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Supply chain risk management and hospital inventory: Effects of system affiliation

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ABSTRACT

In this study we examine the effects of horizontal inter-organizational arrangements on inventory costs for hospitals facing two key environmental conditions, namely the logistics services infrastructure where the hospital is located and the demand uncertainty for clinical requirements that a hospital experiences. Utilizing detailed data from hospitals in the State of California, we investigated the potential mitigating effects of affiliation with multi-hospital systems while controlling for service performance. We argue that these arrangements potentially influence managers' confidence in their supply chains, which in turn impacts inventory accumulation. Results suggest that while affiliation with local, regional, and national systems has mitigating effects under weak logistics services infrastructure, the mitigating effect is greatest for affiliation in local systems. The results also point to potential for improved operating efficiency with system affiliation, a factor that is often not considered in policy discussions regarding hospital system formation. Theoretical and managerial implications are discussed.

1. Introduction

Faced with increasing reimbursement and competitive pressures, many U.S. hospitals are focusing on reducing operating costs through internal process improvements. In this vein, hospitals have been giving growing emphasis to supply chain management. Hospital supply chain costs (i.e., supplies and purchased services) account for as much as 30 percent of a hospital's operating budget and thus represent an important opportunity for cost savings for hospitals individually but also for the US given that hospital budgets collectively account for more than six percent of the country's gross domestic product (Montgomery and Schneller, 2007; Burns and Lee, 2008; McKone-Sweet et al., 2005; CMS, 2011). However, limited systematic research has been conducted to identify practices and strategies for improving hospital supply chain performance.

An area of hospital supply chain management that particularly warrants close study is inventory. Among hospitals and the health care sector in general, inventory accumulation and obsolescence are several times higher than in the retail/industrial sector (Ebel et al., 2013). This is partly because unlike product-based supply chains, cost is typically not the main driver of inventory decisions in the hospital sector. Instead, inventory levels are dictated by the need to meet service performance outcomes. Yet, wide variation exists among hospitals in terms of inventory costs that do not appear to be explained by service performance. For example, Fig. 1 presents inventory costs among top performing California hospitals in 2009 which we define as those in the top 50th percentile on three measures of service performance. As can be seen, hospital inventory costs, as a percentage of their operating budgets, vary markedly within the same peer group for service performance.[1]

The supply chain literature indicates that organizations encounter challenges in managing inventory because of two typical supply chain risks: demand exceeds supply (supply risk) resulting in stockouts or supply exceeds demand (inventory risk) resulting in

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[1] We obtained each hospital's inventory costs from the hospital's balance sheet available from the California Hospital Financial Disclosure Report (CFDR) available from the state Office of Statewide Health Planning and Development (OSHPD) (http://www.oshpd.ca.gov). The hospital service performance measures were obtained from the Medicare Hospital Compare databases (http://www.medicare.gov/hospitalcompare).

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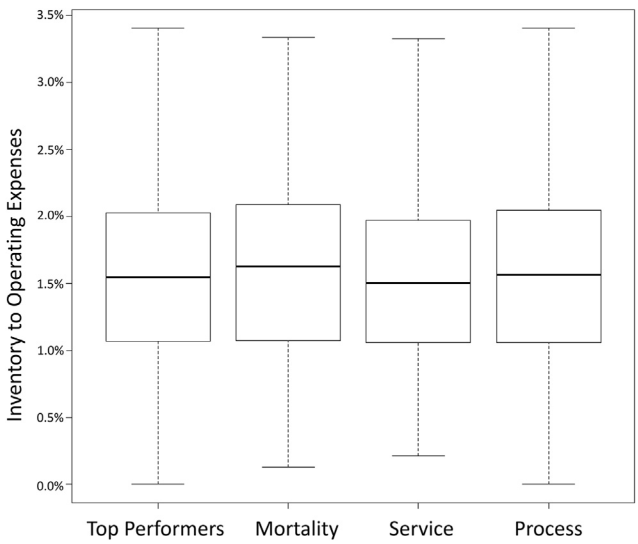

Fig. 1. Distribution of hospital inventory costs for top performing California hospitals in 2009. Top performing hospitals represented by the top 50th percentile in hospital service performance on either of three service performance categories: 30-day pneumonia related mortality rates, timely service patient experience, and surgery patients receiving proper antibiotic to prevent infection.

surplus inventory (Craighead et al., 2007; Kremer & Wassenhove, 2014; Sodhi et al., 2012; Talluri et al., 2013). Much research has focused on relationships between an organization and its suppliers as a key element of an organization's ability to manage supply chain risk (i.e., Wiengarten, et al., 2014; Zsidisin and Ellram, 2003). While this type of vertical inter-organizational arrangement (i.e., relationship between buyer and supplier) is important, far less attention has been devoted to horizontal inter-organizational arrangements among organizations with regard to the management of supply chain risk (Chen et al., 2013).

In this paper, we report results from an investigation of the effects of horizontal inter-organizational arrangements among hospitals on their inventory costs in the context of key drivers of supply chain risk for these organizations. For U.S. hospitals, an increasingly common horizontal inter-organizational arrangement is multi-hospital systems which entail common ownership of two or more hospitals (Burns et al., 2015; Chen et al., 2013). Currently, well over 50 percent of U.S. hospitals are affiliated with such systems (AHA, 2011; Cutler and Morton, 2013). Because these types of horizontal inter-organizational arrangements create opportunities for pooled resources including inventory (Bazzoli et al., 2000; Carey, 2003; Burns et al., 2015), managers of affiliated hospitals may be less likely to be concerned about the need to accumulate excess inventory as a buffer against supply chain risk. In effect, affiliation with a system may mitigate hospital supply chain risks resulting in lower levels of inventory.

To conduct our investigation, we utilized detailed financial data from hospitals in the State of California. We examined the effects of system affiliation on a hospital's inventory accumulation in the presence of supply chain risks arising from its environmental conditions, namely the logistics services infrastructure where the hospital is located and the demand uncertainty for clinical requirements that the hospital experiences. We also examined the potential moderating effects of system affiliation on a hospital's response to these key supply chain risk conditions. Our study makes two primary contributions.

One contribution is to the general supply chain management literature as our study focuses on the largely understudied area of horizontal inter-organizational arrangements and their implications for supply chain management including inventory costs. The extant supply chain literature on integration has tended to focus on vertical integration within the manufacturing sector (i.e., Flynn et al., 2010; Swink et al., 2007; Wiengarten et al., 2014). By comparison, we address integration in the service sector and in the context of horizontal as opposed to vertical arrangements. We build on recent work by Wiengarten et al. (2014) suggesting that, as a form of structural integration, horizontal inter-organizational arrangements are more effective in terms of managing inventory costs under conditions of weak logistics services infrastructure. In particular, we investigate how horizontal linkages among organizations with commonality in assets and resources can be exploited at the operational level where the influence of supply chain risk is more immediate (Narasimhan and Talluri, 2009), and where decisions regarding the deployment of assets and resources are eventually made (Swink et al., 2007). By examining such inter-organizational arrangements in the context of environmental conditions that drive supply chain risks and for organizations where product availability and service are more critical than cost considerations, our study offers new insights regarding the potential operational benefits of horizontal integration. As such, we extend the supply chain integration literature by contributing to the discussion regarding the link between integration and operational performance (i.e., Flynn et al., 2010; Koufteros et al., 2005; Gimenez and Ventura, 2005; Saeed et al., 2005; Germain and Iyer, 2006; Stank et al., 2001; Wiengarten et al., 2014). More specifically, our study provides insights into horizontal inter-organizational arrangements as an efficient alternative to vertical integration with suppliers and customers in service operations where geographic proximity between partners allows for risk pooling benefits.

Another contribution is to US health policy. The growing trend in the number of hospitals that belong to systems has generated much debate among policy makers and industry analysts over whether this form of industry consolidation will enhance hospital operating performance. Numerous studies have been conducted to assess whether system-affiliated hospitals have superior operating performance compared to hospitals that are independent (i.e., Coyne, 1982; Menke, 1997; Carey, 2003; Burns et al., 2015). The results of these studies largely point to little or no advantage for system-affiliated hospitals in terms of operational performance. At the same time, there exists growing concerns that this form of consolidation is driving up hospital prices by enhancing the negotiating leverage of hospitals with health insurance plans (i.e., Gaynor and Town, 2012; Cutler and Morton, 2013; Dafny, 2014). This concern combined with a lack of solid evidence that system affiliation is associated with better hospital operating performance has resulted in calls for more heightened antitrust scrutiny over the formation and expansion of multi-hospital systems (i.e., Daly, 2014). However, the extant literature regarding system affiliation and hospital operating performance is limited in two important ways. First, many of the relevant studies treat system affiliation one dimensionally; that is, whether or not a hospital is system affiliated. This potentially masks substantial variation in the operating performance of system-affiliated hospitals as they vary markedly in terms of the structural characteristics of the systems to which they are affiliated and the environmental conditions to which they are exposed, both of which have implications for their operating performance. Two, the studies largely examine hospital performance based on total operating expenses. While system affiliation potentially enhances hospitals' operating performance in certain areas, it may also impede their operating performance in other areas (Burns et al., 2015). As such, if only aggregate performance measures are used the differences may offset one another. Accordingly, we have conducted our investigation to account for different types of hospital systems and have focused on inventory costs as a more targeted, granular performance measure that, theoretically, pertain to an area of operations where system affiliation can make an appreciable difference for hospitals. Thus although evaluating relationships between horizontal inter-organizational arrangements and performance at the level of total operating costs is important, evaluating performance at a more granular level provides additional insights to the operational benefits for this type of arrangement which has important theoretical and practical implications.

The remainder of this paper is organized as follows. In section 2, we present the study's theoretical foundation and hypotheses. In section 3, we outline the data sources, measures, and the econometric methods employed. In section 4, we present the empirical analysis results. In section 5 we discuss the implications of findings to theory, management practice, and policy making. In section 6, we conclude with the study's limitations and directions for future research.

2. Theoretical foundations and hypotheses

Our conceptual framework is presented in Fig. 2. We present and test several hypotheses, two of which relate to key drivers of hospital supply chain risk that are largely outside the purview of hospital managers (i.e., H1a and H1b). We view these as baseline hypotheses that provide the conceptual foundation for advancing and testing the other hypotheses (i.e., H2a, H2b, H3a and H3b), which focus on the effects of system affiliation on hospital inventory costs.

2.1. Environmental conditions

It is well established that environmental conditions significantly influence an organization's supply chain decisions and operations (Flynn et al., 2010; Wiengarten et al., 2014; Swamidass and Newell, 1987; Ward et al., 1995). We focus on two environmental conditions that are potentially critical with respect to a hospital's inventory management: the state of local logistics services infrastructure and demand uncertainty for clinical requirements (Wiengarten et al., 2014; Gittell, 2002).

