the *CON-CMI* interaction and *CQ* is not robust in our main analysis, this check supports the robustness of the rest of our results.

Second, we use an alternate measurement of EQ to test the robustness of our primary analysis. Instead of the weighted average of communication and responsiveness measures used in the main analysis, we create a weighted average of hospital room quietness and cleanliness measures also contained in the HCAHPS data provided by CMS. Whereas the communication and responsiveness measures address doctor and nurse interactions with patients, the room quietness and cleanliness measures account for the quality of administrative and sanitation practices. Table 3A shows that room quietness and cleanliness measures of EQ behave similarly to the communication and responsiveness measures of EQ. Where *CON* was marginally significantly and negatively related to *EQ* in the main model, the relationship is not significant in

the alternate analysis ($\beta = 0.005$, $p > 0.10$). However, consistent with the main analysis, *CMI* is positively and significantly related to *EQ* ($\beta = 0.264$, $p < 0.01$) and the *CON-CMI* interaction term is significantly and positively associated with *EQ* ($\beta = -0.066$, $p < 0.01$).

Third, to assess the sensitivity of our model specifications to the influence of potential outliers, we reran our analyses with samples trimmed or Winsorized at $\pm$0.5% and $\pm$2.5%. Tables 4A and 5A show results that are largely consistent with our main analyses with the exception that the within-hospital marginally significant CON-CMI interaction relationship with CQ loses significance when outliers are excluded or Winsorized. Fourth, to assess the robustness of our use of hybrid model estimation, we reran our analyses using fixed- and between-effects estimators. Table 6A shows results of this check that are consistent with our main analyses with the exception that the within-hospital marginally significant CON-CMI interaction relationship with CQ loses significance when using the fixed effects estimator and robust standard errors.

Finally, we include a dummy variable to account for any quality improvement effects brought about by the Pay for Performance Plan known as the *Value-Based Purchasing (VBP)* program implemented in fiscal year 2013. *VBP* adjusts hospital reimbursements based on their CQ and EQ performance, thus encouraging hospitals to improve on both dimensions of quality (Senot et al., 2016a). Table 7A shows the results from rerunning our main analyses including the *VBP* variable. VBP is a significant predictor of within-hospital variation in Cost per Discharge, CQ, and EQ, improving both measures of quality while also increasing costs; however, the main effects were unaffected by the inclusion of *VBP*. This robustness check confirms the validity of our models to the effects of VBP.

Post Hoc Analyses

Granular Analysis of Clinical Quality: Survival and Non-readmission

Our results show the opposing effects of CON and CMI on CQ; however, the lack of a highly significant interaction effect between CON and CMI was surprising. To explore possible reasons for these results, we decomposed the *CQ* variable into its two dimensions: (i) *Survival Rate*, the 30-day risk-standardized mortality rate subtracted from 1, and (ii) *Non-readmission Rate*, the 30-day risk-standardized readmission rate subtracted from 1. We then reran our analysis using these outcome variables. Table 6 summarizes the interaction results. Full results are summarized in appendix Tables 8A and 9A. The effects of *CON* and *CMI* on *Survival* and *Non-readmission* are largely similar to those observed in our main estimations; however, in this granular analysis, the CON-CMI interactions result in significant effects. Model 13 shows a significant and negative relationship between the *CON-CMI* interaction term and *Survival* for within-hospital effects (β = -0.005, $p < 0.01$), but a non-significant between-hospital effect (β = -0.002, $p > 0.10$). Model 14 shows a significant and positive relationship between the *CON-CMI* interaction term and *Non-readmission* for within-hospital effects (β = 0.003, $p < 0.05$) and a marginally significant and positive relationship between the *CON-CMI* interaction term and *Non-readmission* for between-hospital effects (β = 0.003, $p < 0.10$).

Table 6: Post hoc: Granular interaction hybrid estimation results for Survival and Non-readmission

	Survival Model 13	Non-readmission Model 14
Within-hospital effects		
Teaching Intensity	0.006*** (0.002)	0.004** (0.002)
Wage Index (adjusting for teaching)	-0.001 (0.002)	0.006*** (0.002)
OPDSH Adj. Factor	0.004** (0.002)	-0.003 (0.002)
Outlier Adj. Factor	-0.007*** (0.002)	-0.001 (0.002)
Beds	0.003*** (0.001)	-0.002*** (0.001)
FTE	0.002*** (0.000)	-0.003*** (0.000)
LOS	0.001* (0.001)	0.005*** (0.001)
Outpatient Mix	-0.010*** (0.002)	0.017*** (0.002)
Proprietary	0.001 (0.001)	0.001** (0.001)
CMI (adjusting for teaching)	0.008*** (0.001)	0.013*** (0.001)
CON x CMI	-0.005*** (0.002)	0.003** (0.001)
Between-hospital effects		
Teaching Intensity	0.013*** (0.002)	-0.018*** (0.001)
Wage Index (adjusting for teaching)	0.009*** (0.002)	-0.003** (0.001)
OPDSH Adj. Factor	-0.003* (0.002)	-0.006*** (0.001)
Outlier Adj. Factor	0.015** (0.006)	0.020*** (0.006)
Beds	0.001 (0.001)	-0.007*** (0.001)
FTE	-0.000 (0.001)	0.004*** (0.001)
LOS	-0.001 (0.002)	-0.004** (0.001)
Outpatient Mix	-0.010*** (0.003)	0.017*** (0.002)
Proprietary	-0.001 (0.001)	-0.001* (0.001)
CMI (adjusting for teaching)	-0.002 (0.002)	0.017*** (0.001)
CON x CMI	-0.002 (0.002)	0.003* (0.002)
CON	-0.003*** (0.000)	-0.003*** (0.000)
Constant	0.854*** (0.008)	0.806*** (0.007)
Year dummies	Yes	Yes
Observations	18,696	18,731
Number of groups	2,653	2,658
χ^2	21,571	28,807
P-value	0.00	0.00

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Distinguishing between the dimensions of CQ in our granular post hoc analysis provides insights into the conflicting effects of the CON-CMI interaction on survival rate and non-readmission rate. Specifically, we find that resource constraints caused by CON regulations reduce hospitals' ability to respond to increasing complexity resulting in increased deaths while encouraging hospitals to take steps to prevent costly readmissions. These results indicate that when hospitals subject to CON regulations are faced with increasing CMI, they are unable to cope with these changes. This alarming finding confirms our rationale that a hospital's ability to adapt to increasing CMI is hindered when they are resource constrained by CON regulation.

CON restricts capital investment in bed capacity and equipment. Given that increasing these types of investments can take time to propose, procure, and implement, hospitals in resource constrained markets may find themselves unable to modernize or expand to provide timely response to increasing case complexity. Interestingly, the CON-CMI interaction produces a sign-change effect in the *Non-readmission* model, meaning that *CMI* reverses the effect of *CON*. While *Non-readmission* is a measure of improved clinical outcome, it is also a cost-related measure. Hospitals with higher *Non-readmission* rates are more effective at treating conditions when patients are first admitted (Senot et al., 2016b). Thus, patients treated at CON-regulated hospitals receive quality of care that prevents readmission at the risk of not surviving their discharge.

Curvilinear Effects of CMI

Our results show an expected significant and negative relationship between the *CON-CMI* interaction term and *EQ* for the between-hospital effect; however, this negative interaction effect occurred in the presence of positive main effects of *CON* and *CMI* individually. This can occur when the interaction term is highly correlated with the square of one of the interacting variables resulting in an unexpected sign change or the interpretation of an interaction when one does not exist (Cortina, 1993; Ganzach, 1997). Thus, researchers recommend adding quadratic terms of continuous variables included in interaction terms to observe whether the interaction effect persists. If it does, the interaction can be interpreted with greater confidence in its effect, regardless of the significance of the quadratic term. However, if the added quadratic term is significant but the interaction term loses its significance, we must conclude that the variation expected to result from the interaction effect is better explained by the curvilinear relationship (Cortina, 1993; Ganzach, 1997; Harring et al. 2015).

To assess whether the effect of the *CON-CMI* interaction is truly attributable to the interaction of these to variables or is actually the result of a curvilinear relationship, we ran an additional regression for each outcome variable that includes a quadratic term of our *CMI* variable. The results of these additional runs are shown in Table 7. Model 15 shows a significant inverted U-shaped relationship between *CMI* and *Cost per Discharge* for both within-hospital effects (β = 1.444, -0.401, $p < 0.01$) and between-hospital effects (β = 2.847, -0.900, $p < 0.01$).

Figure 3A represents the within-hospital curvilinear effect of *CMI* on *Cost per Discharge*, which shows a gradual increase in cost as CMI increases but that this relationship turns gradually negative at the CMI midpoint. Figure 3B represents the between-hospital curvilinear effect of *CMI* on *Cost per Discharge,* which shows a dramatic increase in cost as CMI increases that levels out at the CMI midpoint before turns very gradually negative. Further, the within-hospital interaction coefficient remains significant and negative (β = -0.446, $p < 0.01$) indicating the moderation relationship hypothesized in H3a is confirmed. Figure 3C represents the within-hospital *CON-CMI* interaction in the presence of the curvilinear *CMI* effect. As with Figure 2A, the interaction is represented by the crossing lines; however, the curves of the lines better reflect the diminishing effect of *CMI* on the *CON-CMI* interaction. Model 16 shows a significant U-shaped relationship between *CMI* and *CQ* for both within-hospital (β = -0.148, 0.170, $p < 0.01$) and between-hospital effects (β = -0.100, 0.097, $p < 0.01$).

Table 7: Post hoc: Curvilinear hybrid estimation results for Cost per discharge, Clinical Quality, and Experiential Quality

	Cost/ Dsch Model 15	CQ Model 16	EQ Model 17
Within-hospital effects			
Teaching Intensity	-0.013 (0.044)	0.040*** (0.009)	0.044*** (0.015)
Wage Index (adjusting for teaching)	1.004*** (0.071)	0.025** (0.011)	0.075*** (0.024)
OPDSH Adj. Factor	-0.299*** (0.056)	0.005 (0.009)	0.047** (0.021)
Outlier Adj. Factor	0.112*** (0.043)	-0.017 (0.012)	0.038** (0.018)
Beds	-0.088*** (0.018)	0.004 (0.003)	-0.008 (0.006)
FTE	-0.092*** (0.013)	-0.006*** (0.002)	-0.005 (0.005)
LOS	0.553*** (0.023)	0.028*** (0.004)	-0.048*** (0.008)
Outpatient Mix	-3.090*** (0.068)	0.019 (0.012)	0.179*** (0.024)
Proprietary	0.016 (0.018)	0.007** (0.003)	-0.025*** (0.006)
CMI (adjusting for teaching)	1.444*** (0.261)	-0.148*** (0.025)	
CMI^2	-0.401*** (0.121)	0.170*** (0.015)	
CON x CMI	-0.446*** (0.046)	-0.004 (0.008)	
CMI_{t-1}			0.158** (0.066)
CMI^2_{t-1}			-0.090*** (0.033)
CON x CMI_{t-1}			0.005 (0.016)
Between-hospital effects			
Teaching Intensity	0.236*** (0.061)	-0.046*** (0.007)	-0.022 (0.022)
Wage Index (adjusting for teaching)	0.056 (0.055)	0.023*** (0.007)	-0.182*** (0.019)
OPDSH Adj. Factor	-0.169*** (0.061)	-0.031*** (0.008)	-0.220*** (0.022)
Outlier Adj. Factor	0.931*** (0.084)	0.094*** (0.029)	0.226*** (0.045)
Beds	-0.194*** (0.028)	-0.023*** (0.004)	-0.095*** (0.011)
FTE	0.063** (0.026)	0.020*** (0.003)	0.027*** (0.010)
LOS	0.309*** (0.049)	-0.012 (0.007)	-0.163*** (0.020)
Outpatient Mix	-2.044*** (0.088)	0.016 (0.012)	0.463*** (0.035)
Proprietary	0.294*** (0.024)	-0.006** (0.003)	-0.031*** (0.009)
CMI (adjusting for teaching)	2.847*** (0.428)	-0.100*** (0.029)	
CMI^2	-0.900*** (0.206)	0.097*** (0.017)	
CON x CMI	-0.052 (0.057)	0.007 (0.008)	
CMI_{t-1} (adjusting for teaching)			-1.306*** (0.132)
CMI^2_{t-1}			0.963*** (0.069)
CON x CMI_{t-1}			-0.035 (0.022)
CON	-0.038** (0.018)	-0.021*** (0.002)	0.005 (0.006)
Constant	(0.024) 2.847***	1.691*** (0.047)	2.786*** (0.145)
Year dummies	Yes	Yes	Yes
Observations	20,242	18,739	19,459
Number of groups	2,893	2,660	2,809
χ^2	6,428	7,807	9,404
P-value	0.00	0.00	0.00

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

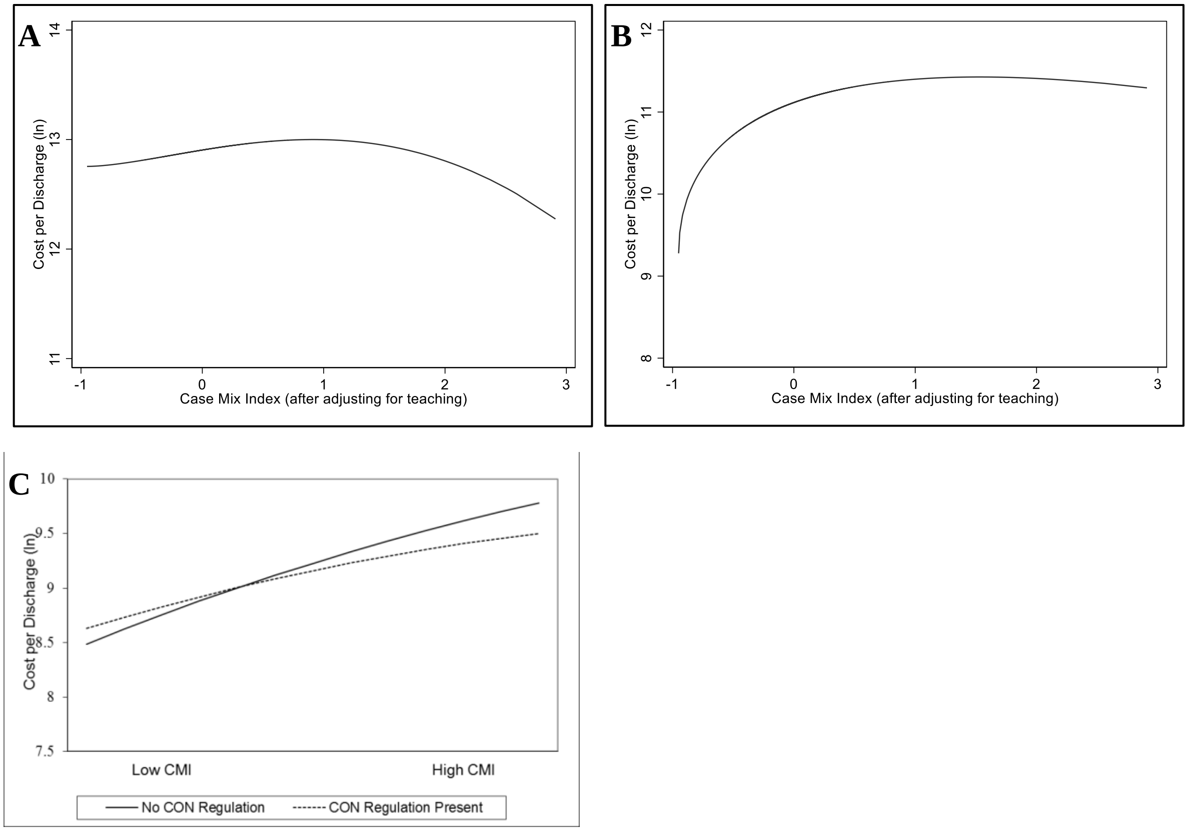

Figure 3: Curvilinear plots for Cost per Discharge (A) within-hospital effects, (B) between-hospital effects, and (C) within-hospital interaction effects.