2.1.1. Logistics services infrastructure

As a macro-level environmental condition that significantly influences the lead time and reliability of the delivery of supplies, logistics services infrastructure where a hospital operates is stipulated to influence inventory accumulation (Wiengarten et al., 2014). In particular, a well-developed logistics services infrastructure can support a range of logistics services and transportation modes enabling suppliers to meet distribution requirements for goods and services (Bookbinder and Tan, 2003). Indeed, the cost and quality of logistics are determined by the availability of competitive logistics service providers as well as by the infrastructure available for them to operate (Arvis et al., 2008). Moreover, logistics services infrastructure affects the level of integration between an organization and its supply chain partners partly because access to well-developed infrastructure minimizes the need for extensive coordination of logistics operations with partners (Wiengarten et al., 2014).

The existing infrastructure that supports local supply chain activity in a geographic region can increase supply risk through its impact on lead times, transportation disruptions, and other adverse events that can negatively affect the timely and accurate delivery of desired supplies (Giunipero and Eltantawy, 2004; Narasimhan and Talluri, 2009; Zsidisin and Ellram, 2003). The economics literature indicates that better developed infrastructure can promote the operating efficiency of organizations by facilitating shorter and more reliable replenishment lead times (Shirley and Winston, 2004). Prior studies in the U.S. and China have found reductions in inventory by manufacturers following transportation infrastructure investment in the regions where the manufacturers were operating in (Li and Li, 2013; Shirley and Winston, 2004). Consequently, logistics services infrastructure is expected to impact a hospital's inventory decisions (Arvis et al., 2008).

Beyond organizations bearing the direct costs associated with moving supplies, they also have to absorb the costs associated with holding higher inventory to hedge against uncertainties resulting from weak logistics services infrastructure (Arvis et al., 2008). As Wiengarten et al. (2014) observes, when logistics services infrastructure is poor, logistics will be slow, unpredictable and expensive. But when logistics services infrastructure is well-developed, logistics will be fast, predictable and inexpensive. As such, lowering replenishment lead times as well as improving their reliability and consistency can be interpreted as a reduction in the degree of exposure to supply chain risk and, therefore, ultimately leading to improved accuracy of forecasts for supplies and reduction in excess inventory (Fisher and Raman, 1996; Lee et al., 1997; Narasimhan

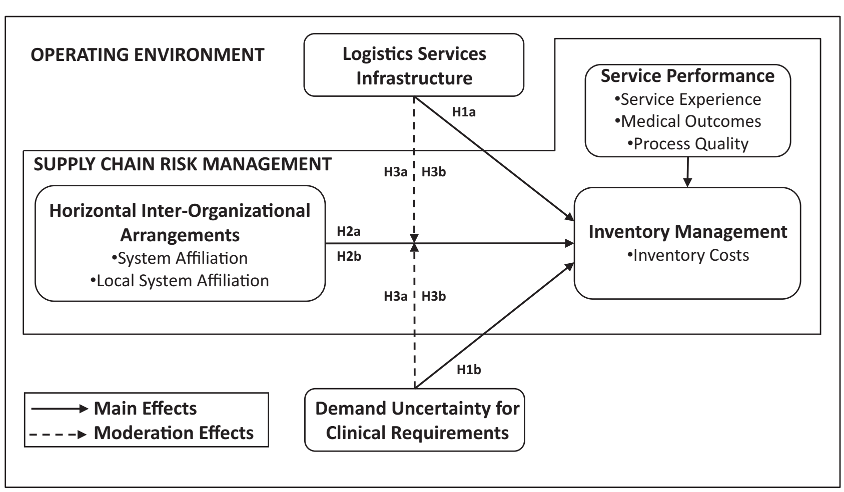

Fig. 2. Research framework in the context of the operating environment for hospital operations depicting the interplay between logistics services infrastructure and demand uncertainty for clinical requirements, horizontal inter-organizational arrangements through system affiliation, and the resulting inventory costs, after controlling for service performance.

and Talluri, 2009). Consequently, we propose that a better developed logistics services infrastructure can influence managers' confidence in their supply chains to support consistent and on-time deliveries, which in turn leads them to determine or recommend lower safety stock (Christopher and Lee, 2004; Davis, 1993).

Because hospital services largely occur locally with hospitals establishing relationships with the patient population that resides in close proximity, supply chain risk should be influenced by the environmental conditions where health care services are provided, in this case the logistics services infrastructure (Chen et al., 2013; Green, 2012; KC & Terwiesh, 2011; Narasimhan and Talluri, 2009; Theokary and Ren, 2011). For example, a hospital located in a remote geographic location (i.e., Del Norte County in California) with relatively underdeveloped logistics services infrastructure faces related supply chain risks that are likely to be much more severe than those faced by a hospital operating in a geographic location with much more developed logistics services infrastructure (i.e., San Diego County in California). Given that hospitals operate in a variety of geographic contexts with varying levels of logistics services infrastructure, this reasoning suggests the following hypothesis:

Hypothesis 1a (H1a). *The better developed a hospital's local logistics services infrastructure, the lower the hospital's inventory costs, after controlling for hospital service performance.*

2.1.2. Demand uncertainty for clinical requirements

Variation in demand is a major factor influencing inventory management and an organization's ability to meet its customer service needs (Lee et al., 1997). High variation in demand tends to lead organizations to hold higher inventory as a buffer against potential shortage and attendant service failure (Fisher and Raman, 1996). In the case of hospitals, demand variation is observed in the clinical requirements to treat patients at any given time (Gittell, 2002). We consider demand uncertainty for clinical requirements to be a salient characteristic of the task environment of hospitals (Ketokivi, 2006). Indeed, for hospitals, the consequences of supply shortages can be particularly severe when the quality of patient care is at stake (Chen et al., 2013). We propose that demand uncertainty for clinical requirements largely depends on the relative demand for the various clinical services that a hospital provides. That is, since hospitals can face demand uncertainty for patient care in terms of both volume and clinical requirements, they need to carefully manage the risk of not having the number and type of items needed in the treatment of each patient. A hospital that consistently experiences demand for one or two clinical services in large volumes relative to the other clinical services it offers is subject to lower demand uncertainty for clinical requirements than a hospital that experiences demand for many different clinical services in relatively equal volumes because the alternatives are equally likely to occur (Gittell, 2002). Consequently, the higher the hospital's demand uncertainty for alternative clinical services, the higher the risk of stockout of needed items because such uncertainty makes it increasingly difficult to reliably forecast the supplies needed to meet demand (Davis, 1993; Lee et al., 1997; Sodhi and Lee, 2007).

Accordingly, from an organization theory perspective, demand uncertainty for clinical requirements is a key element of a hospital's task environment (Argote, 1982; Gittell, 2002). Since the provision of hospital services requires both intangible services supported by supplies as well as supplies supported by intangible services, a hospital's task environment will impact the ability to accurately predict the supplies necessary to carry out required tasks (Berry and Bendapudi, 2007). Consequently, operational failures in hospitals can result from the inability of a hospital's work system to reliably provide supplies when, where, and to whom they are needed (Tucker, 2004). Further, given the lengthy supply lead times observed in the health care sector (Ebel et al., 2013), the lack of an accurate demand signal for required supplies can lead to a further buildup of inventory (Christopher and Lee, 2004; Lee et al., 1997; Paulraj and Chen, 2007). Hence, we posit that the higher the demand uncertainty for clinical requirements that a hospital experiences, the higher the demand uncertainty will be for supplies subsequently increasing inventory costs for hospitals.

Hypothesis 1b (H1b). *The higher the demand uncertainty for a hospital's clinical requirements, the higher the hospital's inventory costs, after controlling for hospital service performance.*

2.2. Horizontal inter-organizational arrangements among hospitals

Organizations within the same industry sectors often collaborate to secure various operational advantages including greater economies of scale, better negotiating leverage with suppliers, and stronger market position (Cruiijssen et al., 2007; Gulati, 1999; Gulati and Singh, 1998; Schmoltzi and Wallenburg, 2011; Zuckerman & D'Aunno, 1990). Past studies have focused on different features of these types of horizontal inter-organizational arrangements such as missions and goals, governance structure, and performance outcomes (Gulati and Singh, 1998; Lunnan and Haugland, 2008). In this study, we focus on horizontal arrangements in the hospital sector. Specifically, we examine affiliation with multi-hospital systems as a mechanism to mitigate supply chain risk for reducing inventory accumulation.

2.2.1. Hospital system affiliation

As noted, substantial consolidation has been occurring in the hospital industry through the formation of hospital systems that entail common ownership of two or more hospitals. As is the case for inter-organizational arrangements generally, hospital systems give rise to different mechanisms by which risk mitigation can occur for inventory management. Oliver (1990, p.246) posits that inter-organizational relationships are often an "adaptive response to environmental uncertainty" because these arrangements enable organizations to "forestall, forecast, or absorb uncertainty in order to achieve an orderly, reliable pattern of resource flows and exchanges." As a form of inter-organizational relationship, system affiliation potentially enables hospitals to mitigate supply chain risk. One such mechanism through which system affiliation can be used to mitigate supply chain risk is enhanced collective bargaining with suppliers and intermediaries (Chen and Roma, 2011; Hardy and Magrath, 1987; Li, 2012). As a group, affiliated organizations pool their orders for products and services, and, in so doing gain from volume economies and better negotiating leverage with suppliers. As such, affiliated organizations extract concessionary transactional terms which can ultimately increase confidence in a supply chain (Christopher and Lee, 2004; Shervani et al., 2007; Tellis, 1989). Group buying helps mitigate supply chain risk because it confers greater price stability, product variety, and product availability for members irrespective of their size and location, which they may otherwise not achieve if they purchased on their own. Such alliances have existed in some form for many years across industries but are more prevalent in sectors such as the hospital industry where buyers can get similar quality from many suppliers so that their purchase decision is based primarily on price (Hardy and Magrath, 1987). For example, Gault (1937) notes that many independent groceries and department stores in 1920s and 1930s extensively used some form of cooperative buying. More recently, logistics service providers, retailers across many industries, and end users such as hospitals have joined group buying organizations and other cooperative arrangements to gain negotiating leverage that comes with collective bargaining (Anand and Aron, 2003; Burns and Lee, 2008; Cruijssen et al., 2007; Hu and Schwarz, 2011; Schmoltzi and Wallenburg, 2011). Because negotiating leverage is conferred through absolute volume of purchases, system-affiliated hospitals will be in a more favorable position than hospitals which operate independently.

Another, perhaps even more important, mechanism is risk pooling (Sodhi and Lee, 2007). By aggregating risk from multiple locations, affiliated organizations can exploit “statistical economies of scale” resulting in what is commonly referred to as the “pooling effect” which reduces inventory costs (Corbett and Rajaram, 2006; Eppen, 1979). This aggregation of risk across the affiliated organizations allows for demand at a stock point that is out of stock to be filled from another stock point that has inventory on hand (Berman et al., 2011; Karsten et al., 2012). That is, inventory is not necessarily physically consolidated at a single location. Instead, organizations have access to inventory physically or virtually that is carried by other affiliated organizations allowing for inventory to be shared among demand locations resulting in lower inventory levels and associated costs while achieving required service levels (Berman et al., 2011; Paterson et al., 2011). As a result, managers have greater confidence that they will have access to supplies when they need them ultimately reducing the overall perception of supply chain risk. Indeed, the reduction in the perception of risk alone can result in lower inventory accumulation among affiliated organizations (Zsidisin and Ellram, 2003). Moreover, risk pooling among such affiliated organizations does not necessarily require explicit policies, directives, or agreements. While risk pooling may occur through such explicit arrangements, it is also possible that risk pooling is tacitly achieved based on a level of familiarity and trust that may occur among managers of different hospitals that are commonly owned. Thus, even though two managers never explicitly agree that they will approve transshipments of supplies for each other, they may assume such cooperation because their hospitals are commonly owned and they possibly meet each other periodically at corporate meetings and engage in other cooperative activities to achieve common system goals. This understanding among managers, though possibly tacit, may lead them to pursue leaner inventories since they know they can rely on other hospitals in the system should an urgent need for supplies arise.

A variety of approaches to risk pooling have been studied in different settings including independent companies forming inter-organizational arrangements related to inventory (see Paterson et al., 2011). In particular, it is generally more efficient for an organization to obtain needed stock from another organization (i.e., risk pooling) that exists at the same level of the supply chain (i.e., sister subsidiaries of the same corporation) than from entities located at higher levels in the supply network (i.e., collective purchasing from a distributor) (Lee, 1987). With this back-up arrangement, organizations can reduce the need to carry safety stock because the ability to access inventory in the system is likely to create a greater psychological sense of security against risks from supply and demand uncertainty. Given the potential for risk pooling or collective purchasing through which system affiliation can be used to mitigate supply chain risk, we propose the following hypothesis.

Hypothesis 2a (H2a). *Hospitals affiliated with systems will have lower inventory costs than independent hospitals, after controlling for hospital service performance.*

Hospital systems differ in many ways including size, geographic scope, and the environmental conditions that affiliated hospitals face. Although several typologies have been put forth to classify hospital systems (i.e., Bazzoli et al., 2000; Burns et al., 2015), key attributes for distinguishing systems are size and (i.e., number of hospitals) and geographic configuration of affiliated hospitals (i.e., Luke, 2006; Burns et al., 2015). On the basis of these attributes, researchers have classified hospital systems as local, regional, or national systems. Local systems are those comprising a relatively small number of hospitals that are geographically proximate to each other whereas regional or national systems comprise a large number of hospitals that are geographically dispersed and, in the case of national systems, span multiple regions of the country (Young et al., 2000; Cuellar and Gertler, 2003; Burns et al., 2015).

Within this typology, the type of system to which a hospital is affiliated may also have implications for its inventory costs. Multi-hospital systems exhibit different levels of integration or what some researchers have referred to as “system-ness” among affiliated hospitals (Burns et al., 2015). The available evidence indicates that compared to regional and national systems, local systems are more tightly integrated based on more centralized coordination of operational activities among affiliated hospitals (Bazzoli et al., 2000; Burns et al., 2012, 2015). This may be due in large part to the fact that such systems have fewer hospitals that are geographically proximate to one another thus enabling a high degree of centralized activity. Burns et al. (2015) also note that national and regional systems tend to have greater bureaucratic impediments for coordinating activities compared to local systems.

Accordingly, local systems appear to have a greater degree of integration relative to those that are national or regional. This greater degree of integration is likely to promote reliable risk pooling arrangements due to greater operational visibility and coordination among system affiliated hospitals. In addition, because local systems have relatively fewer hospitals and these hospitals are in close geographic proximity, the lead time to obtain supplies through transshipments as well as coordination of supply needs within the system is likely to result in lower inventory accumulation for affiliated hospitals. Managers can, therefore, exploit the use of transshipments between affiliated hospitals of such hospital systems as an alternative to relying on the logistic services infrastructure and logistics providers when exercising expedited emergency shipments from suppliers upstream (Tagaras and Cohen, 1992). Such an arrangement is particularly suitable for environments where the transshipment costs between system partners are relatively low compared to the costs of individually holding large amounts of inventory and failing to meet the immediate demand (Paterson et al., 2011). For managers of hospitals affiliated with local systems, just the knowledge that they can obtain supplies within the system in a timely manner may promote the psychological confidence needed to maintain relatively lean inventory levels (Christopher and Lee, 2004).

Hypothesis 2b (H2b). *Hospitals affiliated with local systems will have lower inventory costs than other system affiliated and independent hospitals, after controlling for hospital service performance.*

2.3. Local system affiliation as moderator

As each hospital's environmental conditions vary, a hospital's motivation to exploit the operational benefits of system affiliation may depend on its own environmental conditions. As Flynn et al. (2010) suggest, supply chain integration efforts should be aligned with the environmental context in order to maximize performance. In particular, organizations operating in environments with high supply chain risk can expect to achieve much greater performance improvements from inter-organizational arrangements that enable supply chain integration capabilities than organizations that pursue similar arrangements but face low supply chain risk conditions (Manuj et al., 2014; Wiengarten et al., 2014). This is partly because it is unnecessary for organizations to develop redundant costly logistical and supply chain integration capabilities when operating in munificent and stable environments. Developing strong strategic partnerships to facilitate the understanding and anticipation of supply and demand requirements entails the mutual exchange of information between partners about services, processes, schedules and capabilities (Flynn et al., 2010). As such, organizations facing shorter and more reliable lead-times, and hence have a greater ease in predicting when supplies will arrive, will experience decreasing returns from supply chain integration efforts and thus are better off relying on the more abundant logistics infrastructure and associated logistics services providers. Similarly, when demand is more predictable and stable, organizations face lower risks of stocking out and hence experience decreasing returns from integration efforts with partners and are better off relying on less resource intensive forecast means of coordination. However, since there is much evidence suggesting that the general motivation for hospitals to join hospital systems is for negotiating leverage with insurance plans rather than operating efficiencies (Dafny, 2014; McKone-Sweet et al., 2005), hospitals are likely to find it difficult to exploit the system arrangement and level of integration that provides the greatest benefit in terms of inventory costs (Wiengarten et al., 2014). Consequently, we posit a moderating effect with degree of integration or "system-ness" influencing the impact of supply chain risk on inventory costs. We hypothesize that the mitigating effects of system affiliation for hospitals will vary across supply chain risk conditions with local system affiliation being a more effective risk mitigation approach than national or regional system affiliation when supply chain risk is high.

Hypothesis 3a (H3a). *The relationship between system affiliation and hospital inventory costs is moderated by logistics services infrastructure. Specifically, the effect of system affiliation is stronger for hospitals with weaker logistics services infrastructure with the strongest effect for hospitals affiliated with local systems.*

Hypothesis 3b (H3b). *The relationship between system affiliation and hospital inventory costs is moderated by demand uncertainty for clinical requirements. Specifically, the effect of system affiliation is stronger for hospitals with greater demand uncertainty for clinical requirements with the strongest effect for hospitals affiliated with local systems.*

3. Research methods

3.1. Study design and sample

As noted, in terms of inventory management, service organizations face a risk of stock outs that in a service sector can lead to reduced service performance. As such, it is important to test the study hypotheses while controlling for service performance of the hospitals in the sample. A widely used measure of service performance is available from the Medicare Hospital Compare databases (http://www.medicare.gov/hospitalcompare) which began providing measures from the Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) in 2007 that focuses on patients' perspectives on service experience. Therefore, our study was designed as a 3-year panel analysis of general hospitals in California that were in operation in 2007, 2008, and 2009. We focused on California because the state requires hospitals to submit detailed annual financial reports that include data elements relating to inventory costs. Additionally, California has a large and diverse hospital industry that enabled us to examine the impact of a range of hospital characteristics on inventory costs. By confining the study to a single state, we were able to insulate the study from potential confounders due to interstate differences in regulatory and economic conditions that were not of central interest to the study. To conduct the research study, we combined several sources of secondary data and combining the data for years 2007, 2008, and 2009 to create a pooled, cross-sectional study sample of hospitals.

3.2. Measures

3.2.1. Dependent Variable

The dependent variable for the study was a hospital's inventory costs. We used the California Hospital Financial Disclosure Report (CFDR) available from the state Office of Statewide Health Planning and Development, which provided detailed financial, structural, and operational information for hospitals. Consistent with prior inventory performance research that uses financial reports (i.e., Emery and Marques, 2011; Mishra et al., 2013; Shah and Shin, 2007), we obtained each hospital's inventory costs from the hospital's balance sheet available from the CFDR. There are a variety of ways to operationalize inventory performance (Eroglu and Hofer, 2011; Shah and Shin, 2007). As such, in order to compare inventory costs among the different hospitals and provide a robustness check, we standardized the inventory costs measure in three ways by dividing it by hospital operating expenses, operating revenue, and supply chain expenses also available from the CFDR.[2]

3.2.2. Independent variables

Our study had four independent variables corresponding to the key concepts of supply chain risk and risk buffering. For supply chain risk, we operationalized one measure for logistics services infrastructure (i.e., supply risk) (*LGSINFRA*) and one measure for demand uncertainty for clinical requirements (i.e., demand risk) (*CLINICREQ*). *LGSINFRA* was based on the number of establishments per square mile in the county in which the focal hospital operates in with their core business activity being transportation (i.e., by air, rail, truck, and water) and warehouse operations. We obtained these data from County Business Patterns Database (http://www.census.gov/econ/cbp/) from U.S. Census Bureau by looking at the two digit NAICS code 48 for transportation and warehouse operations and excluding NAICS code 487, scenic and sightseeing transportation operations, which are not related to logistics activity. Consistent with prior macro-level logistics services infrastructure capabilities research, although the *LGSINFRA* measure does not account for the specific infrastructural elements that each hospital employs with regard to inbound supplies, it does provide a representation of key macro-level logistics services infrastructural elements available where a hospital operates, namely those that facilitate transportation and warehousing operations (Arvis et al., 2008; Shirley and Winston, 2004; Wiengarten et al., 2014). The absence of such logistics services infrastructural elements can affect the inward flow of required supplies and ability to meet customer requirements which are risk characteristics observed in Zsidisin (2003) that operations managers commonly perceive and seek to buffer. To provide a notion of the extent of the variation in logistics services infrastructure that U.S. hospitals contend with, California has over 4 times as many transportation and warehouse

[2] We performed additional sensitivity analyses on the dependent variable. To account for the potential association between outsourcing and inventory costs, we excluded the purchased services expenses from the operating budget. In addition, we calculated the ratio of medical to all supplies expenses and applied the ratio to the inventory cost measure. To evaluate the potential impact of inventory costing methods on the dependent variable, we performed the analyses using operating expenses as a control variable and leaving the non-scaled inventory measure as the dependent variable. The results did not change materially, providing robustness to reported results.

operations establishments per square mile than Maine and 2.5 times as many transportation and warehouse operations establishments per square mile than the U.S. overall. Other more urbanized states such as New York and Florida have more comparable logistics services infrastructure to California. Due to the skew of the distribution and to meet the model normality assumptions, we log transformed the variable.