Figure 4A represents the within-hospital curvilinear effect of *CMI* on *CQ*, which shows a level trend at lower levels of *CMI*, before increasing dramatically. Figure 4B represents the between-hospital curvilinear effect of *CMI* on *CQ*, which shows which shows a sharp decrease in *CQ* as *CMI* increases before immediately turning positive. The interaction coefficients remain non-significant for the between-hospital. Interestingly, the within-hospital interaction coefficient is no longer significant (β = -0.004, p > 0.10) in the presence of the curvilinear CMI effect, indicating the moderation relationship hypothesized in H3b is no longer supported. Model 17 shows a significant inverted U-shaped relationship between *CMI* and *EQ* for within-hospital effects (β = 0.158, -0.090, p < 0.01), and a significant U-shaped relationship for between-hospital effects (β = -1.306, 0.963, p < 0.01).

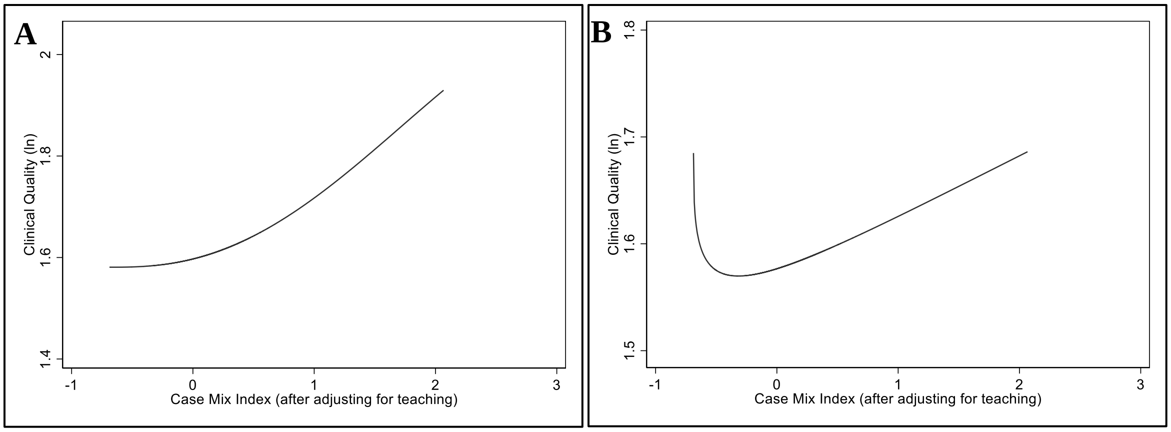

Figure 4: Curvilinear plots for Clinical Quality (A) within-hospital effects and (B) between-hospital effects.

Figure 5A represents the within-hospital curvilinear effect of *CMI* on *EQ*, which shows a sharp increase in *EQ* as *CMI* increases before immediately tapering off. Figure 5B represents the between-hospital curvilinear effect of *CMI* on *EQ*, which shows a sharp decrease in *EQ* as *CMI* increases before immediately turning positive. As with CQ within-hospital interaction effect, the between-hospital interaction coefficient is no longer significant (β = -0.035, $p > 0.10$) in the EQ model once the curvilinear CMI effect is introduced, indicating the moderation relationship hypothesized in H3c is no longer supported.

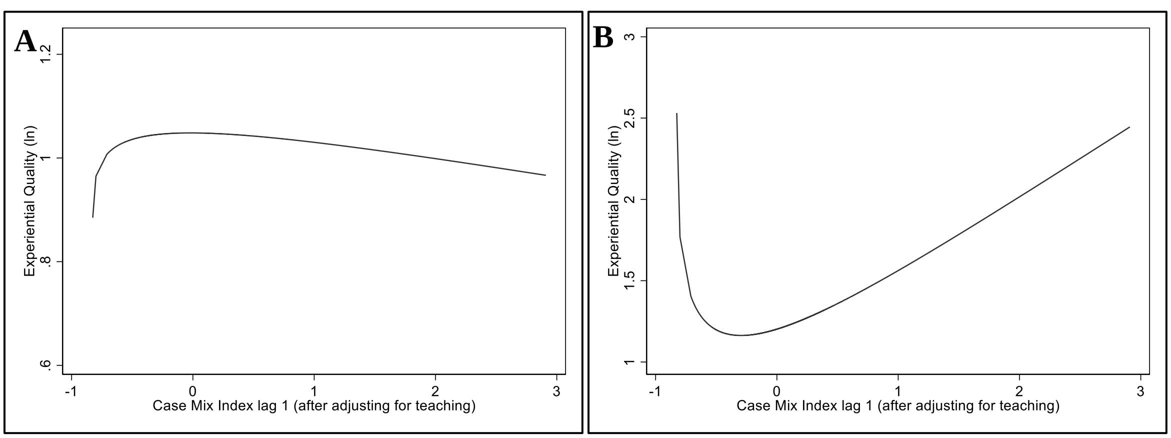

Figure 5: Curvilinear plots for Experiential Quality (a) within-hospital effects and (b) between-hospital effects.

Taken together, the results from our post hoc analysis of the curvilinear effects of CMI on healthcare cost and quality provide new insights into the nature of the impact of CMI as well as a

robustness check of our interaction results. In terms of healthcare costs, our results show that CMI increases costs, but this relationship diminishes at higher levels of CMI. This indicates that as hospitals faced with increased CMI may learn how to deal with increasing complexity by improving processes and efficiency. Essentially, due to resource constraints imposed by CON regulations, hospitals faced with higher CMI learn to do more with less. This rationale is confirmed in previous research that shows that hospitals learn to reduce costs by improving efficiency (Ding, 2014). In terms of both CQ and EQ, hospitals with very low CMI or high CMI will generally have higher quality than hospitals with low to moderate CMI. As with the linear relationship between CMI and CQ, hospitals experiencing higher levels of CMI will provide a higher level of CQ, whereas lower levels of CMI are associated with lower CQ. Hospitals with very low CMI likely deal primarily with routine cases so they are unlikely to experience the uncertainty and variability associated with higher CMI (Peng et al., 2020); whereas high-CMI hospitals are more likely to be specialty hospitals that focus on developing high levels of expertise in dealing with the most complex conditions (McCrum et al., 2014) and designing processes that give patients a better experience (Wani et al., 2018). In contrast, hospitals facing increases within low levels of CMI are associated with increasing EQ; however, according to Figure 5B, additional CMI increases will be associated with reduced EQ. This finding confirms previous findings of lower EQ associated with CMI increases within hospitals that are linked to medical uncertainty and communication challenges resulting from increased variability (Peng et al., 2020).

Discussion

This study examines the counteracting effects of CON regulation and hospital CMI on healthcare costs and quality, namely clinical quality (CQ) and experiential quality (EQ). It is

essential to investigate these counteracting effects because while CON regulation seeks to constrain excess investment in resources, CMI is a key determinant of resource allocation. Further, investigating the effects of the interaction between CON regulation and CMI on multiple measures of hospital performance outcomes highlights the adverse effects of cost-focused regulation implemented without consideration for how healthcare quality will be affected. Our research provides insights into these counteracting and adverse effects.

Using hospital-level data from CMS on U.S. non-governmental acute care hospitals between 2011 and 2018, we use a hybrid estimation approach to modeling how CON regulation and hospital CMI impact healthcare costs and quality. While we observe that CON regulation reduces healthcare costs, it also decreases both CQ and EQ. We also observe that while increased CMI is associated with higher healthcare costs for both within-hospital variation and variation between hospitals, higher CMI is also associated with improved CQ both within hospitals and between hospitals. Higher CMI is also a significant predictor of improved EQ between hospitals. Finally, we observe that CMI interacts with CON to decrease healthcare costs further while worsening CQ as CMI increases in hospitals regulated by CON and producing worse EQ in CON-regulated hospitals with higher CMI that CON-regulated hospitals with lower CMI.

In our robustness checks, we find that the within-hospital CON-CMI interaction effect on CQ is not robust to estimation using the raw form of CQ, trimmed samples, or alternate estimation models. Thus, given the lack of robustness of this relationship, we no longer find support for H3b. However, our post hoc analysis provides further context for this relationship. We find that the stronger negative within-hospital effect of the CON-CMI interaction on survival is significant, whereas we find a weakened positive within-hospital effect of the CON-CMI interaction on readmission. This finding shows that the dimensions of CQ used in our study have

counteracting effects on the results for the aggregate CQ measurement. Finally, our post hoc analyses demonstrate the effect of CMI on all of the study's outcome variables is curvilinear. This finding also confirms the finding of a strengthened negative within-hospital effect of the CON-CMI interaction on cost. The curvilinear effect also illuminates the underlying reason for the negative between-hospital effect of the CON-CMI interaction on EQ in the presence of positive direct effects. The result occurs because of a high correlation of the interaction term and the squared term of CMI. This indicates the curvilinear effect of CMI is a better predictor of EQ than the CON-CMI interaction. Thus, our post hoc analysis results in a lack of support for H3c. Our findings present several implications for theory, practice, and healthcare policy.

Implications for Theory and Research

Our study provides several contributions to the healthcare policy and operations management literature. First, our study contributes to the healthcare policy literature by providing a view of the effects of CON regulation on important healthcare outcomes in the context of CMI. By conducting this study, we contribute to the body of literature that provides context-specific evidence of public policy's influence on operational choices (Joglekar et al., 2016). Our findings confirm the effectiveness of CON regulation in reducing healthcare costs. However, by also evaluating the impact of CON regulation on healthcare quality, we contribute to the literature by demonstrating how cost-focused regulation can negatively affect healthcare quality and patient experience. Additionally, by evaluating these relationships in the context of hospital complexity, we find that the effectiveness of CON regulation varies based on a hospital's level of CMI. CON regulation is associated with higher costs and better quality in hospitals with low CMI, but lower costs and worse quality in hospitals with high CMI.

Second, our study contributes to the healthcare operations management literature by empirically testing the within- and between hospital effects of regulation and complexity using a hybrid estimation approach. Past research of healthcare cost and quality outcomes mainly studies either variation within hospitals over time (Lee et al., 2020; Senot et al., 2016b) or between hospitals during few time periods (Roth et al., 2019). Our use of the hybrid estimation approach highlights the consistent positive effect of CMI on both within- and between-hospital variation on cost and CQ, whereas we find differing effects of CMI on within- and between-hospital variation on EQ. Our study provides a more comprehensive view of the effects of regulation and complexity on healthcare cost and quality by analyzing these effects together.

Finally, our study contributes to the healthcare operations management literature concerning CMI. CMI has repeatedly been shown in prior research to increase healthcare costs (Roth et al., 2019; Senot et al., 2016b) and CQ or the dimensions that comprise our measure of CQ (Lee et al., 2020; McCrum et al., 2014; Senot et al., 2016b). Findings from our main analyses confirm these findings. However, prior research on the effects of CMI on EQ have produced mixed results. Studies have shown CMI to be both positively (Sharma et al., 2020) and negatively associated with CQ and EQ (Peng et al., 2020; Roth et al., 2019). Findings from our main analyses contribute to the literature that finds a positive relationship between CMI and EQ. However, for all outcomes, our post hoc analyses show support for a curvilinear effect of CMI. Specifically, our findings highlight a more nuanced effect of CMI on cost and CQ that adds to the general understanding of this relationship. Whereas the curvilinear relationship between CMI and EQ may act as a bridge for explaining the reason for conflicting results found in extant literature.

Implications for Practice

Our study also offers important implications for hospital operations managers. First, our findings show that hospitals with higher CMI have better CQ and EQ that hospitals with lower CMI. Administrators should be encouraged that this evidence indicates that higher CMI does not automatically translate to worsened quality. Hospitals that consistently face higher case complexity or seek to treat more complex conditions may implement more sophisticated resources and systems to provide improved care (McCrum et al., 2014). Further, where possible, adjusting hospital strategy to seek out more complex cases can reveal additional revenue opportunities (Lee et al., 2020). Therefore, hospital administrators may be able to pursue higher case complexity as a means to justify investments in improved quality. Such investments might include state-of-the-art equipment, staff specializing in treating complex conditions, and process and facility improvements that will enhance patient experience.

Second, our findings show that CON regulation decreases hospital costs, especially in hospitals experiencing increases in CMI, indicating these hospitals are forced to do more with less. Specifically, CON regulation that defends hospital's market position helps them better leverage fixed assets to reduce cost per discharge and delay capital investments they would otherwise be necessary to operate in a more competitive environment. However, this resource constraint may put hospitals in a position to chose financial performance over patient well-being. Prior research shows that while investment in improved CQ and EQ may result in increased spending, improving quality on both fronts simultaneously is no more costly than improving on either dimension individually (Senot et al., 2016b). Further, investing in both CQ and EQ can help prevent revenue loss resulting from penalties associated with the CMS Value-based Purchasing Program—revenue that could be used to cover the costs of further quality

improvements. Thus, we recommend that hospital administrators guard against a focus on the bottom line that puts patients at risk by investing simultaneously in improving CQ and EQ to protect revenue and patient well-being and experience.

Implications for Policymakers

Our study also provides important insights for healthcare policymakers. First, our findings confirm that CON regulation behaves as designed by reducing healthcare costs; however, this cost reduction comes with the adverse effect of also decreasing both CQ and EQ. Policymakers are tasked with creating regulation that corrects market failures and improves social welfare; however, failure to consider all possible consequences of regulation can be detrimental to the public. Structural regulation like CON that limits competition may help reduce healthcare costs, but low healthcare quality could increase healthcare costs over the long run. It is also important for policymakers to understand that efficiency does not automatically lead to quality. Therefore, it is necessary to create regulations that comprehensively account for unintended consequences. Patients seek healthcare to improve their health, longevity, and quality of life. This research highlights the risk associated with creating regulations with a myopic focus on reducing costs. Given the importance of reducing healthcare costs while improving patient health and experience (IHI, 2020), policymakers may want to reevaluate existing CON regulations to ensure that capital constraints provide the intended cost reduction without sacrificing quality. Further, prior to creating any new market structure regulation, which tends to be cost-focused, policymakers should design them with an eye on improving healthcare quality or at least preventing a loss of quality.

Second, our findings show that the significant negative effect of the CON-CMI interaction on healthcare costs occurs within-hospital. This indicates that the cost reduction

benefit resulting from CON regulation constrains a hospital's ability to deal with increasing complexity. Paired with the negative within-hospital effect of the CON-CMI interaction on CQ, our findings show this constraint also produces undesirable patient health outcomes. This alarming finding highlights the danger of constraining capacity that reduces a hospital's ability to deal with changing factors. Similar to this issue is the effect that the COVID-19 pandemic has had on hospital capacity rendering hospitals unable to deal with rapidly changing environmental factors. Based on our findings, we recommend that policymakers consider revising CON regulations to include conditional forward-looking mechanisms supporting more timely capacity expansion when case mix complexity increases from low to high levels.