For *CLINICREQ*, we followed previous research on hospitals that focused on the clinical requirements that a hospital experiences (Argote, 1982; Gittell, 2002). The higher the demand uncertainty for clinical requirements (i.e., increasing the likelihood of alternative clinical requirements), the higher the risks of stockout as hospitals are less able to forecast inventory requirements for their clinical work flows. We used a list of fifteen patient conditions from the CDFR that comprise all conditions that acute care hospitals treat (9 outpatient – i.e., ER, psychiatric, hospice, ambulatory surgery; and 6 inpatient – acute care, psychiatric, chemical dependency, rehabilitation, long-term, and other). For example, a hospital that treats patients among all fifteen of these conditions in relatively equal portions is subject to higher demand uncertainty for clinical requirements and thus greater supply chain risk than a hospital whose patients are largely concentrated in just three or four of these clinical conditions. We computed for each of the conditions the proportion of patients that a hospital experienced and then calculated the variance of the computed proportions at each hospital. Following Gittell (2002), the demand uncertainty for clinical requirements measure was generated by taking the inverse of the variance of the computed proportions. For this study, the *CLINICREQ* at each hospital provides a statistical measure of dispersion for the health care services provided. Therefore, in order to be consistent with Hypothesis 1b, the greater the *CLINICREQ* measure the more homogeneous the distribution of the different health care services are (i.e., lower variance of the computed proportions) and hence the less 'focused' a hospital will be on certain service types. Therefore, an increase in the *CLINICREQ* measure is interpreted as an increase in demand uncertainty for clinical requirements. Due to the skew of the distribution and to meet the model normality assumptions, we log transformed the variable.

For system affiliation, we operationalized two measures: (1) whether a hospital was affiliated with a hospital system (*SYSAFF_DUMMY*) and (2) the type of system to which a hospital was affiliated – local, regional or national (*SYSAFF*). To classify system-affiliated hospitals based on the type of system to which they were affiliated, we followed previous research by focusing on the number and geographic configuration of affiliated hospitals (Cuellar and Gertler, 2003; Burns et al., 2012, 2015). We set *SYSAFF_DUMMY* to one if the hospital reported being affiliated with a hospital system and zero otherwise. For type of system, we assigned each hospital to one of four categories. Specifically, hospitals were assigned a zero if it was not affiliated to a hospital system; a 1 if it belonged to a local system (i.e., number of hospitals is 5 or fewer; the average distance between affiliated hospitals and corporate office was less than 14 miles), a 2 if it belonged to a regional system (i.e., number of hospitals is between 6 and 20 spanning multiple markets; the average distance between affiliated hospitals and corporate office was less than 65 miles, and a 3 if it was affiliated with a national system (i.e., more than 20 hospitals spanning multiple regions of the country; the average distance between affiliated hospitals and the corporate office was over 400 miles). These thresholds, which are comparable to those used in previous research on hospital systems (i.e., Burns et al., 2015), resulted in 126 observations for the local system, 201 for the regional systems, and 202 observations for the national system categories. Our categories are further distinguished based on the location of the system's corporate office as 43% of the observations classified in the national system category have their corporate office located outside the State of California versus only 6% of the observations classified in the local system category (see online appendix). Also, as some researchers measure a system's geographic configuration based on average distance among hospitals (rather than in relation to corporate office), we re-examined our classification of system-affiliated hospitals after using this approach but found that it had almost no impact on how sample hospitals were classified. The data for assigning hospitals into these categories came from the American Hospital Association (AHA).

Additionally, we examined alternative dimensions for classifying hospital systems. As discussed in Burns et al. (2015), an alternative classification of hospital systems, available from the AHA and based on survey data, focuses largely on how centralized a system is in terms of its clinical activities across affiliated hospitals. We examined the agreement between this classification approach and the one we used for the study, which should distinguish systems in part based on centralization of services because, as noted, local systems have been found to be more centralized. We found a moderately strong pattern of agreement between this alternative approach and the one we used that was based on number and geographic configuration of hospitals with 35% of the observations classified in the local system category also falling in the high or moderate degree of centralization across products and services versus only 18% of the observations classified in the national system category. Beyond centralization, our system classification approach captures additional important dimensions that have potential implications for inventory management including geographic proximity of affiliated hospitals. We performed additional robustness analyses that accounted for this centralization dimension and have reported the results in the robustness section.

3.2.3. Control variables

Consistent with suggestions by Brook et al. (1996), hospital service performance should include measures related to medical outcomes, patient experience, and process quality. We obtained various hospital service performance measures available in the Medicare Hospital Compare databases (see Appendix A). Since some hospitals have missing data for these performance measures, we follow Powell et al. (2012) to address the missing hospital service performance data.[3] The ten measures related to patients' perspectives on service experience available in the Medicare Hospital Compare databases relate to overall hospital rating and recommendation, doctor and nurse communication, pain control, hospital cleanliness and quietness. All available measures on the database require more than 300 patients to respond to the HCAHPS survey. Patient service experience (*SERVICE*) was operationalized as an average of two measures: (1) the proportion of patients that reported giving the hospital a rating of 9 or 10 and (2) the proportion of patients that reported receiving timely service when needed. We set *SERVICE* equal to the national hospital average of the two service performance measures when it is missing and include a dummy variable (*SERV_DUMMY*) that takes the value of one when there is no reported patient service experience and zero otherwise.

We followed Andritsos and Tang (2014) to create hospital service performance indexes for medical outcomes and process

[3] The extent of omitted observations used for the service performance variables was: 20.5% (180 out of 878) of the observations did not report a patient service satisfaction measure (*SERV_DUMMY* = 1), 8.7% (70 out of 878) of the observations did not report a mortality rate measure (*MORT_DUMMY* = 1), and 9.0% (79 out of 878) of the observations did not report a process of care measure (*PROC_DUMMY* = 1).

quality. For medical outcomes, three 30-day mortality rates are available in the Medicare Hospital Compare databases, namely heart failure, heart attack, and pneumonia. We operationalized one measure for medical outcomes (*MORTALITY*) by taking the weighted average of two 30-day mortality rates: (1) the mortality rate from hearth failure after 30-days of discharge and (2) the mortality rate for pneumonia after 30-days of discharge. We set *MORTALITY* equal to the national hospital average of the two 30-day mortality rates when it is missing and include a dummy variable (*MORT_DUMMY*) that takes the value of one when there is no reported mortality rate and zero otherwise. Lastly, we operationalized on measure for process of care quality (*PROCESS*) by creating a weighted average of fifteen process of care quality measures related to heart attack, heart failure, pneumonia, surgery, and children with asthma (see Appendix A for a detailed description of each measure). We set *PROCESS* equal to the national average of the fifteen process of care quality measures when it is missing and include a dummy variable (*PROC_DUMMY*) that takes the value of one when there is no reported process of care measure and zero otherwise.[4]

Consistent with previous literature, our analysis included several additional control variables to account for hospital-level or market-level factors that could influence hospital supply chain costs but are not pertinent to study hypotheses. Organization size can influence the extent to which human and financial resources are dedicated for risk reduction and supplier development practices which have been suggested as practices to address supply risk (Zsidisin and Ellram, 2003). We operationalized hospital size with the number of beds (*BEDS*). The number of beds is a good proxy for a hospital's supply chain needs since as the number of beds increases so does the need for supplies. We used the number of beds in operation and obtained these data from the CDFR. Due to the skew of the distribution and to meet the model normality assumptions, we log transformed the variable. Government based payer-mix (*GOVPAYER*) was operationalized by the share of patient revenue that is from the two largest U.S. government insurance programs, Medicare and Medicaid, obtained from the CDFR. Given that the two programs account for a substantial proportion of care provided by hospitals, cost containment efforts and limits on reimbursement rates can significantly impact a hospitals operating ability (Rauscher and Wheeler, 2010).

To obtain data pertaining to hospitals' purchases of supplies through group purchasing organizations (GPOs), we communicated via email and telephone with key representatives of study hospitals. From each representative, we requested they provide for each year of the study and within pre-specified ranges the percentage of total supply purchases that the hospital made, individually or in combination, through five of the country's largest GPOs (i.e., Amerinet, HealthTrust Purchasing Group, MedAssets, Novation, and Premier). We focused on these five GPOs as they are likely to offer hospital's the greatest negotiating leverage with vendors (U. S. GAO, 2014). We cross checked the information we obtained from our own data collection effort with data from AHA data regarding the GPOs hospitals reported having a relationship with. Most hospitals had very consistent purchasing patterns during the study time period. As such, we specified GPO purchasing as a dichotomous variable (*NATGPO*), with 1 indicating that the hospital reported for a given year purchasing more than 60% of its total supply purchases through one or more of the five national GPOs and zero otherwise. In addition, some hospitals are affiliated with medical schools and participate in graduate medical education by training physicians as part of residency and fellowship programs (Clark and Huckman, 2012). We specified teaching status (*TEACH*) as a dichotomous variable with one referring to a hospital that reported having a residency program and zero otherwise. Hospital information technology related to the delivery of health care services (Agarwal et al., 2010) was operationalized by a dichotomous variable with one indicating the existence of an electronic health record system (*EHR*) and zero otherwise. These data were obtained from the annual AHA survey.

From the CDFR database, we included a set of dummy variables to account for a hospital's type of ownership (Bazzoli et al., 2000): not-for-profit (*NONPROF*), government (*PUBLIC*), and private (*PRIVATE*) ownership. In order to account for a hospital's workload level (Kc and Terwiesch, 2009) we included a measure for occupancy rate (*OCCUP*), which indicates the percentage of beds that are occupied on average at any point in time during a twelve month period. Hospitals also vary in terms of the risk levels of the patient population that they provide services for (KC & Terwiesch, 2011). We accounted for the hospital Case Mix Index (*CMI*), which refers to the average level of complexity of a hospital's patients in terms of the resources required to manage their care. A higher hospital Case Mix index is associated with more resources used in managing the care of patients. We obtained these data from the State of California Office of Statewide Health Planning and Development (OSHPD) (www.oshpd.ca.gov/HID/Products/PatDischargeData/CaseMixIndex/). To measure market competition, we used the Hirschman-Herfindahl index (*HHI*) for each hospital market as designated by HRRs reported in Dartmouth Atlas of Health Care (Burgess et al., 2005). We computed the HHI as the sum of the square of the market shares of all hospitals in each HRR. Each hospital's market share was based on its percentage of the total number of hospitals admissions that occurred in the HRR during the year. Finally, we controlled for time-dependent trends by including a continuous variable for the year (*YEAR*). We centered log(*LGSINFRA*), log(*INVCLINICREQ*), and *YEAR* for interpretation of interaction and temporal effects.

3.3. The econometric methods

Using the ZIP Code for the individual hospital, we linked the individual hospitals to their respective county. After merging the various data sources, our sample included 307 unique hospitals that operated in 55 counties that reported providing a total of 127,110,689 services (8,303,518 inpatient and 118,807,171 outpatient) across 15 service categories (6 inpatient and 9 outpatient) in the state of California from 2007 to 2009 (i.e., 878 observations) (see Tables 1 and 2).

To reduce the potential for biased standard errors in estimating the county-level effect of *LGSINFRA*, we employed a linear mixed effects model (LMM) with random intercepts by nesting the individual hospitals in their respective counties to estimate the log(*Inventory Costs*) for hospitals. Mixed-effects models provide statistical tools for the analysis of grouped data including multilevel and longitudinal data, as is the case of the data analyzed in this study (see Pinheiro and Bates, 2000). Let j denote the counties, let i denote the hospitals nested within counties, and let t denote the year. We specify a LMM function which converts the expected log(*Inventory Costs*) in hospital i operating in county j in year t to linear predictors as follows:

$$\log(Inventory\,Costs)_{ijt} = \beta_0 + \boldsymbol{X}_{jt}\boldsymbol{\beta} + \boldsymbol{Z}_{ijt}\boldsymbol{\gamma} + (\boldsymbol{XZ})_{ijt}\boldsymbol{\delta} + (\boldsymbol{ZZ})_{ijt}\boldsymbol{\zeta} + \alpha YEAR_t + u_{0ij} + u_{1ij}YEAR_t + v_{0j} + \varepsilon_{ijt} \quad (1)$$

[4] We included additional individual service performance measures related to medical outcomes (heart attack mortality rates) and patient service experience (hospital recommendation rates). The results of the analysis did not change materially. Due to high colinearity between some of the service performance measures, we retained the service performance measures indicated in Appendix A in the final analyses.

with random effect parameters,

$$\begin{pmatrix} u_{0ij} \\ u_{1ij} \end{pmatrix} \sim N\begin{pmatrix} 0 & \sigma^2_{u0} & \rho \\ 0, & \rho & \sigma^2_{u1} \end{pmatrix},$$
$$v_{0i} \sim N\left(0, \sigma^2_{v0}\right),\ and$$
$$\varepsilon_{ijt} \sim N\left(0, \sigma^2_{\varepsilon}\right)$$

where $\times$ is the vector of regressors at the county level with effects $\boldsymbol{\beta}$, $\boldsymbol{Z}$ is the vector of regressors at the hospital level with effects $\boldsymbol{\gamma}$, ($\boldsymbol{XZ}$) is the vector for interaction between the county level and hospital level with $\boldsymbol{\delta}$ effects, ($\boldsymbol{ZZ}$) is the vector for interaction at the hospital level with $\boldsymbol{\zeta}$ effects. We also expect some year-to-year variation in hospital inventory due to other factors at the level of the hospital and at the level of the county in which the hospital is located. Therefore, α corresponds to the *YEAR* effect to capture a linear time trend, u_{0ij} corresponds to the random intercept for each hospital i operating in county j, u_{1ij} corresponds to the random slope component for each hospital i operating in county j with respect to year t, v_{0j} corresponds to the random intercept for each county j, and ε_{ijt} is the random error term.[5] Our LMM specification allows for the nested structure of the random effect, u_{0ij}, for hospitals in counties and for the correlation, ρ, between the random effects u_{0ij} and u_{1ij} for the same hospital. We utilize the statistical computing software '*R*' and the *lme4* package to estimate the LMM models via maximum likelihood and report the log likelihood, AIC, the marginal and conditional R^2, and goodness of fit chi-square statistic. For mixed-effects models, R^2 can be categorized into marginal R^2 and conditional R^2 where the conditional R^2 includes the variance explained after including the random effects component of the mixed-effects model (Nakagawa and Schielzeth, 2013). Significance of regressors was obtained using the *lmerTest* package which provides *p-values* using the Satterthwaite approximation for the denominator degrees of freedom. After adding the covariates to the model, 11.5% of the variance of log(*Inventory Costs*) was attributed to the county where a hospital is operating ($\widehat{\sigma^2_{v0}}$) with 66.5% of the variance of log(*Inventory Costs*) attributed to the hospitals ($\widehat{\sigma^2_{u0}}$ and $\widehat{\sigma^2_{u1}}$).

4. Results and robustness checks

4.1. Inventory to operating expenditures

Model (1) in Table 3 contains the results of the baseline model which includes the main effects of log(*LGSINFRA*) and log(*CLINICREQ*) on hospital inventory costs as operationalized by inventory to operating expenditures.[6] In support for Hypothesis 1a and Hypothesis 1b, we find that the coefficient of log(*LGSINFRA*) is negative and significant ($\beta = -0.070$, *p-value* $= 0.031$) and the coefficient of log(*CLINICREQ*) is positive and significant ($\gamma = 0.097$, *p-value* $= 0.008$) suggesting that logistics services infrastructure is associated with lower hospital inventory costs and demand uncertainty for clinical requirements is associated with higher hospital inventory costs, after controlling for hospital service performance. These results provide support for the association between operating environment drivers of supply chain risk (i.e., weaker logistics services infrastructure and higher demand uncertainty for clinical requirements) and hospital inventory costs. With respect to the control variables, the following results remained consistent across all models. We find that the coefficient of *CMI* ($\gamma = 0.203$, *p-value* $= 0.043$) is positive and significant suggesting that a greater CMI index is associated with higher hospital inventory costs. In contrast, we find that the coefficients of *PROCESS* ($\gamma = -0.005$, *p-value* $= 0.005$), *GOVPAYER* ($\gamma = -0.003$, *p-value* $= 0.022$), and *OCCUP* ($\gamma = -0.003$, *p-value* $= 0.006$) are negative and significant suggesting that better process of care quality, a greater reliance on reimbursements from government insurance plans, and higher occupancy rates are associated with lower hospital inventory costs.

Models (2) and (3) in Table 3 contain the main effect results after adding *SYSAFF_DUMMY* and *SYSAFF* to Model (1), the baseline model. In contrast to our hypothesis, we find the coefficient for *SYSAFF_DUMMY* is not significant and therefore the results do not support Hypothesis 2a that hospital system affiliation is associated with lower inventory costs. Consistent with the results in Model (2), we find that the coefficients for the different types of *SYSAFF* are not significant and therefore the results do not support Hypothesis 2b that hospitals affiliated with local systems (*SYSAFF* $= 1$) have lower inventory costs than other system affiliated (*SYSAFF* $= 2$ and 3) and independent hospitals (*SYSAFF* $= 0$).

Models (4) and (5) in Table 3 contain the results of adding the interaction of *SYSAFF_DUMMY* with log(*LGSINFRA*) and log(*CLINICREQ*), respectively. The significance of an interaction coefficient corresponds to a statistically significant difference in the effects of log(*LGSINFRA*) and log(*CLINICREQ*) on inventory costs between hospitals affiliated with a system (*SYSAFF_DUMMY* $= 1$) and those hospitals without a system affiliation (*SYSAFF_DUMMY* $= 0$). We find that the coefficient for the interaction term between *SYSAFF_DUMMY* and log(*LGSINFRA*) is positive and marginally significant ($\delta = 0.063$, *p-value* $= 0.068$). As expected, the interaction plot in Fig. 3 shows that the effect of weak logistics services infrastructure on higher hospital inventory costs is less severe for hospitals affiliated with a hospital system (*SYSAFF_DUMMY* $= 1$) than those that are independent (*SYSAFF_DUMMY* $= 0$). Thus the results support Hypothesis 3a that hospital system affiliation buffers hospitals from the effect of weak logistics services infrastructure on inventory costs. In contrast to our expectation, we find the coefficient for the interaction between *SYSAFF_DUMMY* and log(*CLINICREQ*) is not significant and therefore the results do not support Hypothesis 3b that hospital system affiliation buffers hospitals from the effect of demand uncertainty for clinical requirements on inventory costs.

Models (6) and (7) in Table 3 contain the results of adding the interaction of *SYSAFF* with log(*LGSINFRA*) and log(*CLINICREQ*), respectively. In contrast to Models (4) and (5), the significance of an interaction coefficient corresponds to a statistically significant difference in the effects of log(*LGSINFRA*) and log(*CLINICREQ*) on inventory costs between hospitals affiliated with different types of systems (*SYSAFF* $= 1, 2, 3$) and those that are independent (*SYSAFF* $= 0$). With respect to Hypothesis 3a, which concerns local system affiliated hospitals' potential to buffer the effect of weak logistics services infrastructure on inventory costs, we find that the coefficient for the interaction of hospitals affiliated with local hospital systems (*SYSAFF* $= 1$) with log(*LGSINFRA*) is positive and significant ($\delta = 0.183$, *p-value* $= 0.006$). As expected, the interaction plot in Fig. 4 shows that the effect of weak logistics services infrastructure on higher hospital inventory costs is much less severe for

[5] The linear time trend captures some of the unobserved time series heterogeneity in our model. While individual dummy variables can also be employed, we consider a linear time trend in our specification to capture trends related to increasing pressures observed in the hospital industry for cost reduction and quality improvement. We also tested an alternative specification using dummy variables for each year to capture specific year effects while retaining the u_{1ij} random slope component with respect to the time trend. The results did not change materially.

[6] We used the *vif.mer* function in '*R*' to check for multicollinearity in the independent variables of the LMM main effects model. All variance inflation factors were well below 10 thus alleviating concerns of unstable coefficients.

Table 1
Summary statistics; N = 878, hospitals = 307, counties = 55.

Variable	Description	Min	Max	Mean	SD
INV to EXP	Inventory to operating expenses	0.001	0.058	0.016	0.008
INV to REV	Inventory to operating revenue	0.001	0.054	0.016	0.008
INV to SC	Inventory to supply chain expenses	0.004	0.304	0.064	0.038
LGSINFRA	County level logistics services infrastructure	0.00	7.55	0.88	1.24
CLINICREQ	Demand uncertainty for clinical requirements	5.20	139.00	35.69	21.30
SYSAFF_DUMMY	0 = independent, 1 = hospital system	0.00	1.00	0.61	0.49
SYSAFF	0 = independent, 1 = local, 2 = regional, 3 = national	0.00	3.00	1.29	1.21
SERV_DUMMY	1 = hospital did not report a *TIMELYSERVC* measure	0.00	1.00	0.21	0.40
MORT_DUMMY	1 = hospital did not report a *MAORTALITY* measure	0.00	1.00	0.08	0.27
PROC_DUMMY	1 = hospital did not report a *PROCESS* measure	0.00	1.00	0.09	0.29
SERVICE	Average of percent of patients giving the hospital a high rating and the percent of patients reporting having received timely service	25.00	81.00	51.66	9.45
MORTALITY	Weighted average of heart failure and pneumonia related mortality rate after 30 days	0.00	19.00	12.41	4.22
PROCESS	Weighted average for 15 process of care quality measures related to heart attack, heart failure, pneumonia, surgery, and children with asthma	34.32	100.00	87.85	10.55
BEDS	Hospital beds	10.00	942.00	214.80	160.26
GOVPAYER	Percent of net patient revenue from medicare/medicaid	11.74	99.19	55.68	18.90
MSA	1 = county is a metropolitan statistical area	0.00	1.00	0.90	0.31
HHI	Hirschman-Herfindahl index	0.00	1.00	0.06	0.14
OCCUP	Occupancy rate	10.75	99.90	60.33	15.63
CMI	Case mix index	0.52	3.36	1.15	0.27
NATGPO	1 = hospital reported purchasing more than 60% through national GPOs	0.00	1.00	0.53	0.50
EHR	1 = hospital reported having an electronic health record	0.00	1.00	0.27	0.44
TEACH	1 = hospital has a teaching program	0.00	1.00	0.22	0.41
PUBLIC	1 = hospital is public	0.00	1.00	0.21	0.41
FORPROFIT	1 = hospital is for profit	0.00	1.00	0.24	0.43
YEAR	Year	2007	2009	2008	0.82

hospitals affiliated with small local hospital systems (*SYSAFF* = 1) than those that are independent (*SYSAFF* = 0). Further, we find that the coefficients for the interaction for hospitals affiliated with regional (*SYSAFF* = 2) or national (*SYSAFF* = 3) hospital systems and log(*LGSINFRA*) are positive but not significant ($\delta = 0.022$, *p-value* = 0.610 and $\delta = 0.065$, *p-value* = 0.140). Therefore, hospitals with weaker logistics services infrastructure that are affiliated with local hospital systems exhibit lower inventory costs compared to hospitals that operate independently or are affiliated with relatively larger hospital systems. Lastly, although we find that the coefficient for the interaction of hospitals affiliated with a small hospital system (*SYSAFF* = 1) with log(*CLINICREQ*) is negative, it is not significant ($\zeta = -0.141$, *p-value* = 0.160) and therefore the results do not support Hypothesis 3b.