Limitations and Directions for Future Research

As with all empirical research, our study has several limitations. First, our study builds on the reasoning that CON regulation affects healthcare cost and quality by constraining hospital capacity and thus increasing utilization. However, estimating moderated mediation models using panel data is beyond the current capabilities of statistical tools. Future research could capitalize on improvements in statistical tools to estimate these complex relationships. In the near term, researchers could estimate the effects of CON regulation and CMI on hospital capacity and utilization to develop this line of research further. Second, our study utilizes outcome measures to estimate clinical quality; however, these measures do not directly measure adherence to processes. Future research could investigate additional dimensions of quality, such as process of care measures, to assess our findings' robustness. Third, our study uses a dichotomous variable to measure CON regulation. Cook et al. (1983) posits that as regulatory intensity increases, hospital administrators take strategic actions to defend against the effects of regulation. Future research could leverage a measure of CON regulation intensity to identify inflection points that may

further contextualize our research. Fourth, aside from the state-level CON regulation measurements, all our study variables were at the hospital level. Because of this, patient-level factors are not accounted for in our study. Future research could include patient-level variables to explore the effects of these factors on the relationships tested in our study. Finally, although our estimations include a comprehensive set of control variables and leverage hybrid models to capitalize on the strengths of fixed effects models in accounting for unobserved heterogeneity, we cannot completely remove bias caused by omitted variables.

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Appendices

Table 1A: Robustness check: Hybrid estimation results for non-transformed Clinical Quality

	Model 1	**Model 2**	**Model 3**	**Model 4**
Within-hospital effects				
Teaching Intensity	0.005*** (0.001)	0.005*** (0.001)	0.006*** (0.001)	0.006*** (0.001)
Wage Index (adjusting for teaching)	0.005*** (0.002)	0.005*** (0.002)	0.004** (0.002)	0.004** (0.002)
OPDSH Adj. Factor	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Outlier Adj. Factor	-0.001 (0.002)	-0.001 (0.002)	-0.002 (0.002)	-0.002 (0.002)
Beds	0.001* (0.000)	0.001* (0.000)	0.001 (0.000)	0.001 (0.000)
FTE	-0.001* (0.000)	-0.001* (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
LOS	0.004*** (0.001)	0.004*** (0.001)	0.004*** (0.001)	0.004*** (0.001)
Outpatient Mix	0.001 (0.002)	0.002 (0.002)	0.002 (0.002)	0.002 (0.002)
Proprietary	0.001** (0.000)	0.001** (0.000)	0.001** (0.000)	0.001** (0.000)
CMI (adjusting for teaching)			0.010*** (0.001)	0.011*** (0.001)
CON x CMI				-0.002 (0.001)
Between-hospital effects				
Teaching Intensity	-0.006*** (0.001)	-0.006*** (0.001)	-0.006*** (0.001)	-0.006*** (0.001)
Wage Index (adjusting for teaching)	0.003*** (0.001)	0.002** (0.001)	0.003*** (0.001)	0.003*** (0.001)
OPDSH Adj. Factor	-0.005*** (0.001)	-0.006*** (0.001)	-0.004*** (0.001)	-0.004*** (0.001)
Outlier Adj. Factor	0.025*** (0.004)	0.021*** (0.004)	0.014*** (0.004)	0.014*** (0.004)
Beds	-0.003*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)
FTE	0.003*** (0.000)	0.003*** (0.000)	0.002*** (0.000)	0.002*** (0.000)
LOS	-0.003*** (0.001)	-0.002* (0.001)	-0.001 (0.001)	-0.001 (0.001)
Outpatient Mix	-0.002 (0.002)	-0.001 (0.002)	0.002 (0.002)	0.002 (0.002)
Proprietary	-0.001 (0.000)	-0.001* (0.000)	-0.001** (0.000)	-0.001** (0.000)
CMI (adjusting for teaching)			0.005*** (0.001)	0.005*** (0.001)
CON x CMI				0.000 (0.001)
CON		-0.003*** (0.000)	-0.003*** (0.000)	-0.003*** (0.000)
Constant	0.818*** (0.005)	0.822*** (0.005)	0.829*** (0.005)	0.829*** (0.005)
Year dummies	Yes	Yes	Yes	Yes
Observations	18,740	18,740	18,739	18,739
Number of groups	2,660	2,660	2,660	2,660
χ^2	7,169	7,272	7,621	7,625
P-value	0.00	0.00	0.00	0.00
Δ AIC (base: Model 1)	-	-95.8	-345.3	-343.9
Δ BIC (base: Model 1)	-	-88.0	-321.9	-304.7

Table 2A: Robustness check: Hybrid estimation results for non-transformed Experiential Quality

	Model 5	**Model 6**	**Model 7**	**Model 8**
Within-hospital effects				
Teaching Intensity	0.009*** (0.003)	0.009*** (0.003)	0.009*** (0.003)	0.009*** (0.003)
Wage Index (adjusting for teaching)	0.018*** (0.004)	0.018*** (0.004)	0.018*** (0.004)	0.019*** (0.005)
OPDSH Adj. Factor	0.013*** (0.004)	0.013*** (0.004)	0.012*** (0.004)	0.012*** (0.004)
Outlier Adj. Factor	0.007** (0.003)	0.007** (0.003)	0.007* (0.003)	0.007* (0.003)
Beds	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
FTE	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
LOS	-0.008*** (0.002)	-0.008*** (0.002)	-0.008*** (0.002)	-0.008*** (0.002)
Outpatient Mix	0.033*** (0.004)	0.033*** (0.004)	0.033*** (0.004)	0.032*** (0.004)
Proprietary	-0.004*** (0.001)	-0.004*** (0.001)	-0.004*** (0.001)	-0.004*** (0.001)
CMI lag 1 (adjusting for teaching)			-0.002 (0.002)	-0.003 (0.002)
CON x CMI lag 1				0.002 (0.003)
Between-hospital effects				
Teaching Intensity	0.007 (0.004)	0.007* (0.004)	0.001 (0.004)	0.001 (0.004)
Wage Index (adjusting for teaching)	-0.045*** (0.004)	-0.046*** (0.004)	-0.040*** (0.004)	-0.040*** (0.004)
OPDSH Adj. Factor	-0.063*** (0.004)	-0.063*** (0.004)	-0.043*** (0.004)	-0.043*** (0.004)
Outlier Adj. Factor	0.066*** (0.008)	0.065*** (0.008)	0.039*** (0.008)	0.040*** (0.008)
Beds	-0.021*** (0.002)	-0.021*** (0.002)	-0.016*** (0.002)	-0.016*** (0.002)
FTE	0.011*** (0.002)	0.011*** (0.002)	0.002 (0.002)	0.002 (0.002)
LOS	-0.044*** (0.004)	-0.043*** (0.004)	-0.025*** (0.004)	-0.025*** (0.004)
Outpatient Mix	0.046*** (0.006)	0.047*** (0.006)	0.091*** (0.006)	0.091*** (0.006)
Proprietary	-0.003** (0.002)	-0.004** (0.002)	-0.008*** (0.002)	-0.008*** (0.002)
CMI_{t-1} (adjusting for teaching)			0.043*** (0.003)	0.048*** (0.003)
$CON \times CMI_{t-1}$				-0.011*** (0.004)
CON		-0.002* (0.001)	0.001 (0.001)	0.001 (0.001)
Constant	0.834*** (0.015)	0.835*** (0.015)	0.819*** (0.014)	0.816*** (0.014)
Year dummies	Yes	Yes	Yes	Yes
Observations	19,459	19,459	19,459	19,459
Number of groups	2,809	2,809	2,809	2,809
χ^2	8,934	8,943	9,463	9,481
P-value	0.00	0.00	0.00	0.00
Δ AIC (base: Model 1)	-	-1.0	-253.0	-257.0
Δ BIC (base: Model 1)	-	7.0	-229.0	-218.0

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 3A: Robustness check: Hybrid estimation results for alternative Experiential Quality dependent variable, combined room quietness and cleanliness

	Model 1	**Model 2**	**Model 3**	**Model 4**
Within-hospital effects				
Teaching Intensity	0.003 (0.020)	0.003 (0.020)	0.002 (0.020)	0.002 (0.020)
Wage Index (adjusting for teaching)	0.058* (0.031)	0.058* (0.031)	0.059* (0.031)	0.061** (0.031)
OPDSH Adj. Factor	0.041 (0.026)	0.041 (0.026)	0.040 (0.026)	0.039 (0.026)
Outlier Adj. Factor	-0.007 (0.023)	-0.007 (0.023)	-0.008 (0.023)	-0.008 (0.023)
Beds	-0.014* (0.008)	-0.014* (0.008)	-0.014* (0.008)	-0.014* (0.008)
FTE	-0.015*** (0.006)	-0.015*** (0.006)	-0.015** (0.006)	-0.015** (0.006)
LOS	-0.093*** (0.011)	-0.093*** (0.011)	-0.093*** (0.011)	-0.093*** (0.011)
Outpatient Mix	0.179*** (0.031)	0.179*** (0.031)	0.176*** (0.031)	0.174*** (0.031)
Proprietary	-0.013 (0.008)	-0.013 (0.008)	-0.013 (0.008)	-0.013 (0.008)
CMI (adjusting for teaching)			-0.014 (0.012)	-0.023* (0.014)
CON x CMI				0.023 (0.020)
Between-hospital effects				
Teaching Intensity	0.011 (0.031)	0.010 (0.031)	-0.039 (0.029)	-0.037 (0.029)
Wage Index (adjusting for teaching)	-0.468*** (0.028)	-0.467*** (0.028)	-0.423*** (0.027)	-0.426*** (0.027)
OPDSH Adj. Factor	-0.171*** (0.031)	-0.170*** (0.031)	-0.015 (0.031)	-0.021 (0.031)
Outlier Adj. Factor	0.693*** (0.064)	0.696*** (0.064)	0.500*** (0.062)	0.504*** (0.062)
Beds	-0.127*** (0.015)	-0.127*** (0.015)	-0.093*** (0.015)	-0.092*** (0.015)
FTE	0.004 (0.013)	0.004 (0.013)	-0.062*** (0.013)	-0.059*** (0.013)
LOS	-0.416*** (0.027)	-0.418*** (0.027)	-0.279*** (0.027)	-0.276*** (0.027)
Outpatient Mix	-0.051 (0.045)	-0.053 (0.046)	0.287*** (0.048)	0.285*** (0.048)
Proprietary	0.031** (0.012)	0.031** (0.012)	-0.000 (0.012)	-0.001 (0.012)
CMI (adjusting for teaching)			0.332*** (0.020)	0.382*** (0.024)
CON x CMI				-0.112*** (0.030)
CON		0.005 (0.009)	0.028*** (0.009)	0.031*** (0.009)
Constant	1.425*** (0.112)	1.424*** (0.112)	1.302*** (0.107)	1.278*** (0.107)
Year dummies	Yes	Yes	Yes	Yes
Observations	19,459	19,459	19,459	19,459
Number of groups	2,809	2,809	2,809	2,809
χ^2	4,196	4,196	4,728	4,760
P-value	0.00	0.00	0.00	0.00
Δ AIC (base: Model 1)	-	1.0	-260.0	-271.0
Δ BIC (base: Model 1)	-	10.0	-235.0	-231.0

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 4A: Robustness check: Hybrid estimation results using data trimmed and Winsorized at 0.5% and 99.5%

	Trimmed			Winsorized		
	Cost/ Dsch	**CQ**	**EQ**	**Cost/ Dsch**	**CQ**	**EQ**
Within-hospital effects						
Teaching Intensity	0.003 (0.027)	0.038*** (0.009)	0.042*** (0.015)	-0.017 (0.043)	0.041*** (0.009)	0.043*** (0.015)
Wage Index (adjusting for teaching)	0.185*** (0.044)	0.021* (0.011)	0.065*** (0.024)	0.970*** (0.069)	0.023** (0.011)	0.071*** (0.024)
OPDSH Adj. Factor	-0.194*** (0.034)	0.007 (0.009)	0.045** (0.020)	-0.300*** (0.054)	0.007 (0.009)	0.045** (0.020)
Outlier Adj. Factor	0.127*** (0.031)	-0.012 (0.012)	0.020 (0.020)	0.125*** (0.041)	-0.017 (0.012)	0.034* (0.018)
Beds	-0.049*** (0.011)	0.003 (0.003)	-0.009 (0.006)	-0.086*** (0.017)	0.004 (0.003)	-0.011* (0.006)
FTE	-0.037*** (0.008)	-0.005** (0.002)	-0.004 (0.005)	-0.085*** (0.013)	-0.005** (0.002)	-0.005 (0.005)
LOS	0.615*** (0.014)	0.027*** (0.004)	-0.045*** (0.008)	0.543*** (0.022)	0.029*** (0.004)	-0.045*** (0.008)
Outpatient Mix	-1.349*** (0.044)	0.025** (0.012)	0.165*** (0.024)	-2.920*** (0.065)	0.022* (0.012)	0.173*** (0.024)
Proprietary	0.003 (0.011)	0.006** (0.003)	-0.027*** (0.006)	0.014 (0.018)	0.007** (0.003)	-0.025*** (0.006)
CMI (adjusting for teaching)	0.154*** (0.020)	0.078*** (0.007)		0.253*** (0.030)	0.082*** (0.007)	
CON x CMI	-0.169*** (0.028)	-0.009 (0.008)		-0.375*** (0.043)	-0.012 (0.008)	
CMI lag 1 (adjusting for teaching)			0.004 (0.011)			-0.008 (0.011)
CON x CMI lag 1			0.001 (0.016)			0.010 (0.016)
Between-hospital effects						
Teaching Intensity	0.129*** (0.049)	-0.039*** (0.007)	0.015 (0.020)	0.137** (0.057)	-0.040*** (0.007)	0.019 (0.021)
Wage Index (adjusting for teaching)	0.476*** (0.045)	0.028*** (0.006)	-0.210*** (0.018)	0.128** (0.052)	0.025*** (0.007)	-0.207*** (0.019)
OPDSH Adj. Factor	-0.308*** (0.050)	-0.029*** (0.007)	-0.200*** (0.021)	-0.149** (0.058)	-0.031*** (0.007)	-0.205*** (0.022)
Outlier Adj. Factor	0.990*** (0.095)	0.078*** (0.027)	0.203*** (0.044)	0.791*** (0.080)	0.095*** (0.028)	0.226*** (0.044)
Beds	0.036 (0.023)	-0.021*** (0.003)	-0.101*** (0.010)	-0.106*** (0.026)	-0.022*** (0.004)	-0.101*** (0.010)
FTE	-0.026 (0.021)	0.017*** (0.003)	0.014 (0.009)	0.061** (0.024)	0.017*** (0.003)	0.011 (0.009)
LOS	0.195*** (0.041)	-0.010 (0.007)	-0.140*** (0.019)	0.240*** (0.047)	-0.008 (0.007)	-0.149*** (0.019)
Outpatient Mix	-1.327*** (0.074)	0.034*** (0.011)	0.419*** (0.033)	-1.760*** (0.084)	0.024** (0.012)	0.439*** (0.034)
Proprietary	0.284*** (0.020)	-0.006** (0.003)	-0.040*** (0.008)	0.297*** (0.023)	-0.006** (0.003)	-0.037*** (0.008)
CMI (adjusting for teaching)	0.530*** (0.037)	0.041*** (0.007)		0.509*** (0.043)	0.039*** (0.007)	
CON x CMI	-0.052 (0.047)	0.002 (0.008)		-0.047 (0.054)	0.002 (0.008)	
CMI_{t-1} (adjusting for teaching)			0.275*** (0.017)			0.283*** (0.017)
CON x CMI_{t-1}			-0.062*** (0.020)			-0.063*** (0.021)
CON	-0.059*** (0.014)	-0.020*** (0.002)	0.009 (0.006)	-0.040** (0.017)	-0.021*** (0.002)	0.008 (0.006)
Constant	10.513*** (0.163)	1.576*** (0.035)	1.542*** (0.074)	10.740*** (0.178)	1.583*** (0.037)	1.541*** (0.076)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,066	18,553	19,289	20,242	18,739	19,459
Number of groups	2,883	2,655	2,797	2,893	2,660	2,809
χ^2	7,069	7,840	9,169	6,413	7,957	9,345
P-value	0.0	0.0	0.0	0.0	0.0	0.0