4.2. Robustness checks

4.2.1. Alternative inventory costs measures

As a robustness check, we performed the previously discussed analyses using alternative inventory costs measures. Models (8)–(11) in Appendix B contain the results of the moderation effects of hospital system affiliation on hospital inventory costs as operationalized by inventory to operating revenue.[7] Models (12)–(15) in Appendix B contain the moderation effects of hospital system affiliation on hospital inventory costs as operationalized by inventory to supply chain expenses. We combined the costs of supplies and purchased services in computing supply chain expenses. In both cases, the coefficients of interaction between (*SYSAFF* = 1) and log(*LGSINFRA*), were positive and significant ($\delta = 0.204$, *p-value* = 0.003 and $\delta = 0.276$, *p-value* < 0.001) suggesting that the effect of weak logistics services infrastructure on higher hospital inventory costs is less severe for hospitals affiliated with local hospital systems (*SYSAFF* = 1) than those that are independent (*SYSAFF* = 0) or affiliated with regional or national hospital systems (*SYSAFF* = 2 and 3).

4.2.2. Propensity score analysis

We employed a matching procedure as outlined by Ho et al. (2011) in order to create a data set that looks closer to one that would result from a perfectly blocked and possibly randomized experiment where the treatment variable of interest is a hospital's affiliation in a small hospital system. This matching approach works toward creating a subset of the data with the distribution of covariates to be as similar as possible within the matched treated and control groups. The 2-step approach preprocesses the data by generating propensity scores employing a logit model with a dichotomous dependent variable of whether or not a hospital is affiliated with a small hospital system and generates a subset of the original data comprising a matched set of hospitals based on balancing the propensity score distribution between the treatment and control groups based on the control variables in the model. We employ the *MatchIt* package in 'R' and used the *genetic* algorithm with replacement and a ratio of 2 matched controls for every treated hospital in the matched sample. We select the option to allow the matching algorithm to retain all treated hospitals and choose a subset or repeated hospitals from the control group. The second step of the matching analysis employs weighted LMM parametric analysis following matching to account for the repeated use of certain observations used as controls. The matched sample consisted of 126 observations in the treatment group and 158 observations in the control group for a total matched sample of 284 observations across the three year panel, 97, 88, and 99 observations respectively.[8] The difference in the mean propensity score for affiliating with a small hospital system (*SYSAFF* = 1) between the

[7] All variance inflation factors were well below 10 thus alleviating concerns of unstable coefficients.

[8] We included independent (*SYSAFF* = 0) as well as regional (*SYSAFF* = 2) and national (*SYSAFF* = 3) system affiliated hospitals in the control group since we did not did not find (i.e., Models 6 and 7) a statistically significant difference in their slopes across supply chain risk conditions.

Table 2
Correlation coefficients of variables.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
1 log(*INV to EXP*)	1.00																								
2 log(*INV to REV*)	**0.98**	1.00																							
3 log(*INV to SC*)	**0.89**	**0.90**	1.00																						
4 log(*LGSINFRA*)	**−0.21**	**−0.20**	**−0.34**	1.00																					
5 log(*CLINICREQ*)	**0.09**	0.05	−0.02	**0.09**	1.00																				
6 *SYSAFF_DUMMY*	0.02	−0.04	**−0.17**	**0.19**	**0.13**	1.00																			
7 *SYSAFF*	0.06	−0.01	**−0.12**	**0.12**	**0.15**	**0.86**	1.00																		
8 *SERV_DUMMY*	−0.01	0.04	**0.13**	**−0.22**	**−0.18**	**−0.26**	**−0.28**	1.00																	
9 *MORT_DUMMY*	0.03	0.05	**0.14**	**−0.20**	**−0.12**	**−0.16**	**−0.16**	**0.54**	1.00																
10 *PROC_DUMMY*	0.00	0.04	**0.12**	**−0.21**	**−0.14**	**−0.19**	**−0.20**	**0.55**	**0.77**	1.00															
11 *SERVICE*	0.03	0.05	**0.09**	**−0.16**	**−0.10**	**−0.09**	**−0.11**	**0.64**	**0.35**	**0.37**	1.00														
12 *MORTALITY*	**0.07**	0.03	−0.05	**0.07**	**0.26**	**0.16**	**0.22**	**−0.23**	**0.08**	−0.05	**−0.11**	1.00													
13 *PROCESS*	**−0.10**	**−0.14**	**−0.21**	**0.08**	**0.07**	**0.30**	**0.36**	**−0.32**	0.04	**0.07**	**−0.13**	**0.39**	1.00												
14 log(*BEDS*)	**−0.14**	**−0.15**	**−0.27**	**0.53**	**0.30**	**0.23**	**0.17**	**−0.39**	**−0.38**	**−0.36**	**−0.19**	**0.35**	**0.24**	1.00											
15 *GOVPAYER*	**−0.18**	**−0.08**	−0.05	**0.12**	−0.05	**−0.13**	**−0.18**	**0.22**	0.05	0.06	**−0.09**	**−0.15**	**−0.33**	0.02	1.00										
16 *MSA*	**−0.18**	**−0.19**	**−0.32**	**0.65**	**0.11**	**0.08**	0.05	**−0.27**	**−0.30**	**−0.28**	**−0.21**	**0.12**	0.04	**0.50**	0.04	1.00									
17 *HHI*	**0.12**	**0.12**	**0.22**	**−0.50**	**−0.16**	**−0.12**	−0.06	**0.12**	**0.12**	**0.11**	**0.11**	**−0.08**	−0.06	**−0.35**	**−0.13**	**−0.31**	1.00								
18 *OCCUP*	−0.06	**−0.07**	**−0.07**	0.04	**0.13**	**0.09**	0.01	**−0.12**	**−0.10**	**−0.10**	−0.06	**0.16**	0.04	**0.37**	0.07	**0.12**	**−0.09**	1.00							
19 *CMI*	0.06	0.04	**−0.11**	**0.27**	−0.05	**0.18**	**0.15**	**−0.18**	0.00	−0.02	−0.05	**0.20**	**0.29**	**0.31**	**−0.24**	**0.18**	**−0.15**	0.03	1.00						
20 *NATGPO*	0.04	0.03	0.03	−0.05	**0.08**	0.06	−0.01	**−0.12**	**−0.08**	**−0.14**	−0.01	**0.15**	**0.12**	**0.18**	−0.06	**−0.07**	−0.04	**0.19**	**0.12**	1.00					
21 *EHR*	0.01	−0.01	0.00	0.00	0.04	0.00	−0.01	**−0.15**	**−0.12**	**−0.12**	−0.02	**0.15**	**0.19**	**0.23**	**−0.08**	0.00	−0.04	**0.10**	**0.09**	**0.35**	1.00				
22 *TEACH*	**−0.07**	−0.06	**−0.09**	**0.18**	**−0.08**	0.06	**−0.09**	**−0.09**	**−0.07**	**−0.08**	0.02	0.06	**0.09**	**0.33**	**−0.07**	**0.09**	**−0.11**	**0.20**	**0.31**	**0.21**	**0.10**	1.00			
23 *PUBLIC*	−0.06	0.04	**0.16**	**−0.32**	**−0.25**	**−0.41**	**−0.42**	**0.25**	**0.16**	**0.22**	**0.09**	**−0.17**	**−0.21**	**−0.19**	**0.20**	**−0.17**	**0.18**	**0.09**	**−0.28**	0.03	**−0.08**	0.01	1.00		
24 *FORPROFIT*	−0.01	−0.02	**−0.09**	**0.29**	0.00	**0.12**	**0.19**	**0.07**	0.00	0.03	**−0.09**	**−0.10**	**−0.09**	−0.03	**0.24**	**0.17**	**−0.18**	**−0.19**	**0.08**	**−0.26**	**−0.19**	**−0.12**	**−0.29**	1.00	
25 *YEAR*	−0.03	−0.04	−0.02	0.00	−0.03	0.01	0.01	**−0.23**	0.05	0.02	**−0.52**	−0.01	**0.32**	−0.01	0.00	−0.01	0.00	−0.02	**0.13**	0.00	0.01	0.00	0.00	0.00	1.00

Note: Bold values indicate $p < 0.05$.

control and matched groups was improved by 95% by employing propensity score matching. Models (16)–(18) in Appendix B contain the results for the propensity score analysis for evaluating the effect of the interaction between ($SYSAFF = 1$) and log(*LGSINFRA*) on the three different operationalization for inventory costs suggesting that the effect of weak logistics services infrastructure on higher hospital inventory costs is less severe for hospitals affiliated with local hospital systems ($SYSAFF = 1$) than the controls.

4.2.3. Alternative system integration (“system-ness”) measure

As noted, we examined an alternative classification of hospital systems based on centralization of clinical activities (*SYSCENT*). As this alternative dimension of hospital systems might foster lower inventory costs, we conducted robustness analyses that accounted for this dimension. Following the approach discussed in Burns et al. (2015), we operationalized a dichotomous centralization measure by coding *SYSCENT* as a one if a hospital was affiliated with a centralized or moderately centralized hospital system and zero otherwise. The category $SYSCENT = 1$ consists of hospital systems with a high or moderate degree of centralization across clinical services (Burns et al., 2015). We include *SYSCENT* as a control variable to account for potential strategic and structural differences related to the degree of centralization and find no material difference in the results. Models (19)–(21) in Appendix B contain the results including *SYSCENT* as a control for the main effects and moderation effects of hospital system affiliation on hospital inventory costs as operationalized by inventory to operating expenses.[9] Consistent with pervious results, the coefficient of interaction between ($SYSAFF = 1$) and log(*LGSINFRA*), was positive and significant ($\delta = 0.184$, $p\text{-}value = 0.006$) suggesting that the effect of weak logistics services infrastructure on higher hospital inventory costs is less severe for hospitals affiliated with hospitals affiliated with local hospital systems ($SYSAFF = 1$) than those that are independent ($SYSAFF = 0$) or affiliated with regional or national hospital systems ($SYSAFF = 2$ and 3).