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 5A: Robustness check: Hybrid estimation results using data trimmed and Winsorized at 2.5% and 97.5%

	Trimmed			Winsorized		
	Cost/ Dsch	**CQ**	**EQ**	**Cost/ Dsch**	**CQ**	**EQ**
Within-hospital effects						
Teaching Intensity	-0.004 (0.016)	0.031*** (0.009)	0.045*** (0.015)	-0.005 (0.019)	0.037*** (0.009)	0.039*** (0.015)
Wage Index (adjusting for teaching)	-0.099*** (0.025)	0.012 (0.011)	0.048** (0.023)	0.167*** (0.030)	0.021** (0.011)	0.060*** (0.023)
OPDSH Adj. Factor	-0.202*** (0.020)	0.008 (0.009)	0.061*** (0.020)	-0.206*** (0.023)	0.008 (0.009)	0.048** (0.020)
Outlier Adj. Factor	0.079*** (0.022)	-0.000 (0.011)	0.033 (0.021)	0.075*** (0.018)	-0.015 (0.011)	0.031* (0.017)
Beds	-0.049*** (0.006)	0.002 (0.003)	-0.006 (0.006)	-0.057*** (0.007)	0.003 (0.003)	-0.009 (0.006)
FTE	-0.014*** (0.005)	-0.004* (0.002)	-0.004 (0.004)	-0.033*** (0.005)	-0.005** (0.002)	-0.007 (0.004)
LOS	0.546*** (0.009)	0.026*** (0.004)	-0.049*** (0.009)	0.452*** (0.010)	0.027*** (0.004)	-0.043*** (0.008)
Outpatient Mix	-0.808*** (0.025)	0.006 (0.011)	0.161*** (0.024)	-1.344*** (0.028)	0.017 (0.011)	0.165*** (0.023)
Proprietary	0.013** (0.006)	0.003 (0.003)	-0.023*** (0.006)	0.011 (0.008)	0.006** (0.003)	-0.023*** (0.006)
CMI (adjusting for teaching)	0.050*** (0.012)	0.070*** (0.007)		0.102*** (0.013)	0.075*** (0.006)	
CON x CMI	-0.013 (0.016)	-0.003 (0.008)		-0.100*** (0.019)	-0.009 (0.008)	
CMI lag 1 (adjusting for teaching)			-0.013 (0.012)			-0.014 (0.010)
CON x CMI lag 1			0.015 (0.016)			0.015 (0.015)
Between-hospital effects						
Teaching Intensity	0.171*** (0.042)	-0.028*** (0.006)	0.010 (0.018)	0.169*** (0.044)	-0.037*** (0.007)	0.015 (0.019)
Wage Index (adjusting for teaching)	0.505*** (0.038)	0.019*** (0.006)	-0.186*** (0.017)	0.441*** (0.040)	0.025*** (0.006)	-0.195*** (0.017)
OPDSH Adj. Factor	-0.345*** (0.042)	-0.026*** (0.006)	-0.164*** (0.019)	-0.297*** (0.045)	-0.030*** (0.007)	-0.185*** (0.020)
Outlier Adj. Factor	0.976*** (0.097)	0.053** (0.023)	0.220*** (0.039)	0.586*** (0.058)	0.088*** (0.027)	0.208*** (0.040)
Beds	0.102*** (0.020)	-0.017*** (0.003)	-0.091*** (0.009)	0.014 (0.020)	-0.021*** (0.003)	-0.091*** (0.010)
FTE	-0.072*** (0.018)	0.015*** (0.003)	0.013 (0.008)	-0.016 (0.018)	0.016*** (0.003)	0.008 (0.008)
LOS	0.091*** (0.035)	-0.013** (0.006)	-0.108*** (0.017)	0.181*** (0.036)	-0.008 (0.007)	-0.124*** (0.018)
Outpatient Mix	-1.220*** (0.064)	0.031*** (0.010)	0.326*** (0.031)	-1.403*** (0.064)	0.027** (0.011)	0.406*** (0.031)
Proprietary	0.274*** (0.016)	-0.004* (0.002)	-0.049*** (0.007)	0.288*** (0.017)	-0.006** (0.003)	-0.043*** (0.008)
CMI (adjusting for teaching)	0.458*** (0.032)	0.034*** (0.006)		0.502*** (0.032)	0.038*** (0.007)	
CON x CMI	-0.043 (0.040)	0.004 (0.007)		-0.048 (0.041)	0.003 (0.008)	
CMI_{t-1} (adjusting for teaching)			0.208*** (0.015)			0.247*** (0.016)
CON x CMI_{t-1}			-0.054*** (0.019)			-0.055*** (0.019)
CON	-0.049*** (0.011)	-0.018*** (0.002)	0.009* (0.006)	-0.045*** (0.012)	-0.020*** (0.002)	0.009 (0.006)
Constant	10.604*** (0.147)	1.588*** (0.030)	1.425*** (0.065)	10.984*** (0.132)	1.587*** (0.035)	1.505*** (0.070)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,355	17,804	18,528	20,242	18,739	19,459
Number of groups	2,807	2,649	2,749	2,893	2,660	2,809
χ^2	9,854	7,088	8,059	10,220	7,888	9,230
P-value	0.0	0.0	0.0	0.0	0.0	0.0

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 6A: Robustness check: Fixed- and between-effects estimation results

	Fixed Effects			Between Effects		
	Cost/ Dsch	**CQ**	**EQ**	**Cost/ Dsch**	**CQ**	**EQ**
Teaching Intensity	-0.024 (0.036)	0.042*** (0.012)	0.044 (0.027)	0.173*** (0.062)	-0.040*** (0.008)	0.021 (0.022)
Wage Index (adjusting for teaching)	1.003*** (0.225)	0.027 (0.017)	0.075** (0.031)	0.091 (0.056)	0.018** (0.007)	-0.209*** (0.020)
OPDSH Adj. Factor	-0.298*** (0.076)	0.006 (0.013)	0.045 (0.032)	-0.202*** (0.063)	-0.030*** (0.008)	-0.203*** (0.023)
Outlier Adj. Factor	0.106* (0.055)	-0.018 (0.018)	0.038 (0.041)	0.880*** (0.080)	0.094*** (0.029)	0.242*** (0.047)
Beds	-0.090** (0.039)	0.004 (0.004)	-0.009 (0.010)	-0.177*** (0.028)	-0.024*** (0.004)	-0.099*** (0.011)
FTE	-0.094*** (0.026)	-0.005** (0.003)	-0.005 (0.006)	0.096*** (0.026)	0.018*** (0.003)	0.008 (0.010)
LOS	0.554*** (0.048)	0.029*** (0.006)	-0.048*** (0.013)	0.296*** (0.050)	-0.007 (0.008)	-0.153*** (0.020)
Outpatient Mix	-3.075*** (0.380)	0.015 (0.022)	0.182*** (0.038)	-1.964*** (0.089)	0.011 (0.012)	0.461*** (0.036)
Proprietary	0.015 (0.031)	0.007* (0.004)	-0.026*** (0.010)	0.302*** (0.025)	-0.007** (0.003)	-0.035*** (0.009)
CMI (adjusting for teaching)	0.243*** (0.076)	0.086*** (0.011)		0.437*** (0.045)	0.033*** (0.007)	
CON x CMI	-0.392*** (0.087)	-0.017 (0.014)		-0.011 (0.058)	0.004 (0.008)	
CMI_{t-1} (adjusting for teaching)			-0.012 (0.016)			0.296*** (0.018)
CON x CMI_{t-1}			0.012 (0.023)			-0.068*** (0.022)
CON				-0.067*** (0.020)	-0.022*** (0.002)	0.004 (0.007)
Constant	12.971*** (0.484)	1.602*** (0.039)	1.080*** (0.094)	10.902*** (0.229)	1.581*** (0.040)	1.330*** (0.095)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,242	18,739	19,459	20,242	18,739	19,459
Number of groups	2,893	2,660	2,809	2,893	2,660	2,809
R^2	0.184	0.312	0.259	0.454	0.149	0.535
F-statistic	30.01	609.1	173.3	125.8	24.24	169.1

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 7A: Robustness check: Hybrid estimation results with addition of VBP control

	Cost/ Dsch	CQ	EQ
Within-hospital effects			
Teaching Intensity	-0.023 (0.044)	0.042*** (0.009)	0.044*** (0.015)
Wage Index (adjusting for teaching)	1.003*** (0.071)	0.027** (0.011)	0.074*** (0.024)
OPDSH Adj. Factor	-0.298*** (0.056)	0.007 (0.009)	0.045** (0.021)
Outlier Adj. Factor	0.106** (0.043)	-0.018 (0.012)	0.038** (0.018)
Beds	-0.090*** (0.018)	0.004 (0.003)	-0.009 (0.006)
FTE	-0.094*** (0.013)	-0.005** (0.002)	-0.005 (0.005)
LOS	0.554*** (0.023)	0.029*** (0.004)	-0.048*** (0.008)
Outpatient Mix	-3.073*** (0.068)	0.016 (0.012)	0.181*** (0.024)
Proprietary	0.015 (0.019)	0.007** (0.003)	-0.026*** (0.006)
VBP	0.286*** (0.010)	0.004** (0.002)	0.078*** (0.003)
CMI (adjusting for teaching)	0.243*** (0.031)	0.085*** (0.007)	
CON x CMI	-0.390*** (0.045)	-0.015* (0.008)	
CMI lag 1 (adjusting for teaching)			-0.012 (0.011)
CON x CMI lag 1			0.012 (0.016)
Between-hospital effects			
Teaching Intensity	0.159*** (0.060)	-0.041*** (0.007)	0.020 (0.022)
Wage Index (adjusting for teaching)	0.091* (0.055)	0.020*** (0.007)	-0.207*** (0.020)
OPDSH Adj. Factor	-0.181*** (0.062)	-0.031*** (0.008)	-0.207*** (0.023)
Outlier Adj. Factor	0.933*** (0.084)	0.102*** (0.029)	0.243*** (0.046)
Beds	-0.175*** (0.028)	-0.024*** (0.004)	-0.100*** (0.011)
FTE	0.096*** (0.025)	0.018*** (0.003)	0.009 (0.010)
LOS	0.273*** (0.050)	-0.009 (0.007)	-0.158*** (0.020)
Outpatient Mix	-1.986*** (0.088)	0.016 (0.012)	0.454*** (0.035)
Proprietary	0.304*** (0.024)	-0.007** (0.003)	-0.036*** (0.009)
VBP	0.360** (0.158)	-0.005 (0.021)	0.058 (0.056)
CMI (adjusting for teaching)	0.440*** (0.045)	0.037*** (0.007)	
CON x CMI	-0.023 (0.057)	0.003 (0.008)	
CMI_{t-1} (adjusting for teaching)			0.293*** (0.018)
$CON \times CMI_{t-1}$			-0.066*** (0.022)
CON	-0.043** (0.018)	-0.020*** (0.002)	0.008 (0.007)
Constant	10.417*** (0.193)	1.586*** (0.037)	1.476*** (0.077)
Year dummies	Yes	Yes	Yes
Observations	20,242	18,739	19,459
Number of groups	2,893	2,660	2,809
χ^2	6,309	7,718	9,141
P-value	0.00	0.00	0.00

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 8A: Post hoc: Full results of granular hybrid estimation results for Survival

	Model 1	Model 2	Model 3	Model 4
Within-hospital effects				
Teaching Intensity	0.006*** (0.002)	0.006*** (0.002)	0.007*** (0.002)	0.006*** (0.002)
Wage Index (adjusting for teaching)	0.000 (0.002)	0.000 (0.002)	-0.000 (0.002)	-0.001 (0.002)
OPDSH Adj. Factor	0.004** (0.002)	0.004** (0.002)	0.004** (0.002)	0.004** (0.002)
Outlier Adj. Factor	-0.006*** (0.002)	-0.006*** (0.002)	-0.007*** (0.002)	-0.007*** (0.002)
Beds	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)
FTE	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)
LOS	0.001* (0.001)	0.001* (0.001)	0.001* (0.001)	0.001* (0.001)
Outpatient Mix	-0.010*** (0.002)	-0.010*** (0.002)	-0.010*** (0.002)	-0.010*** (0.002)
Proprietary	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
CMI (adjusting for teaching)			0.005*** (0.001)	0.008*** (0.001)
CON x CMI				-0.005*** (0.002)
Between-hospital effects				
Teaching Intensity	0.013*** (0.002)	0.013*** (0.002)	0.013*** (0.002)	0.013*** (0.002)
Wage Index (adjusting for teaching)	0.010*** (0.001)	0.009*** (0.001)	0.009*** (0.002)	0.009*** (0.002)
OPDSH Adj. Factor	-0.001 (0.002)	-0.002 (0.002)	-0.003* (0.002)	-0.003* (0.002)
Outlier Adj. Factor	0.014** (0.006)	0.011* (0.006)	0.015** (0.006)	0.015** (0.006)
Beds	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
FTE	-0.001 (0.001)	-0.001 (0.001)	-0.000 (0.001)	-0.000 (0.001)
LOS	-0.001 (0.002)	-0.000 (0.002)	-0.001 (0.002)	-0.001 (0.002)
Outpatient Mix	-0.010*** (0.003)	-0.008*** (0.003)	-0.010*** (0.003)	-0.010*** (0.003)
Proprietary	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
CMI (adjusting for teaching)			-0.003** (0.001)	-0.002 (0.002)
CON x CMI				-0.002 (0.002)
CON		-0.003*** (0.000)	-0.003*** (0.000)	-0.003*** (0.000)
Constant	0.855*** (0.008)	0.859*** (0.008)	0.854*** (0.008)	0.854*** (0.008)
Year dummies	Yes	Yes	Yes	Yes
Observations	18,697	18,697	18,696	18,696
Number of groups	2,653	2,653	2,653	2,653
χ^2	21,444	21,484	21,547	21,571
P-value	0.00	0.00	0.00	0.00
Δ AIC (base: Model 1)	-	-28.9	-48	-55.2
Δ BIC (base: Model 1)	-	-21.1	-24.5	-16.1

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 9A: Post hoc: Full results of granular hybrid estimation results for Non-readmission

	Model 5	**Model 6**	**Model 7**	**Model 8**
Within-hospital effects				
Teaching Intensity	0.003* (0.002)	0.003* (0.002)	0.004** (0.002)	0.004** (0.002)
Wage Index (adjusting for teaching)	0.007*** (0.002)	0.007*** (0.002)	0.006*** (0.002)	0.006*** (0.002)
OPDSH Adj. Factor	-0.002 (0.002)	-0.002 (0.002)	-0.003 (0.002)	-0.003 (0.002)
Outlier Adj. Factor	0.000 (0.002)	0.000 (0.002)	-0.001 (0.002)	-0.001 (0.002)
Beds	-0.001*** (0.001)	-0.001*** (0.001)	-0.002*** (0.001)	-0.002*** (0.001)
FTE	-0.003*** (0.000)	-0.003*** (0.000)	-0.003*** (0.000)	-0.003*** (0.000)
LOS	0.005*** (0.001)	0.005*** (0.001)	0.005*** (0.001)	0.005*** (0.001)
Outpatient Mix	0.016*** (0.002)	0.017*** (0.002)	0.017*** (0.002)	0.017*** (0.002)
Proprietary	0.001** (0.001)	0.001** (0.001)	0.001** (0.001)	0.001** (0.001)
CMI (adjusting for teaching)			0.014*** (0.001)	0.013*** (0.001)
CON x CMI				0.003** (0.001)
Between-hospital effects				
Teaching Intensity	-0.018*** (0.002)	-0.018*** (0.002)	-0.018*** (0.001)	-0.018*** (0.001)
Wage Index (adjusting for teaching)	-0.003** (0.001)	-0.004*** (0.001)	-0.003** (0.001)	-0.003** (0.001)
OPDSH Adj. Factor	-0.010*** (0.002)	-0.011*** (0.002)	-0.006*** (0.001)	-0.006*** (0.001)
Outlier Adj. Factor	0.049*** (0.006)	0.044*** (0.006)	0.020*** (0.006)	0.020*** (0.006)
Beds	-0.007*** (0.001)	-0.007*** (0.001)	-0.007*** (0.001)	-0.007*** (0.001)
FTE	0.007*** (0.001)	0.007*** (0.001)	0.004*** (0.001)	0.004*** (0.001)
LOS	-0.008*** (0.002)	-0.006*** (0.002)	-0.004*** (0.001)	-0.004** (0.001)
Outpatient Mix	0.005** (0.002)	0.007*** (0.002)	0.017*** (0.002)	0.017*** (0.002)
Proprietary	0.000 (0.001)	-0.000 (0.001)	-0.001* (0.001)	-0.001* (0.001)
CMI (adjusting for teaching)			0.019*** (0.001)	0.017*** (0.001)
CON x CMI				0.003* (0.002)
CON		-0.004*** (0.000)	-0.003*** (0.000)	-0.003*** (0.000)
Constant	0.774*** (0.008)	0.780*** (0.008)	0.806*** (0.007)	0.806*** (0.007)
Year dummies	Yes	Yes	Yes	Yes
Observations	18,732	18,732	18,731	18,731
Number of groups	2,658	2,658	2,658	2,658
χ^2	27,756	27,821	28,792	28,807
P-value	0.00	0.00	0.00	0.00
Δ AIC (base: Model 1)	-	-3,197.7	-3,667.0	-3,670.2
Δ BIC (base: Model 1)	-	-3,189.9	-3,643.5	-3,631.0

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

IV. Essay 3: Investigating the Effects of Nuclear Verdicts on Motor Carrier Safety and Insurance Spending

Introduction

Nuclear verdicts are awards larger than $10 million that may be provided by the courts to victims of crashes involving large trucks that resulted in serious injury and death (ATRI, 2020). These awards, which are decided after successfully litigated lawsuits brought by plaintiffs, are meant to compensate the injured victims or their families, punish offending defendants (i.e., motor carriers), and deter other carriers from committing similar harmful acts (LLI, 2021). According to popular and industry press, large truck nuclear verdicts have increased over the last decade in terms of both frequency and magnitude (Kingston, 2019). A study by the American Trucking Research Institute (ATRI) found that average verdict size increased from $2.3 million in 2010 to $22.3 million in 2018 (ATRI, 2020). Rising verdicts have been cited as a cause of rising trucking insurance premiums (Holm, 2020). Insurers cite three main reasons for these increases: (i) mistrust of corporations (Edelman, 2020), (ii) an increase in litigation financing (Sutton, 2018), and (iii) juror bias in favor of plaintiffs (Demberger, 2018; Liberty Mutual, 2019). Popular press has reported that carriers are reducing coverage to save money in response to rising premiums (Brewer & Young, 2021).

The risk of litigation and rising insurance rates have been cited in the motor carrier safety literature as key motivators for improving motor carrier safety (Corsi & Fanara, 1988; Cantor, Corsi, & Grimm, 2006). However, few studies have looked at the relationship between insurance and motor carrier safety (Corsi, Fanara, & Jarrell, 1988). Also, a growing body of literature has investigated the relationship between public policy—resulting from statutory and regulatory law—and motor carrier safety performance (Savage, 2011; Scott, Balthrop, & Miller, 2021; Scott & Nyaga, 2019); however, to the best of our knowledge, none have explored the effects of public policy resulting from litigation on motor carrier safety performance. This research seeks to

address the following questions: (i) How do nuclear verdicts affect motor carrier safety performance and insurance spending? and (ii) What is the nature of the relationship between motor carrier safety performance and insurance spending? To address these questions, we draw on institutional theory to generate our hypothesized predictions. We hypothesize that nuclear verdicts subject motor carriers to coercive and mimetic institutional pressures. In response to the threat of nuclear verdicts, motor carriers may improve safety behaviors to seek legitimacy in the eyes of the courts and public opinion and increase insurance spending to reduce uncertainty by limiting exposure to these verdicts. We also hypothesize a dynamic relationship between motor carrier safety performance and insurance spending motivated as by institutional pressures.

We test our hypothesized predictions by aggregating data from millions of roadside inspections conducted on large motor carriers (100+ power units) between January 2015 and December 2019 to a monthly industry-level time series. We retrieved the inspection data from the Federal Motor Carrier Safety Administration's (FMCSA) Safety Management System (SMS) and combined it insurance expense data provided by the Truckload Carriers Association Profitability Program (TPP), which we retrieved from FreightWaves SONAR as well as nuclear verdicts data we collected manually. Our study measures motor carrier safety performance using unsafe driving violations, a time- and severity-weighted measure that has been positively associated with accident rates by the FMCSA (Volpe Center, 2020) and the American Trucking Research Institute (ATRI, 2018). Unsafe driving has also been used extensively in the study of motor carrier safety (Miller, Golicic, & Fugate, 2018). We then apply an autoregressive distributed lag model (ARDLM) time series estimation approach to our time series data to estimate the relationships between our variables.

Our results reveal interesting insights. First, we find that nuclear verdicts are associated with improved industry-level motor carrier safety performance. However, we find that these changes in safety performance revert to previous levels over the long run. Next, we find that nuclear verdicts produce an unintended consequence of increasing insurance spending by motor carriers; however, we find these spending increases are also short-lived. Finally, our findings do not confirm our hypotheses concerning the dynamic relationship between motor carrier safety and insurance spending.

This study contributes to theory and the motor carrier safety literature in three ways. First, through our application of institutional theory to generate our hypotheses, we explore how the mechanisms of coercive and mimetic pressures drive carriers to improve safety performance. Second, our study highlights the ambiguous nature of litigation. Prior research focuses on the effects of regulations like the electronic logging device (ELD) mandate that provide relatively concrete requirements for compliance (Scott et al., 2021). As such, this research expands the scope of SCM literature pertaining to how public policy impacts motor carrier safety. Finally, our study examines the dynamic relationship between insurance expense and motor carrier safety; however, our findings do not support conventional wisdom regarding the effects of motor carrier safety on insurance spending.

This study also has implications for managers and policymakers. First, our findings highlight the importance of improving and sustaining improved motor carrier safety at the industry level to reduce exposure to nuclear verdicts. Second, our findings highlight the industry-level increase in insurance spending following nuclear verdicts that revert to prior levels shortly thereafter. It is important that carriers either resist unnecessary spending spikes or protect from reducing necessary coverage following spikes in insurance premiums. Next, policymakers may

want to consider the effectiveness of nuclear verdicts as “corrective social instruments” (Diamond, 1974, p. 367) given their short-term effect on industry safety. Finally, our findings highlight how nuclear verdicts may create unintended consequences related to increased insurance spending.

The remainder of the paper is structured as follows. We first explore the supply chain management (SCM) literature pertaining to public policy and motor carrier safety. Then we discuss our theoretical frame and document our hypothesis development. Next, we describe our research methods and discuss our results. Finally, we discuss the implications of our findings to theory and research, practice, and policymakers before offering our concluding thoughts.

Literature Review

Motor carrier safety has been the subject of extensive research in the logistics and SCM literature (Miller, Golicic, & Fugate, 2017) in four broad areas of study: the effects of carrier performance (e.g., Bruning, 1989), carrier characteristics (e.g., Corsi, Grimm, Cantor, & Sienicki, 2012), driver characteristics (e.g., Sullman, Meadows, & Pajo, 2002), and public policy (e.g., Scott et al., 2021). Many studies cite public policy as key motivation for improving motor carrier safety performance (Mejza, Barnard, Corsi, & Keane, 2003; Miller et al., 2017). A direct link has been found between enforcement of safety regulations through resource-intensive compliance reviews and a sustained reduction in crash rates (Chen, 2008). Scholars have also studied the variation in compliance with safety regulations. For example, medium-sized motor carriers are more likely than small motor carriers to comply with mandates for implementing safety technologies like electronic logging devices and national and super-regional carriers are more likely to comply than regional carriers (Miller, Bolumole, & Schwieterman, 2020).

Scholars have advocated for expansion of or changes to existing regulations or the creation of new safety regulations. For example, Corsi, Grimm, Cantor, & Wright (2014) advocates for subjecting smaller commercial trucks to safety regulations following the perceived success of large truck safety regulation in decreasing the rate of fatal crashes. And Saltzman & Belzer (2002) advocates for strengthening HOS rules due to potential safety and economic benefits. Whereas Savage (2011) argues for more comprehensive motor carrier safety regulation that includes assigning liability to shippers for carrier crashes. However, scholars have also found evidence of the unintended consequences or ineffectiveness of safety regulations. In a study of the effectiveness of electronic logging device mandates, it was found that while the mandate reduce HOS compliance violations, it did not decrease crashes for either small or large motor carriers; however, small carriers increased unsafe driving behaviors (Scott et al., 2021). Safety regulations have also been found to lack effectiveness in mitigating unsafe behaviors when drivers face tight deadlines, fatigue, and low pay (Braver, et al., 1992; Kemp, Kopp, & Kemp, 2013). Relatedly, it was found that owner-operators respond to price increases by violating safety regulations, whereas larger asset-based carriers do not (Scott & Nyaga, 2019).

While insurance is cited as a key reason for improving motor carrier safety (Corsi & Fanara, 1988), there is a paucity of research that investigates this relationship. Chow (1989) analyzed a small sample of general freight carriers over a ten-year period and found that financially healthy carriers spend more on insurance and safety programs and have better safety conduct. Corsi et al. (1988) explored the relationship between insurance expense and accident rates before and after the deregulation of the trucking industry by the Motor Carrier Act of 1980, finding that increased motor carrier spending on insurance was contemporaneously linked with increased accident rates across multiple periods. While both of these studies provide a

longitudinal perspective of this relationship at the carrier level, no study has examined the macro-economic relationship between insurance expense and motor carrier safety.

This study contributes to the motor carrier safety literature on in two ways. First, it extends the body of knowledge that has explored the impact of policy on motor carrier safety by examining whether the threat of civil litigation, namely nuclear verdicts, compels motor carriers to operate more safely. Extant research has explored the effects of policy resulting from regulatory laws from the FMCSA. Regulatory laws are specific rules and regulations generated and enforced by federal and state agencies that have been created by legislative statutes (LLI, 2017), whereas nuclear verdicts vary widely from state to state and case to case (ATRI, 2020). Second, this research highlights the role of macro-level conditions in affecting motor carrier safety. Whereas prior studies have explored the impact of policy or insurance expense on individual driver safety behaviors or motor carrier safety performance, little is known about overall industry safety performance in response to these variables. By conducting a longitudinal macro-econometric investigation of the effects of nuclear verdicts and insurance expense on motor carrier safety, we provide insights into the overall effectiveness of key variables cited to have an industry-wide impact.

Figure 1 represents our conceptualization of the effects of nuclear verdicts on motor carrier safety and insurance expense as well as the relationship between motor carrier safety and insurance expense, which we will use to develop our hypotheses in the next section.

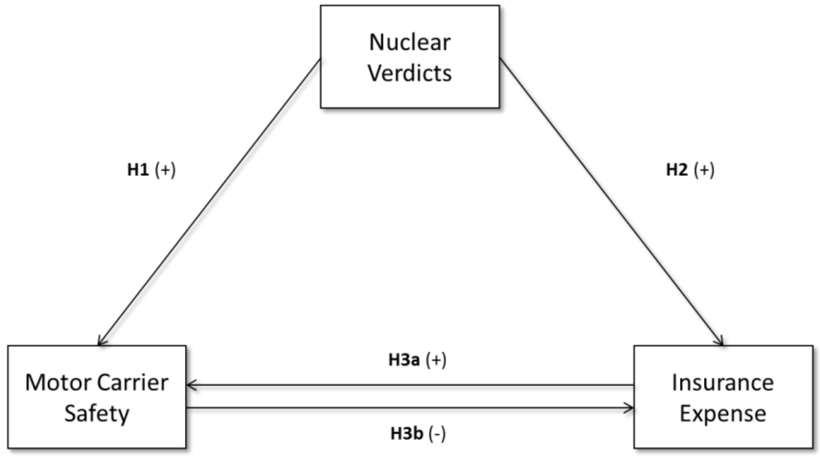

Figure 1: Conceptual framework

Theory and Hypothesis Development

Institutional Theory

Institutional theory posits that firms respond to influence from the institutional environment by altering their structure, behaviors, and practices. These influences come in the form of social norms, values and assumptions that define the standard for acceptable behavior (North, 1990). Institutions include but are not limited to professional groups, powerful firms, laws, courts, regulators, and public opinion (Meyer & Rowan, 1977). They can exert formal or informal pressures on firms to conform to acceptable standards (DiMaggio & Powell, 1983). When exposed to these pressures to conform and adhere to rules and norms, they do so in order to establish or maintain legitimacy or to minimize uncertainty (DiMaggio & Powell, 1983; Oliver, 1991). Legitimacy occurs when a firm's behaviors align with the standards of socially acceptable behaviors (Scott, 1995). Legitimacy is necessary for both firm competitive advantage and supply chain performance (Yang, Sheng, Wu, & Zhou, 2018).

Institutional pressures come in three forms: coercive, mimetic, and normative (DiMaggio & Powell, 1983). Coercive pressures can be exerted by both government entities with formal authority and powerful organizations or arrangements that can exercise informal influence. For

example, within the context of buyer-supplier relationships in emerging markets, both government enforcement of contracts and guanxi, an informal set of rules governing business relationships in China, have been found to be effective in reducing undesirable behaviors such as opportunism in these relationships (Yang et al., 2018). Firms seek legitimacy by complying with regulations and political pressures, which results in behavior that is more aligned with expectations. Mimetic pressures stem from uncertainty. When firms experience uncertainty, regardless of whether the uncertainty is internal or caused by the external environment, they seek to reduce uncertainty by copying behaviors of other firms they perceive to be more legitimate or successful (DiMaggio & Powell, 1983). Imitation can be enabled through formal or informal benchmarking against competitors and need not be tied to strategic goals (Ketokivi & Schroeder, 2004) or even intentional or conscious (Oliver, 1991). Normative pressures stem from professionalization or membership in professional associations. To establish legitimacy within a field, accrediting bodies may be formed to define conditions against which members are measured before they are admitted to the group (DiMaggio & Powell, 1983). Normative pressures can also be an enabler for coercive pressures; thus, they may not be seen as separate and distinct pressures. For example, manufacturers may pursue ISO certification in order to qualify as a supplier to a buyer that requires ISO certification. The certification is an example of normative pressure while the buyer's requirement that suppliers be certified is an example of coercive pressure (Ketokivi & Schroeder, 2004).