4.2.4. Tests for endogeneity

We follow Andritsos and Tang (2014) to test for an endogenous relationship between inventory costs and hospital system affiliation by lagging the hospital system affiliation measure by one year ($SYSAFF_{LAG}$) as well as examine whether changes in inventory costs have an impact on hospitals' system affiliation status. Models (22)–(24) in Appendix B contain the results of the effects of $SYSAFF_{LAG}$ on hospital inventory costs as operationalized by inventory to operating expenses. Consistent with pervious results, the coefficient for the interaction between ($SYSAFF_{LAG} = 1$) and log(*LGSINFRA*) was positive and significant ($\delta = 0.174$, $p\text{-}value = 0.009$) suggesting that, after lagging the hospital system affiliation measure, the effect of weak logistics services infrastructure on higher hospital inventory costs is less severe for hospitals affiliated with hospitals affiliated with local hospital systems ($SYSAFF_{LAG} = 1$) than those that are independent ($SYSAFF_{LAG} = 0$) or affiliated with regional or national hospital systems ($SYSAFF_{LAG} = 2$ and 3). Additionally, Model (25) in Appendix B contains the results of the effects of log(*Inventory Costs*), as operationalized by inventory to operating expenses, on local hospital system affiliation ($SYSAFF = 1$). We find that the coefficient of log(*Inventory Costs*) is positive but not significant ($\delta = 0.134$, $p\text{-}value = 0.520$). Thus, we find no evidence of an endogenous relationship.

[9] The additional categories of *SYSCENT* described in Burns et al. (2015) were collinear with *SYSAFF* and therefore were excluded from the *SYSCENT* operationalization.

Table 3
LMM results with random intercepts for each hospital and each county and random slope for each hospital; Dependent variable: log(Inventory to Operating Expenses); N = 878, hospitals = 307, counties = 55.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	−3.680***	−3.684***	−3.632***	−3.699***	−3.686***	−3.716***	−3.606***
log(*LGSINFRA*)	−0.070*	−0.072*	−0.065	−0.106**	−0.071*	−0.109**	−0.064*
log(*CLINICREQ*)	0.097**	0.097**	0.098**	0.097**	0.114*	0.102**	0.112*
SYSAFF_DUMMY	–	0.024	–	0.015	0.023	–	–
SYSAFF = 1	–	–	0.044	–	–	−0.055	0.036
SYSAFF = 2	–	–	−0.034	–	–	−0.031	−0.032
SYSAFF = 3	–	–	0.070	–	–	0.062	0.052
SYSAFF_DUMMY × log(*LGSINFRA*)	–	–	–	0.063+	–	–	–
SYSAFF_DUMMY × log(*CLINICREQ*)	–	–	–	–	−0.027	–	–
SYSAFF = 1 × log(*LGSINFRA*)	–	–	–	–	–	0.183**	–
SYSAFF = 2 × log(*LGSINFRA*)	–	–	–	–	–	0.022	–
SYSAFF = 3 × log(*LGSINFRA*)	–	–	–	–	–	0.065	–
SYSAFF = 1 × log(*CLINICREQ*)	–	–	–	–	–	–	−0.141
SYSAFF = 2 × log(*CLINICREQ*)	–	–	–	–	–	–	−0.046
SYSAFF = 3 × *l* log(*CLINICREQ*)	–	–	–	–	–	–	0.107
SERV_DUMMY	−0.042	−0.041	−0.043	−0.042	−0.041	−0.041	−0.046
MORT_DUMMY	0.008	0.009	0.011	−0.004	0.010	−0.007	0.031
PROC_DUMMY	−0.019	−0.017	−0.014	−0.018	−0.017	−0.014	−0.015
SERVICE	0.001	0.001	0.001	0.001	0.001	0.001	0.001
MORTALITY	0.004	0.004	0.004	0.004	0.004	0.004	0.003
PROCESS	−0.005**	−0.005**	−0.005**	−0.005**	−0.005**	−0.005**	−0.005**
log(*BEDS*)	−0.032	−0.035	−0.039	−0.038	−0.035	−0.042	−0.035
GOVPAYER	−0.003*	−0.003*	−0.003*	−0.003*	−0.003*	−0.003*	−0.003*
MSA	−0.028	−0.021	−0.041	−0.008	−0.022	0.037	−0.049
HHI	0.165	0.167	0.150	0.165	0.172	0.198	0.141
OCCUP	−0.003**	−0.003**	−0.003**	−0.004**	−0.003**	−0.004**	−0.004**
CMI	0.203*	0.204*	0.209*	0.216*	0.207*	0.235*	0.198*
NATGPO	0.071	0.070	0.073	0.067	0.070	0.067	0.083
EHR	0.017	0.019	0.024	0.030	0.020	0.034	0.034
TEACH	−0.049	−0.049	−0.058	−0.057	−0.053	−0.075	−0.077
PUBLIC	−0.119	−0.110	−0.117	−0.144+	−0.108	−0.154+	−0.117
PRIVATE	0.077	0.076	0.058	0.065	0.076	0.032	0.087
YEAR	−0.009	−0.009	−0.009	−0.010	−0.009	−0.010	−0.008
LogLik	−278.1	−278.0	−277.4	−276.4	−278.0	−273.2	−275.0
AIC	608.2	610.1	612.7	608.8	612.0	610.5	613.9
Marginal R^2	0.116	0.118	0.117	0.127	0.117	0.143	0.118
Conditional R^2	0.891	0.891	0.890	0.891	0.891	0.892	0.892
χ^2	65.1***	65.3 ***	66.6***	68.6***	65.4***	74.9***	71.4***
$\Delta\chi^2$		0.2	1.5	3.3+	0.1	8.3*	4.8

+$p < 0.10$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

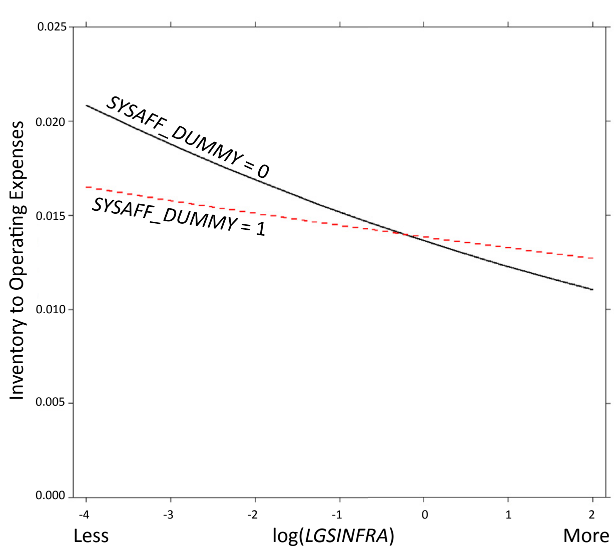

Fig. 3. Interaction plots for Model (3) between log(*LGSINFRA*) and *SYSAFF_DUMMY*; Dependent Variable = Inventory to Operating Expenses.

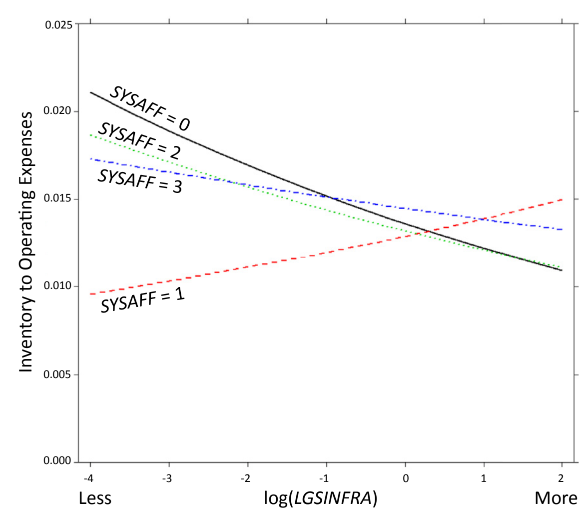

Fig. 4. Interaction plots for Model (3) between log(*LGSINFRA*) and *SYSAFF*; Dependent Variable = Inventory to Operating Expenses.

These results demonstrate the robustness of the previous analyses suggesting an association between operating environment drivers of supply chain risk, namely logistics services infrastructure and clinical requirements, and hospital inventory costs and that hospitals with weaker logistics services infrastructure that are affiliated with local systems exhibit lower inventory levels compared to hospitals that are independent or are affiliated with regional or national hospital systems.

5. Discussion and implications

In this study, we propose that inter-organizational arrangements among hospitals mitigate supply chain risk resulting in lower inventory costs. The key finding from our study is that affiliation with a local system buffers hospitals from supply chain risk under conditions of weak logistics services infrastructure. In line with this finding, affiliated hospitals may be able to pool their respective supply risk by relying on one another, even if largely a matter of psychological security, for needed supplies. Such risk pooling does not necessarily require a physical pooling of inventory but rather can result from a network of close hospital partners from whom inventory can be drawn thus reducing the risk of stock outs (Sodhi and Lee, 2007; Zsidisin and Ellram, 2003). In essence, hospitals are able to 'virtually' pool their inventory through an agreement without necessarily 'physically' consolidating their respective inventory (Berman et al., 2011; Eppen, 1979). Thus, hospitals are able to carry less safety stock inventory to mitigate supply chain risk, which may be particularly important in the presence of weak logistics services infrastructure.

Consistent with Wiengarten et al. (2014), hospitals affiliating with a local system appear to obtain greater operational benefits under conditions of high supply chain risk. Although, at least theoretically, all system-affiliated hospitals have the potential to improve their inventory performance through enhanced negotiating leverage based on increased size or scale, our finding that hospitals affiliated with local systems are better able than those affiliated with regional or national systems to mitigate the effects of weak logistics services infrastructure is directly in line with our theoretical perspective regarding opportunities and benefits of risk pooling. Thus, the results provide support for prior studies which suggest that, in terms of inventory costs, it can be more efficient for an organization to obtain needed stock from affiliates within the same system than from locations at higher levels in the supply network while maintaining high service levels (Lee, 1987; Paterson et al., 2011; Tagaras and Cohen, 1992). Thus, our study provides important insights into horizontal inter-organizational arrangements as an efficient alternative to vertical integration with suppliers. That is, horizontal integration offers potential operational efficiency benefits that may involve less governance problems, resource commitments, and other transactional costs that are typically associated with vertical integration. As study results show, these arrangements offer potential risk mitigating benefits as well as operational efficiencies, which point to an opportunity for greater research on operational benefits of horizontal arrangements as an alternative to vertical integration in both service and manufacturing sectors.

Our findings regarding system affiliation have important policy implications given the substantial level of hospital consolidation occurring as part of U.S. health care reform (Burns et al., 2012). Such consolidation has sparked concerns about reduced competition in the hospital industry that can spur price growth (i.e., Dranove, 2000; Vogt and Town, 2006). Policy makers and antitrust enforcement officials have long been concerned about whether hospital system formation is primarily a vehicle to strengthen the price negotiating position of hospitals in relation to health plans and other purchaser of hospital services (Department of Justice/Federal Trade Commission, 1996). Academic research has also produced evidence that systems frequently fail to fulfill their promise of better operating efficiencies for affiliated hospitals (i.e., Carey, 2003; Shortell, 1988). As such, the potential for greater hospital operating efficiencies through increased scale must be balanced against the risk of price growth. Our findings suggest that there is merit to the perspective that hospital consolidation can improve operating efficiencies through better inventory management, which may well be a marker for improved operating efficiencies in other areas as well. However, for antitrust enforcement officials who for any given hospital merger or acquisition must balance the risk of future price growth with the promise of better operating efficiencies, hospitals affiliated with local systems may be particularly good candidates to exploit better operating efficiencies particularly those facing more stringent environmental conditions.