Nuclear Verdicts as Coercive Pressure

Particularly germane to our study of the impact of nuclear verdicts on motor carrier safety is the role of civil litigation in influencing public opinion and public policy. Civil litigation can occur as a result of intentional torts, negligence, or strict liability (LLI, 2021). Intentional torts

occur when a defendant commits an action that is intended to cause harm, whereas negligence occurs when a defendant failed to prevent harm when they had a duty to do so or behaved in an unsafe manner. Strict liability occurs when a defendant is liable for harm regardless of intent. Product liability, a subtype of strict liability, has motivated numerous studies within the operations management literature (Marucheck, Greis, Mena, & Cai, 2011). There is little other exploration of civil litigation in the operations or SCM literature outside of the economic modeling of decision-making around whether to engage in litigation (Levy, 1985).

To determine the level of defendant's liability in an accident, they must be found to have acted negligently at the time of the accident and that the plaintiff's actions must not have contributed to the cause of the accident through their own negligence (Diamond, 1974). Once a lawsuit is brought against a firm, they do not have a choice of whether to participate in the suit; however, the suit automatically reduces the firm's economic worth because regardless of outcome, the suit at the very least incurs legal expenses. To minimize the overall reduction of economic worth, firms prefer to attempt settlement to avoid costly additional legal fees and the threat of a larger loss via a large monetary verdict if the suit goes to court (Levy, 1985). By awarding damages to a plaintiff due to the negligent actions of the defendant, the courts provide a "corrective social instrument" that establishes the standards by which negligence may be judged in future cases (Diamond, 1974, p. 367). Acting as corrective social instruments, these awards can draw the attention of the public, which in turn can lead to shifts in publicly held beliefs, attitudes, and values held by the public. These shifts in public opinion can provide the impetus for the strengthening or creation of statutory law or regulatory agencies (Dale, 1998).

Consistent with institutional theory (North, 1990), we argue that since nuclear verdicts are awarded to serve as a corrective social instrument and thus represent the punishment for

failing to conform to social expectations of motor carrier safety, nuclear verdicts can be considered a social norm by which motor carriers are expected to adhere. Also, institutional theory posits that the courts can serve as a source of institutional pressure (Meyer & Rowan, 1977). While nuclear verdicts resulting from civil litigation do not create enforceable laws, they do provide the threat of legal punishment, i.e., verdicts passed down by the courts must be complied with. Hence, we argue that nuclear verdicts can be considered a form of coercive pressure (DiMaggio & Powell, 1983). Thus, we posit that firms will perceive improved safety performance as a way to establish legitimacy in the eyes of the courts. Further, given the public nature of nuclear verdicts both in their potential to broadcast unsafe behaviors that result in injury or death and to heighten social awareness of the importance of and public opinion surrounding motor carrier safety, motor carriers are likely to improve their safety performance to establish legitimacy with the public. Conformance to public expectations of safety is particularly important given that shippers and brokers may be less likely to use carriers that demonstrate unsafe performance (ATRI, 2011). Additionally, firms that do not obtain legitimacy through conformance may face increased insurance premiums and legal exposure (Meyer & Rowan, 1977). Therefore, we hypothesize,

H1. *Industry-level motor carrier safety will improve in response to increasing nuclear verdict amounts.*

Nuclear Verdicts as Mimetic Pressure

Uncertainty can arise when firms do not understand how the institutional environment is changing, how these changes will affect them, or what the appropriate response to these changes would be (Milliken, 1987). Given their ambiguous and unpredictable nature, nuclear verdicts can also be seen as a source of uncertainty for motor carriers. According to institutional theory,

uncertainty can lead to mimetic pressures that lead firms to mimic other firms to minimize their exposure to uncertainty (DiMaggio & Powell, 1983). When firms observe operational losses at similar firms, knowledge acquisition of how to prevent the risk of similar losses increases because search costs and causal ambiguity are reduced by this similarity (Hora & Klassen, 2013). Thus, when faced with new and unexpected events in their environment, firms will look to other firms to understand how they are responding to these events. When motor carriers are exposed to news of other carriers that are handed nuclear verdicts, they are likely to try to identify ways to prevent the same from happening to them.

As motor carriers contend with uncertainty, they may follow the wisdom of the crowd. Thus, carriers may imitate actions taken by a large number of other carriers, which are then adopted without thinking about whether the action will actually benefit the carrier. This behavior is strengthened as uncertainty increases (Haunschild & Miner, 1997). Motor carriers may turn to trucking associations for information on how to protect themselves and may see that other carriers are increasing their insurance coverage in response to rising nuclear verdicts. Firms are unable to assign realistic probabilities to unlikely events and may underreact or overreact to them (Milliken, 1987). Additionally, to reduce exposure to uncertainty, firms may create slack resources to serves as a buffer to unexpected future changes (Cyert & March, 1963). So, while it may be sensible to focus on improving safety, carriers may instead overestimate their risk of exposure to nuclear verdicts and may increase insurance spending. Also, nuclear verdicts can also lead to rising premiums. When determining insurance premiums, insurers consider the possibility of incurred losses based on a variety of factors including the frequency of accidents, the probability of liability, and the likelihood of litigation (King, 1971). Given that motor carriers may increase spending on insurance in response to uncertainty created by nuclear verdicts and

that insurance premiums may also be higher due to concerns regarding the risk of nuclear verdicts, we hypothesize,

H2. *Industry-level insurance spending by motor carriers will increase in response to increasing nuclear verdict amounts.*

Dynamic Responses to Institutional Pressures

We now turn to the relationship between motor carrier safety and insurance spending. According to institutional theory (DiMaggio & Powell, 1983), we postulate that increased insurance spending signals to the motor carrier that its conduct may not conform to external expectations and thus acts as a coercive pressure to alter safety behavior. In response, firms focused on profitability will try to find ways to reduce expenses and may exert additional attention to improving driver safety as a means for reducing excess expenses. As such, upper echelons of an organization may exert coercive pressures on lower echelons to conform to specific behaviors or practices (Kostova & Roth, 2002). As safety behaviors improve, motor carriers may perceive less exposure to uncertainty in their operating environment and may devote fewer slack resources to buffer against uncertainty (Cyert & March, 1963). Therefore, we hypothesize that there is a dynamic relationship between industry-level motor carrier safety and industry-level insurance spending by motor carriers such that,

H3a. *Industry-level motor carrier safety will improve in response to increasing industry-level insurance spending by motor carriers.*

H3b. *Industry-level insurance spending by motor carriers will decrease in response to improved industry-level motor carrier safety.*

Methodology and Results

Data Collection

We collected the data for our study from three sources. First, our safety data come from the publicly available FMCSA's Safety Management System (SMS), which has collected and reported safety data since 2010 from inspections of commercial motor vehicles (CMV) to monitor and report on motor carrier safety (FMCSA, 2021). Data in this system are collected from roadside inspections conducted by inspectors or law enforcement officers, which are initiated based on predetermined intervention programs, crashes, observation of unsafe or non-compliant behavior, or checkpoints. They are stored in three files used in this analysis: inspection files, violation files, and census files. The inspection files contain details about the inspections themselves, including the reason for the inspection and its location, identifying information about the carrier and the type of equipment used, and the number of violations observed during the inspection. The violation files provide detailed information about each violation found during an inspection including the violation category and severity. Violations can fall into one of eight categories: unsafe driving, crashes, HOS compliance, vehicle maintenance, controlled substance, hazardous materials compliance, driver fitness, and insurance or other issues. Each violation is assigned a severity weight between one and ten based on the level of crash risk associated with the violation. For example, texting and making phone calls is considered a high crash risk and is assigned a severity weight of ten, whereas unlawfully parking is deemed a low crash risk and is assigned a severity weight of one. The severity and recency of violations are used to calculate the Behavior Analysis and Safety Improvement Category (BASIC) score[1] for each violation

[1] For detailed information on how BASIC scores are calculated, please refer to the explanation provided in Miller (2017) and the FMCSA SMS Methodology document (FMCSA, 2021) available at https://csa.fmcsa.dot.gov/documents/smsmethodology.pdf.

category, which is used by the FMCSA to compare carriers and determine the need for intervention. We linked the data from the inspection and violation files with data from the census file, which contains information about the motor carrier, which includes carrier size measured by total power units, vehicle miles travelled, and type of freight hauled.

Second, we retrieved our insurance expense data from the Truckload Carriers Association Profitability Program (TPP). The TPP is an online benchmarking platform that contains operational and financial performance data provided by 175 large truckload carriers that are members of the program. The time series data are available via FreightWaves SONAR and are aggregated monthly beginning January 2015 (FreightWaves, 2020).

Third, our nuclear verdicts data were manually collected using information from VerdictSearch, a verdict and settlement repository of over 200,000 cases in the United States during the last twenty years (VerdictSearch, 2021), and ProQuest, a repository of news articles (ProQuest, 2021). To build our verdicts time series, we began by searching the VerdictSearch database for cases with verdicts and settlements[2] of $10 million or greater that occurred between January 2010 and December 2020 and involved a commercial truck or motor carrier. We recorded information for each case, including award date, award state, award amount, # people killed in crash, # people injured in crash, crash date, crash state, crash cause, crash description, whether case resulted in a verdict or settlement, and name of carrier(s) involve in the crash. We then removed cases that did not involve crashes or where the motor carrier was not found liable for the accident. For example, a May 2019 verdict in Texas in the amount of $80 million was

[2] While this study focuses on the effects of nuclear verdicts, settlements, which are not considered verdicts because they are not decided by the courts, that are larger than $10 million and are made public are expected to have a similar effect to verdicts on motor carrier behavior.

awarded to a truck driver because the courts found his employer instructed him to alter his work logs (see Lozano v. Marin, 2019). Next, we searched ProQuest to identify at least one news article to verify the information about each of these cases. To ensure the comprehensive nature of our data, we then searched ProQuest for news articles and press releases about additional verdicts and settlements not included in the VerdictSearch database[3]. We validated information about verdicts or settlements identified in this step using at least one additional independent news source. As settlements and their amounts are not always made public, this series cannot be considered comprehensive in its inclusion of all settlements involving CMVs; however, this series should be considered sufficient for this study as it is meant to explore the effect of public disclosure of verdicts and settlements on motor carrier safety and insurance expense.

To develop the population of large general freight motor carriers used in our time series, we follow Miller at al. (2017) and Scott and Nyaga (2019) by excluding motor carriers with fewer than 100 or more than 50,000 power units. This resulted in a population of 1,687 motor carriers. Then, we removed carriers founded later than 2014 because they would not have been operating during all years of our study, resulting in 1,640 motor carriers. We aggregated the FMCSA SMS data to the monthly level and merged it with time series data from the TPP and our manually collected nuclear verdicts time series to create our time series data set of 60 monthly periods between January 2015, and December 2019.

Measure Descriptions

We measure motor carrier safety using the FMCSA SMS unsafe driving BASIC measure. This measure includes violations for unsafe behaviors committed by the driver while operating a

[3] We used a combination of search terms during this step, including "verdict", "judgment", "settlement", and "decision", "truck", "rig", "crash", "accident", etc.

CMV, which includes texting or making phone calls while driving, speeding, and reckless or dangerous driving (FMCSA, 2021). While the FMCSA SMS includes eight violation categories, we focus our analysis on unsafe driving for two reasons. First, unsafe driving as well as HOS compliance are linked with the highest crash risk (Volpe Center, 2020). Since nuclear verdicts are directly linked to crashes, measurement of this behavior is the logical focus of this study. Second, while HOS compliance is an important predictor of crash risk, HOS compliance was directly affected by the ELD mandate, which occurred during the timeframe of this analysis (Scott et al., 2021). Since this measure captures both the number and severity of unsafe driving violations, lower values indicate better safety performance. To measure insurance expense, we use the insurance expense time series provided by the TPP. This series measures the amount spent by member carriers on physical damage insurance, cargo insurance, liability insurance, and accident and driver damage self-insurance as a percent of linehaul and accessorial revenue (FreightWaves, 2020). Finally, we measure nuclear verdicts using the monthly aggregate dollar amounts of verdicts over $10 million identified during our manual data collection process. We denote unsafe driving as *UD*, insurance expense as *ins_exp*, and nuclear verdict amounts as *verdict_amt.*

Statistical Analysis

Our hypothesized predictions focus on the effects of the exogenous variable *verdict_amt* on *UD* and *ins_exp*. The estimation of these relationships is based in the estimation of the transfer function, which is a polynomial that shows the effects of movements in exogenous variables on the time path of exogenous variables (Enders, Sandler, & Parise, 1992). However, direct estimation of transfer functions is challenging, and few statistical packages are available to accomplish the task. As such, we use autoregressive distributed lag models (ARDLM) to test our

hypothesized predictions, which offers a simplified method for estimating the long-run effects of exogenous variables without needing to estimate a transfer function. ARDLMs are useful for identification and estimation of long-run relationships between non-stationary endogenous and exogenous variables (Enders, 2010) that may be integrated at different levels (Pesaran, Shin, & Smith, 2001). This estimation approach has been used in the study of policy and economics in several areas including trade policy (Belloumi, 2014), energy demand (Bentzen & Engsted, 2001), money demand (Akinlo, 2006), and the effects of terrorism on tourism (Enders et al., 1992). A variation of the ARDL approach has bee applied to the study of the interaction between the ELD mandate and truckload pricing dynamics (Miller, Scott, & Williams, 2020).

To test our hypotheses using ARDLMs, we must first test whether our variables are non-stationary. That is, we test whether the variables exhibit deterministic features like trend, drift, seasonality, or structural breaks (Enders, 2010). The augmented Dickey-Fuller (ADF) test determines whether our variables have a unit root and is thus non-stationary. The results of the ADF tests at level and first difference are given in Table 1 and indicate that *UD* is an I(1) process while *ins_exp* and *verdict_amt* are both I(0) processes. This means *ins_exp* and *verdict_amt* are both stationary at the level and *UD* is stationary at first differences. Thus, we transformed *UD* using month-over-month differences for our analyses, which created the variable ΔUD.

Table 1: Augmented Dickey-Fuller tests for unit root

	Level		First difference	
	t-Stat	Critical value at 5%	t-Stat	Critical value at 5%
UD	-0.488	-3.488	-4.473***	-3.488
ins_exp	-4.51***	-3.488	-7.919***	-3.488
verdict_amt	-9.132***	-3.488	-4.355***	-3.488

Models with constant and trend ***p<0.01, **p<0.05

Descriptive statistics are summarized in Table 2. As expected, *ΔUD* is negatively correlated with *ins_exp* and *verdict_amt* and *ins_exp* is positively correlated with *verdict_amt*.

Table 2: Descriptive statistics and correlation matrix

	Mean	Std. Dev.	*ΔUD*	*ins_exp*
ΔUD	0.001	0.009		
ins_exp	4.096	0.696	-0.004	
verdict_amt	20.028	58.119	-0.212	0.068

Next, we establish the existence of a long-run relationship between our variables using the Johansen test for cointegration, which provides indication of both the existence and quantity of cointegration relationships (Johansen, 1991). Table 3 shows the results of our Johansen test for cointegration among *UD*, *ins_exp*, and *verdict_amt*. The first result shows we can strongly reject the null hypothesis of no cointegrating relationships (r=0). The second result indicates that we cannot reject the null hypothesis of at most one cointegrating relationship ($r\leq 1$). Thus, our results indicate the presence of a single unique long-run relationship among our variables.

Table 3: Johansen test for the number of cointegrating vectors

Rank, *r*	Eigenvalue	Trace stat	5% Critical value	P-value
0	0.484	51.619	29.797	0.000
≤1	0.176	13.224	15.495	0.107
≤2	0.033	1.972	3.841	0.160

Given that we have established the existence of a long-run relationship among *UD*, *ins_exp*, and *verdict_amt*, we now turn our focus to testing our hypothesized predictions with a series of ARDLMs. Past research has demonstrated the autoregressive relationship between past and future values of unsafe driving (Miller et al., 2017) and insurance (Fung, Lai, Patterson, & Witt, 1998). Thus, we control for previous changes in unsafe driving by including ΔUD_{t-1} and for previous values of insurance expense by including ins_exp_{t-1}. We also included dummy variables

for each month and year to capture deterministic features like seasonality and macroeconomic trends. To test our hypotheses, we specified the following equations:

$$\Delta UD_t = a_{10} + a_{11}\Delta UD_{t-1} + \sum_{i=0}^{q} a_{12i} ins\_exp_{t-i} + \sum_{i=0}^{n} a_{13i} verdict\_amt_{t-i} + \sum_{i=1}^{5} a_{14i} year_t + \sum_{i=1}^{12} c_{15i} month_t + \varepsilon_{1t}$$

$$ins\_exp_t = a_{20} + a_{21} ins\_exp_{t-1} + \sum_{i=0}^{q} a_{22i}\Delta UD_{t-i} + \sum_{i=0}^{n} a_{23i} verdict\_amt_{t-i} + \sum_{i=1}^{5} a_{24i} year_t + \sum_{i=1}^{12} c_{25i} month_t + \varepsilon_{2t}$$

Where ε_t represents the error term. A benefit of the ARDLM approach is that the lags of each variable need not be identified *a priori* to estimation as each combination of lags is tested and the best fitting model is chosen using AIC criteria. However, to prevent identifying overparameterized models, it important to identify the maximum number of allowable lags prior to identification and estimation. To do this, we begin by obtaining the cross-correlogram between verdict amount and unsafe driving to identify the lags associated with a relationship change. We found that the relationship strengthens at lag one and begins to weaken at lag six; thus, we chose a maximum of lag length of six.

The results from our first set of ARDLMs can be found in Table 4. In this set, our dependent variable is unsafe driving. We tested for the exogenous effects of *verdict_amt*, the dynamic effect of *ins_exp*, and the autoregressive effects of ΔUD. The best fitting model included three lags of *verdict_amt* and only contemporaneous effects of *ins_exp*. Model 1 looks at the exogenous effects of *verdict_amt* on ΔUD, and Model 2 adds in the dynamic effect *ins_exp*. First, we find that the effect of ΔUD_{t-1} is positive and highly significant (a = 0.302; p <

0.01. Next, the results in Model 1 show that the contemporaneous effect of *verdict_amt* is negative and marginally significant (a = -0.082; $p < 0.1$) while the lagged effects of *verdict_amt* are negative and significant for months one and two (β = -0.084, -0.094; $p < 0.05$, respectively). Given that **H1** posits that *verdict_amt* would have a negative effect on ΔUD, i.e., a positive effect of safety performance, these findings provide support for **H1**.

Table 4: ARDLM results with ΔUD as the dependent variable

	1	2
ΔUD_{t-1}	0.302 (0.132) **	0.291 (0.135) **
$verdict\_amt_t$	-0.082 (0.047) *	-0.079 (0.045) *
$verdict\_amt_{t-1}$	-0.084 (0.034) **	-0.088 (0.038) **
$verdict\_amt_{t-2}$	-0.094 (0.038) **	-0.095 (0.04) **
$verdict\_amt_{t-3}$	-0.116 (0.075)	-0.119 (0.072)
ins_exp_t		2.956 (6.04)
Constant	-2749.65 (4965.061)	-845.452 (6218.456)
Year dummies	Included	Included
Month dummies	Included	Included
R-squared	0.394	0.399
S.E. of regression	18.22	18.34
Breusch–Godfrey test	0.32	0.24
White test	0.48	0.57
Jarque–Bera test	0.79	1.46
Ramsey RESET test	0.168	0.139

Standard errors in parentheses; ***p<0.01, **p<0.05, *p<0.1

H3a posits that *verdict_amt* would be negatively associated with ΔUD, i.e., a positive relationship between insurance spending and safety performance; however, our results show a positive and non-significant contemporaneous effect (a = 2.956; $p > 0.10$) of *ins_exp* on ΔUD. Thus, we do not find support for **H3a**. Diagnostic tests suggest that Models 1 and 2 are well specified. The Breusch–Godfrey (LM) test F-statistic is not significant, indicating no serial correlation. The White test F-statistic is not significant, indicating no heteroskedasticity. The

Jarque–Bera test F-statistic is not significant, indicating normality of errors. And the Ramsey RESET test F-statistic is not significant, indicating linearity.

Next, the results from our second set of ARDLMs can be found in Table 5. In this set, our dependent variable is *verdict_amt.* We tested for the exogenous effects of *verdict_amt,* the dynamic effect of ΔUD, and the autoregressive effect of *ins_exp*. The best fitting model included one lag of *verdict_amt* and only contemporaneous effects of ΔUD. Model 3 looks at the exogenous effects of *verdict_amt* on *ins_exp*, and Model 4 adds in the dynamic effect of ΔUD. First, we find that ins_exp_{t-1} is strongly predictive of ins_exp_t ($a = 0.485$; $p < 0.01$). The results in Model 3 show that the contemporaneous effect of *verdict_amt* is not significant ($a = -0.001$; $p > 0.1$), whereas the coefficient for the lagged effect is positive and significant in month one ($a = -0.001$; $p > 0.1$). Given that **H2** posits that *verdict_amt* would have a positive relationship with *ins_exp*, these findings provide support for **H2**.

Table 5: ARDLM results with *ins_exp* as the dependent variable

	3	4
ins_exp_{t-1}	0.485 (0.117) ***	0.482 (0.118) ***
$verdict\_amt_t$	-0.001 (0.002)	-0.001 (0.002)
$verdict\_amt_{t-1}$	0.002 (0.001) **	0.002 (0.001) **
ΔUD_t		0.002 (0.003)
Constant	-322.903 (109.367) ***	-325.047 (109.45) ***
Year dummies	Included	Included
Month dummies	Included	Included
R-squared	0.576	0.579
S.E. of regression	0.47	0.48
Breusch–Godfrey test	0.61	0.47
White test	0.43	0.62
Jarque–Bera test	3.87	3.43
Ramsey RESET test	0.413	0.274

Standard errors in parentheses; ***p<0.01, **p<0.05, *p<0.1

H3b posits that *ΔUD* would also be positively associated with *ins_exp*. The results in Model 4 show that the contemporaneous effect of *ΔUD* on *ins_exp* is not significant (a = 0.002; p > 0.1). Thus, we do not find support for **H3b**. Diagnostic tests suggest that Models 3 and 4 are also well specified.

To aid in interpretation of our results, we plot the impulse response functions of the exogenous effects of *verdict_amt* on *ΔUD* and *ins_exp*. Impulse response functions are sets of coefficients that represent the behavior of errors over time when exposed to one standard deviation (SD) exogenous shocks (Enders, 2010). Figures 2A-B reveal important findings from our analysis. First, Figure 2A shows that when *verdict_amt* experiences a one SD shock, *ΔUD* shows a contemporaneous negative response that is sustained through two months before beginning its return to zero. That *ΔUD* returns to zero indicates that the effects of *verdict_amt* on *ΔUD* is sustained for a short period of time but that in the long run, *ΔUD* returns to prior levels. Second, Figure 2B shows that when *verdict_amt* experiences a one SD shock, *ins_exp* exhibits a slightly negative contemporaneous response that spikes positive in the following month before returning to zero in the long run. This return to zero indicates a delayed response in the form of higher spending on insurance that is not sustained in the long run.

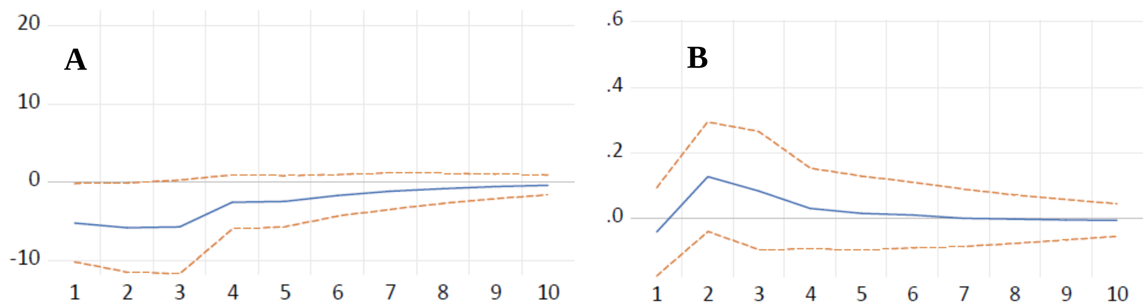

Figure 2: Plot of the impulse response function of a one SD shock of *verdict_amt* on (A) *ΔUD* and (B) *ins_exp* ± 2 standard errors

Discussion

In addition to compensating victims of crashes for damages and pain and suffering, nuclear verdicts can be used to punish at-fault motor carriers for unsafe behaviors that result in harm to others as well as to warn other motor carriers to improve their safety performance or face similar punishment. In this study we investigated the long-run impact of nuclear verdicts on motor carrier safety and found that nuclear verdicts do in fact lead motor carriers to improve their safety performance, particularly unsafe driving, but that the performance improvements are not sustained over the long run. We also found that in response to nuclear verdicts that motor carriers increase their spending on insurance; however, our findings suggest that those spending increases may be short-lived. We also tested the dynamic relationship between insurance expense and safety performance and our results did not confirm this relationship.

Implications for Theory and Research

This study makes several contributions to theory. First, this study contributes to theory by devising and testing hypotheses that draw on institutional theory (DiMaggio & Powell, 1983) to explain motor carrier safety behavior in response to the threat of litigation. Specifically, institutional theory explains our findings that (1) the coercive pressures applied via large nuclear verdicts may lead to improved industry-level motor carrier safety performance and (2) mimetic

pressures resulting from uncertainty created by large nuclear verdicts may lead to increased industry-level insurance spending. Using this theoretical frame, we highlight how policies meant to pressure industries to conform to desired behaviors can also produce unintended consequences like heightened uncertainty that must also be contended with. Little research has focused on the effects of institutional pressures on motor carrier safety. This approach aligns with calls for scholars to investigate how institutional effects of policies can influence SCM decision-making (Pagell, Fugate, & Flynn, 2018) as well as how public policies influence operational choices (Joglekar, Davies, & Anderson, 2016).

Second, this study contributes to theory by suggesting that public policy stemming from litigation can lead to improved motor carrier safety performance. These findings are important because while many regulations aimed at the trucking industry (e.g., ELD mandate, HOS rules, etc.) provide concrete requirements and predictable punishments for non-compliance, nuclear verdicts provide unpredictable punishments for violating ambiguous requirements. Prior research that explores the relationship between more concretely defined regulations and motor carrier safety highlights the ineffectiveness of these policies (e.g., Scott et al., 2021), whereas this research suggests that ambiguous policies may result in sustained safety improvement. Further complicating the ambiguity of nuclear verdicts is that jurors responsible for deciding verdicts are unlikely to be transportation experts or to differentiate between a defendant that is a trucking company or any other company that has harmed a person. Thus, investigating the impact of non-trucking specific policy on motor-carrier safety can expand our understanding of the mechanisms that drive motor-carrier safety.

Third, this study contributes to theory by testing the dynamic relationship between insurance expense and motor carrier safety. While prior research has explored variation in safety

performance in response to insurance spending (Chow, 1989; Corsi et al., 1988), the inverse relationship has been yet unexplored to the best of our knowledge. This is interesting given that conventional wisdom often cited insurance as a key reason for improving safety performance. Findings from our study suggest that at the industry level this dynamic relationship does not exist. While this lack of significance does not contradict previous research, it does fail to confirm previous findings.

Implications for Practice

This study also has implications for carrier managers. First, our findings provide evidence that nuclear verdicts are effective in improving industry-level motor carrier safety; however, our findings also indicate a stable long-run relationship between verdicts and safety performance meaning that industry-level safety performance tends to revert to prior levels over the long run. One goal of nuclear verdicts is improving motor carrier safety. Our findings that the industry response to nuclear verdicts of improved safety followed by reversion to previous safety levels may lead jurors to sustain or increase the frequency and size of nuclear verdicts to affect longer-term safety improvement. Thus, carriers may want to consider investing in sustained safety improvements both proactively and following nuclear verdicts to contribute to sustained improvements in industry-level safety performance. This can also have the effect of establishing a history of focus on improving safety that may provide a safety net should litigation become unavoidable for a carrier. Nuclear verdicts can occur when juries believe firms do not behave ethically and that crashes are a result of this unethical behavior (Demberger, 2018; Vieth, 2019). By demonstrating a trend of ethical behavior, motor carriers may be able to reduce the likelihood of a nuclear verdict (Huff, 2021).

Second, our findings revealed that industry-level insurance spending increased in response to nuclear verdicts, but that those increases dwindle to previous levels in subsequent months. One potential explanation for this behavior is that the initial increase in insurance spending was a knee-jerk response to news of new nuclear verdicts that was slowly decreased as the news cycle focused less on the verdicts. This suggests that the initial increases in spending are unnecessary because individual carrier risk did not increase, and motor carrier managers may want to guard against these fluctuations. An alternative explanation for this behavior is that initial increases in insurance spending could be the result of rising insurance premiums in response to nuclear verdicts and that subsequent decreases in insurance spending could be due to motor carriers decreasing the amount of insurance they buy. In this case, motor carriers may be creating risk for themselves that could result in them going out of business if faced with even a small verdict that exceeds their liability insurance limits.

Implications for Policymakers

Finally, this study has implications for policymakers. First, our findings reveal that industry-level motor carrier safety improvements in response to nuclear verdicts are impermanent, which indicates that nuclear verdicts may provide only a short-term remedy for industry safety issues. Further, the frequency and size of nuclear verdicts appear to be somewhat unpredictable, and they only occur after a harmful crash occurs and a lawsuit has been filed. Thus, while nuclear verdicts may serve as a public and dramatic corrective social instrument, their unpredictable and undesirable occurrence indicates that these verdicts may not be a suitable mechanism for generating sustained safety improvement. As such, policymakers may want to consider the ceiling of effectiveness of nuclear verdicts in doing so and whether they will be effective at all once they become commonplace.

Second, our finding that nuclear verdicts are positively associated with insurance spending highlights an unintended consequence of these verdicts. While juries do intend for nuclear verdicts to punish offending carriers and warn unsafe carrier, it is unlikely they are aware of the additional effects that verdicts have on operating costs for carriers who may already be operating safely. Increased expenses in the trucking industry may be passed on to shippers in the form of higher freight prices (Miller, Muir, Bolumole, & Griffis, 2020). Also, industry press paints a bleak picture of this issue, citing that rising insurance premiums are putting smaller carriers out of business (Kingston, 2019). While our study does not investigate the effects of nuclear verdicts on small motor carriers or motor carrier failure, it is reasonable to consider that rising insurance expenses can strain the financial performance of small carriers. Further, in response to increasing verdict size, legislators have repeatedly put forth bills intended to raise insurance minimums (see H.R.3781— 116th Congress (2019) and H.R.2687 — 117th Congress, (2021). Policymakers may want to evaluate whether the benefits of short-term safety improvements resulting from nuclear verdicts outweigh the potential impact increasing insurance expenses have on shippers.

Limitations and Directions for Future Research

Like all studies, our study has several limitations. First, our sample was limited to general freight motor carriers with between 100 and 50,000 power units. Thus, generalization of our findings to smaller carriers should be done with caution. However, smaller carriers and owner-operators may be at risk concerning nuclear verdicts due to their limited access to financial resources that may be more accessible to larger carriers. Future research may look into whether there are differences in response to nuclear verdicts between small carriers or owner-operators and the large carriers studied in this research. Second, this study aggregates safety performance

across all carriers in the sample. This is an intended feature of the study as our focus was industry-level safety performance; however, this aggregation approach precludes this study from investigating the effects of nuclear verdicts on individual motor carrier or driver behaviors, or from understanding how nuclear verdicts affect carriers of different sizes. However, future research may explore the role of carrier size in safety response to nuclear verdicts similarly to how Scott et al. (2021) investigated the effect carrier size on changes in HOS compliance and unsafe driving in response to the ELD mandate. Further, as individual drivers may be found personally liable in lawsuits resulting from their unsafe driving behaviors, future research could explore how knowledge of nuclear verdicts may influence individual driver safety behaviors.

Third, our study examined the industry-level response to news reports of nuclear verdicts. We did this because news of nuclear verdicts is broadcasted through national channels and is disseminated through industry associations. Given the interstate nature of the trucking industry, this approach seems sufficient. However, evaluating industry-level response to nuclear verdicts prevented investigation of more nuanced carrier responses to local verdicts. Future research may explore whether there is a local impact associated with nuclear verdicts. For example, scholars may want to explore whether carriers that operate in a state where a nuclear verdict is decided behave differently that carriers that do not operate within the state. Fourth, our study used the TPP series that captures insurance expense for 175 large truckload carriers as a proxy for the industry insurance expense. This is because we could not measure insurance expense for each of the motor carriers included in this sample. Given we do not have knowledge of the specific motor carriers measured by the TPP, it is possible that the TPP sample may not be fully representative of the sample of carriers used to create our safety data set. Thus, future research may employ improved measures of insurance expense of specific carriers used in the

sample or find ways to capture insurance premium information that could reflect insurers' responses to nuclear verdicts.

Fifth, our ARDLM approach uses the lag length specification that produces the best fitting models using AIC criteria. While we modeled additional lag length specifications to as a robustness check, the best fitting models may be different than a theoretically driven lag length specification. Thus, while alternative models produced results that were consistent with the results presented in this study, future research may explore lag length specifications that are both theoretically and statistically driven. Finally, the timeframe of our study is short. This is due to the relative newness of the nuclear verdict phenomenon and limited data availability. While the ARDLM approach sufficient for the number of time periods analyzed, the following consideration should be made when reviewing our findings. The last several periods of our dataset saw a dramatic and sustained increased in the size of nuclear verdict awards, indicating that more can be learned about the phenomenon as the trend continues to develop. However, beginning in the next few periods after our analysis timeframe, the COVID-19 pandemic substantially disrupted the U.S. economy. VMT and freight shipments declined dramatically (Cass Information Systems, 2021; FHA, 2021) and many courts discontinued or delayed hearing cases due to social safety protocols (Justia, 2021). These events will likely impact all the variable studied in this analysis. Thus, future research will need to account for these disruptions.

In addition to future research that can build on the limitations of this study, three additional research opportunities may extend from this study. First, our study explores the role of nuclear verdicts as a corrective social instrument that may warn motor carriers to improve safety performance. Future research may also investigate whether safety performance improved for motor carriers that were defendants in litigation that resulted in a nuclear verdict. Assuming the

carrier does not go out of business after being handed a nuclear verdict, do these carriers become safer as a result? Organizational learning literature has explored whether coal mining companies learn from direct or vicarious experience with prior disasters and become safer (Madsen, 2009). Future research could expand on this work by exploring whether organizational learning effects are present following nuclear verdicts and the crashes that prompt them. Second, this research raises the question of who should pay for motor carrier safety? The costs associated with nuclear verdicts are incurred directly by defendant motor carriers and indirectly by motor carriers throughout the industry via increased insurance premiums. This differs from the costs of regulation and enforcement provided by the FMCSA, which are funded by taxpayers. Future research could explore the cost-benefit tradeoffs between litigation and agency regulation as alternatives for improving motor carrier safety. Finally, tort reforms can potentially limit the size of verdicts in states where they are enacted. Given our findings that growing nuclear verdicts reduce unsafe driving, investigating the safety performance effects of limiting the size of nuclear verdicts through tort reform may reveal interesting insights.

Conclusion

Researchers have found that while resource-intensive enforcement activities can improve motor carrier safety (Chen, 2008), safety regulations can be ineffective in contextual situations (Braver, et al., 1992; Kemp et al., 2013; Scott & Nyaga, 2019) or can bring about unintended consequences (Scott et al., 2021). We extend the study of how policy impacts motor carrier safety by examining the effects of nuclear verdicts on industry-level motor carrier safety and their unintended effect on insurance spending. Trucking industry media has sounded the alarm that nuclear verdicts are on the rise and may have devastating implications for motor carriers' financial performance due to rising insurance rates (Holm, 2020). Given that nuclear verdicts are passed

down by the courts partly as a warning to unsafe carriers, we sought out to investigate nuclear verdicts are accomplishing the goal of the courts. We also examined the effects of nuclear verdicts on insurance spending and investigated the dynamic relationship between safety performance and insurance spending. We tested these relationships using ARDLMs to identify the long run cointegrating relationships between these variables. While we find that nuclear verdicts do reduce unsafe driving, we also find that they increase insurance spending. However, we do not find evidence supporting the dynamic relationship between motor carrier safety and insurance spending. These results highlight the short-term effectiveness of nuclear verdicts as a corrective social instrument and the unintended consequences that can result.

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V. Conclusion

This dissertation examined the unintended consequences of policy on SCM. In the first essay, I used a qualitative approach to theorizing new barriers to collaboration unique to a relationship-focused regulatory environment. Findings reveal that relationship-focused regulations meant to promote social welfare by constraining the flow of alcohol to consumer also constrain choice in supply chain relationships that negatively affect supply chain collaboration. In the second essay, I examined how capacity-limiting structural regulation in healthcare, specifically certificate of need (CON) laws, interacts with case complexity to affect hospital operational performance. Using a hybrid estimation approach to analyze a unique data set collected from multiple sources, I tested a conceptual model developed on the structure-conduct-performance (SCP) framework and the complex adaptive systems (CAS) perspective. Findings indicate that CON is associated with reduced costs but worsened quality, whereas case complexity is associated with increased costs but improved quality. However, case complexity intensifies the relationship between CON and costs but has limited impact on the relationship between CON and quality. In the third essay, I examined whether nuclear verdicts over $10 million resulting from harm caused by large truck crashes lead to improve industry-level motor carrier safety performance. I used time series econometrics to test my hypotheses, which were developed using institutional theory. Findings indicate that nuclear verdicts produce short-term safety improvements but also increase insurance spending. Collectively, these essays demonstrate the effectiveness of the policies studied in accomplishing their intended purposes and highlight the unintended consequences of policy on SCM.

Through decades of literature aimed at defining and justifying the importance of supply chain management, the themes like of coordination (Cooper, Lambert, & Pagh, 1997), efficiency (Fawcett, Waller, & Bowersox, 2011), strategic enablement (Mentzer, et al., 2001), and

delivering customer value (Fawcett & Waller, 2013) have been emphasized. As policy and regulations increasingly focus on or impact supply chains, the importance of understand their effect on these themes must be understood (Pagell, Fugate, & Flynn, 2018). Further, the study of public policy should provide evidence into how regulations affect performance in specific operational contexts (Joglekar, Davies, & Anderson, 2016). This dissertation answers these calls first by extending a nascent but growing body of knowledge concerning the effects of policy on SCM and second by studying the effects of policy in contextual settings. It also provides a foundation for future research by exploring the effects of policy in important areas of SCM research such as healthcare and trucking. Essays two and three examine policies that impact the provision of cost-effective and safe healthcare and compel improved motor carrier safety. Future research can build on these topics to examine the effects of similar policies on other aspects of the aspects of the supply chain. Further, all three essays highlight the unintended consequences of policy that have unexpected and even dire effects on supply chain and firm performance.

This dissertation also contributes to theory by developing new mid-range theory and testing the boundary conditions of existing theory, which are important ways to contribute new knowledge to a discipline (Brown & Dant, 2008; Ladik & Stewart, 2008). Essay one contributes by theorizing new barriers to collaboration that are not well-explained by existing theories due to their core assumptions that firms may choose whether to continue in an exchange relationship or take actions to correct imbalances or agency issues. Essay two joins two seemingly unrelated theoretical frames, the SCP framework and the CAS perspective, to explain the nuanced relationship between capacity-limiting regulation and case complexity. Essay three leverages institutional theory to explain yet unexamined phenomenon to provide insights into the effects of litigation on safety behavior of the motor carrier industry.

For managers and policymakers, this dissertation provides guidance on both the intended and unintended consequences of policy on SCM. By examining the intended consequences of policy in SCM, I highlight the motivations for policy and demonstrate the effectiveness of policy in bringing about changes in SCM. Findings from essay two show that capacity-limiting regulations achieve their goal of reducing hospital costs. Findings from essay three show that nuclear verdicts achieve a goal of improving carrier safety. For managers, these findings put a spotlight on the importance of proactive improvement on matters of public opinion. By addressing these issues proactively as an industry, managers may be able to head off policies that create challenges and uncertainty in their operating environment. For policymakers, these findings present a clear case for targeted policymaking.

However, managers and policymakers should also take note of the unintended consequences policy can have on firm and supply chain performance. Findings from essay one show the negative effects of relationship-focused regulations that can make supply chain collaboration all but impossible. Findings from essay two demonstrate the added peril patients may face because of capacity-limiting regulation that may drive hospitals to adopt a myopic cost-reduction focus. Findings from essay three highlight potentially irrational changes in industry-wide insurance buying behavior due to increased uncertainty resulting from nuclear verdicts. Managers should guard against uncalculated responses to policy that can produce bad behaviors and habits that may worsen performance or reduce supply chain effectiveness. Policymakers should guard against myopic policymaking that creates undesired impacts or the need for additional policies to account for the unintended consequences of existing policy.

Policies can also tip the scales, which may prevent firms and supply chains from competing on a level playing field. In essay one, the relationship-focused regulations that were

enacted to prevent large suppliers from controlling their distributors shifted power to distributors who as a result have incredible influence on the success or failure of suppliers, especially small and young suppliers. In essay two, capacity-limiting regulations that favor incumbents reduced competition that could motivate life-saving healthcare quality improvements. In essay three, nuclear verdicts were found to increase insurance spending that may impact motor carriers' ability continue operations or to offer competitive prices.

As firms analyze industry conditions, they must also determine how policies and regulations affect these conditions (Porter, 2008). This is no different for SCM researchers working to develop a comprehensive body of knowledge. Taken together, this dissertation takes policy from its previous role in SCM research as a covariate or contextual setting (Pagell et al., 2018) and brings it to the forefront. The purpose of this dissertation is not to say that all policy is bad or that policies in general hurt supply chains or compromise managers' ability to accomplish their tasks of running great supply chains. However, these essays do open the dialogue regarding the exploration of how policy affects SCM, both in intended and unintended ways.

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VI. Appendices

Appendix A: Institutional Review Board Protocol Approval

UNIVERSITY OF ARKANSAS

To:	Jonathan Phares BELL 4188
From:	Douglas James Adams, Chair IRB Committee
Date:	03/09/2020
Action:	**Expedited Approval**
Action Date:	03/06/2020
Protocol #:	1911228796
Study Title:	Grounded Theory Research on Beer Supply Chains
Expiration Date:	11/18/2020
Last Approval Date:	

The above-referenced protocol has been approved following expedited review by the IRB Committee that oversees research with human subjects.

If the research involves collaboration with another institution then the research cannot commence until the Committee receives written notification of approval from the collaborating institution's IRB.

It is the Principal Investigator's responsibility to obtain review and continued approval before the expiration date.

Protocols are approved for a maximum period of one year. You may not continue any research activity beyond the expiration date without Committee approval. Please submit continuation requests early enough to allow sufficient time for review. Failure to receive approval for continuation before the expiration date will result in the automatic suspension of the approval of this protocol. Information collected following suspension is unapproved research and cannot be reported or published as research data. If you do not wish continued approval, please notify the Committee of the study closure.

Adverse Events: Any serious or unexpected adverse event must be reported to the IRB Committee within 48 hours. All other adverse events should be reported within 10 working days.

Amendments: If you wish to change any aspect of this study, such as the procedures, the consent forms, study personnel, or number of participants, please submit an amendment to the IRB. All changes must be approved by the IRB Committee before they can be initiated.

You must maintain a research file for at least 3 years after completion of the study. This file should include all correspondence with the IRB Committee, original signed consent forms, and study data.

cc: Brian S Fugate, Investigator

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Appendix B: Institutional Review Board Renewal Approval

UNIVERSITY OF ARKANSAS

To:	Jonathan Phares BELL 4188
From:	Douglas J Adams, Chair IRB Expedited Review
Date:	04/09/2021
Action:	**Expedited Approval**
Action Date:	04/06/2021
Protocol #:	1911228796R001
Study Title:	Grounded Theory Research on Beer Supply Chains
Expiration Date:	04/05/2022
Last Approval Date:	04/06/2021

The above-referenced protocol has been approved following expedited review by the IRB Committee that oversees research with human subjects.

If the research involves collaboration with another institution then the research cannot commence until the Committee receives written notification of approval from the collaborating institution's IRB.

It is the Principal Investigator's responsibility to obtain review and continued approval before the expiration date.

Protocols are approved for a maximum period of one year. You may not continue any research activity beyond the expiration date without Committee approval. Please submit continuation requests early enough to allow sufficient time for review. Failure to receive approval for continuation before the expiration date will result in the automatic suspension of the approval of this protocol. Information collected following suspension is unapproved research and cannot be reported or published as research data. If you do not wish continued approval, please notify the Committee of the study closure.

Adverse Events: Any serious or unexpected adverse event must be reported to the IRB Committee within 48 hours. All other adverse events should be reported within 10 working days.

Amendments: If you wish to change any aspect of this study, such as the procedures, the consent forms, study personnel, or number of participants, please submit an amendment to the IRB. All changes must be approved by the IRB Committee before they can be initiated.

You must maintain a research file for at least 3 years after completion of the study. This file should include all correspondence with the IRB Committee, original signed consent forms, and study data.

cc: Brian S Fugate, Investigator

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