In financial terms, our results imply that, for two identical hospitals in all respects with average hospital characteristics in our sample except for location (i.e., an operating budget of $200 million and an operating margin approaching 0%), operating in an area with weak logistics services infrastructure such as San Bernardino, CA (i.e., lower 25th percentile) compared to an area with strong logistics services infrastructure such as Los Angeles, CA (i.e., upper 25th percentile) would result in a difference in inventory costs of as much as 40 percent (approximately $1.3 million).[10] That is, operating in areas with logistics services infrastructure at the lower percentile (weak logistics services infrastructure) can lead an average hospital to increase its inventory costs by as much as 40 percent. In contrast, given that logistics services infrastructure is a macro-level indicator and therefore managers have less control over it, strategically affiliating with a local hospital system to obtain risk pooling benefits would translate to a 20% decrease in inventory costs resulting in $650,000 in savings, an amount that has the potential to situate the hospital in a more favorable financial position.

6. Limitations and suggestions for future research

This study has several limitations that offer opportunities for future research. First, we conducted the study based on a sample of hospitals from a single state. Although we do not believe that California has any general health policy or regulatory conditions that limit the generalizability of the study results, California is a highly urbanized state with well-developed logistics services infrastructure. As such, our results may not extend to states that are more rural with less mature infrastructure in terms of roads, airports, warehouses, and logistics services providers. In addition, beyond the geographic location measures that we control for, there may be additional location factors that influence the mix of services offered by a hospital. Thus, there is a need to extend this study with a more geographically diverse sample of hospitals. Moreover, we hope researchers will test our ideas in settings other than the hospital industry where horizontal inter-organizational arrangements are prevalent.

Second, while we find support for a relationship between demand uncertainty for a hospital's clinical requirements and a hospital's inventory costs, we did not find support for the hypothesis that demand uncertainty for clinical requirements moderates the relationship between system affiliation and a hospital's inventory costs. We consider demand uncertainty for a hospital's clinical requirements to be a dimension of a hospital's task environment which we measured based on the distribution of the clinical conditions the

[10] For years 2007 to 2009, 41.1% of California hospitals reported a three-year average operating margin that was negative. The three-year average operating margin itself was 1.1% (www.oshpd.ca.gov/HID/Products/Hospitals/AnnFinanData/HospFinanPerform/HospitalFinancialPerformance.pdf).

hospital treats. Alternative dimensions of demand uncertainty (i.e., demand variability and demand predictability) for clinical requirements can provide additional insights regarding the effects of a hospital's task environment on its operations. For example, providing health care services for various clinical conditions can be conceptualized as make-to-order production for various product groups which has implications regarding how a hospital can operate effectively when responding to demand variability and predictability for clinical requirements (Ketokivi, 2006). Alternative dimensions would require more granular longitudinal demand information (i.e., monthly) for the different clinical conditions that a hospital treats in order to operationalize variability as well as the predictability of the demand for the various clinical conditions experienced.

Third, we focused on inventory costs as the performance measure for evaluating the benefits of system affiliation on hospital operating performance. Consequently, an opportunity exists to extend our work by examining the impact of inter-organizational arrangements in the hospital industry on other measures of operational performance. As previously discussed, the controversy over hospital systems has motivated many comparative studies of total operating costs of system affiliated versus independent hospitals. Although many of these studies do not find any advantage in favor of system affiliation, our results suggest that total operating costs may be too broad of a measure and that the operational advantages from system affiliation are more fine grained. As such, we recommend that researchers conduct studies that target specific areas of operations where system affiliation is most likely to have a positive impact.

Fourth, there also exists an opportunity to extend this study by examining the nature and impact of different levels of integration or “system-ness” (Burns et al., 2015). A variety of risk pooling arrangements are plausible for organizations to implement (Paterson et al., 2011). While we argue that managers of system-affiliated hospitals have relatively greater confidence in their ability to access supplies when they need them, a better understanding of the nature of the specific risk pooling mechanisms would provide additional insights as to the benefits obtained from such horizontal inter-organizational arrangements. As noted, health care analysts have contended for many years that multi-hospital systems have not lived up to their full potential in enhancing operating efficiency (Shortell, 1988). Part of this challenge may be that systems have not developed or exploited synergies across affiliated hospitals that allow for a realization of more system benefits. There is therefore a need to explore in greater depth the issue of the degree of integration or “system-ness” and its impact on hospitals' supply chain operations.

Fifth, in addition to the hypothesized relationships, our results suggest some interesting opportunities for future research. The positive association between CMI and inventory costs suggests that as the resources a hospital needs to manage patient care increases, hospitals tend to require more supplies and subsequently carry more inventory. In contrast to the demand uncertainty for clinical requirements, the CMI captures the complexity of clinical conditions treated by the hospital and associated resource requirements. Therefore, while more complex patients may require more resources, it is not clear as to why hospitals should need to carry additional inventory for such patients. Our results also suggest that better process quality and occupancy rates are associated with lower inventory costs indicating that better managed hospitals tend to operate leaner. This points to research opportunities for studying the role of management competencies in achieving such operational outcomes. In addition, the study results suggest that a greater reliance on government reimbursement is associated with lower inventory costs. This result may highlight the need for hospitals with a greater portion of their revenue stemming from government insurance programs (i.e., Medicare and Medicaid) to reduce costs due to increasingly tighter reimbursement policies for Medicare and Medicaid, the two largest government insurance programs.

Finally, regarding our empirical approach, the LMM with random intercepts model employed allows for estimation of multi-level effects for both time-varying and non-time-varying variables in observational data. Yet, multi-level random effects estimators run the risk of omitted variable bias due to potential correlation between omitted variables and the regressors of interest (Kim and Frees, 2007). Although we performed various tests for endogeneity and conducted alternative estimation approaches including a propensity analysis for the association between system-affiliation and inventory costs, a study that accounts for additional explanatory variables that drive the system-affiliation decision would provide a more comprehensive contingency view of horizontal inter-organizational arrangements. The identification of such explanatory variables can also facilitate a two-stage instrumental variables approach where the explanatory variable is used as an instrument for the type of horizontal inter-organizational arrangement. In addition, while the hypothesized relationships in our proposed research framework build on established theory, the concern remains for potential reverse causality between regressors of interest (i.e., logistics services infrastructure, demand uncertainty for clinical requirements, and service performance) and hospital inventory costs. Therefore, there are potential alternative explanations for our results. For example, hospitals with greater operational cost control may operate in specific geographic locations for reasons that logistics services providers may also find favorable (i.e., tax incentives). Similarly, operational decisions regarding the scope of hospital service offerings and the associated inventory management policies may result in the observed variation in demand for the different service offerings. Lastly, as previously discussed, better managed hospitals in terms of inventory cost control may perform better across a wider range of operational metrics including service performance. In addressing the potential endogeneity concerns, rather than identifying external instruments for each regressor, future research could consider employing alternate approaches that fit linear models with potentially endogenous regressors using internal instrumental variables methods (i.e., Kim and Frees, 2007; Lewbel, 1997; Park and Gupta, 2012). That is, after satisfying the specific assumptions for each approach, internal instrumental variables methods correct for endogeneity when no strong, valid external instrumental variables are available by building internal instruments using functional forms of variables already in the linear model.

In conclusion, to our knowledge, this study is the first to examine whether inter-organizational arrangements in the hospital industry buffer hospitals from supply chain risk in relation to inventory accumulation. Given the dearth of scholarly work examining inventory practices in the face of supply chain risks within service sectors of the economy (Chen et al., 2013; Talluri et al., 2013) as well as a need for more empirical research on supply chain risk management (SCRM) (Sodhi et al., 2012), this study addresses a major gap in the SCRM literature, and hopefully will inform discussions about and advance our understanding of risk management in supply chains.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.jom.2016.04.002

Appendix A. Hospital service performance measures.

Patient service experience (*SERVICE*).

Survey question	% Patients who answered (300 +)
How do patients rate the hospital overall?	Patients who gave a rating of 9 or 10 (high)
Would patients recommend the hospital to friends and family? *	YES, patients would definitely recommend the hospital*
How often did patients receive help quickly from hospital staff?	Patients usually received help as soon as they wanted

* Excluded from final patient service experience measure due to colinearity with other service performance measures.

Medical outcomes (*MORTALITY*).

Mortality measure name	Patient condition
Hospital 30-Day Death (Mortality) Rates for Heart Failure	Heart Failure
Hospital 30-Day Death (Mortality) Rates for Heart Attack *	Heart Attack*
Hospital 30-Day Death (Mortality) Rates for Pneumonia	Pneumonia

* Excluded from final mortality measure due to colinearity with other service performance measures.

Process quality (*PROCESS*).

Process measure name	Patient condition
Heart attack patients Given aspirin at arrival	Heart attack or chest pain process of care measure AM_1
Heart attack patients given aspirin at discharge	Heart attack or chest pain process of care measure AM_2
Heart attack patients given ACE inhibitor or ARB for left ventricular systolic dysfunction (LVSD)	Heart attack or chest pain process of care measure AM_3
Heart attack patients given beta blocker at discharge	Heart attack or chest pain process of care measure AM_5
Children who received reliever medication while hospitalized for asthma	Children's asthma process of care measure CAC_1
Children who received systemic corticosteroid medication (oral and IV medication that reduces inflammation and controls symptoms) while hospitalized for asthma	Children's asthma process of care measure CAC_2
Heart failure patients given an evaluation of left ventricular systolic (LVS) function	Heart failure process of care measure HF_2
Heart failure patients given ACE inhibitor or ARB for left ventricular systolic dysfunction (LVSD)	Heart failure process of care measure HF_3
Pneumonia patients assessed and given pneumococcal vaccination	Pneumonia process of care measure PN_2
Pneumonia patients whose initial emergency room blood culture was performed prior to the administration of the first hospital dose of antibiotics	Pneumonia process of care measure PN_3b
Pneumonia patients given initial antibiotic(s) within 6 h after arrival	Pneumonia process of care measure PN_5c
Pneumonia patients given the most appropriate initial antibiotic(s)	Pneumonia process of care measure PN_6
Pneumonia Patients assessed and given influenza vaccination	Pneumonia process of care measure PN_7
Surgery patients who were given an antibiotic at the right time (within one hour before surgery) to help prevent infection	Surgical care improvement project process of care measures SCIP_INF_1
Surgery patients whose preventive antibiotics were stopped at the right time (within 24 h after surgery)	Surgical care improvement project process of care measures SCIP_INF_3
Surgery patients whose doctors ordered treatments to prevent blood clots after certain types of surgeries	Surgical care improvement project process of care measures SCIP_VTE_1

Appendix B. Robustness tests.

LMM results with random intercepts for each hospital and each county and random slope for each hospital; Dependent variable: log(Inventory to Operating Revenue); N = 878, hospitals = 307, counties = 55.

LMM results with random intercepts for each hospital and each county and random slope for each hospital; Dependent variable: log(Inventory to Supply Chain Expenses); N = 878, hospitals = 307, counties = 55.

	(8)	(9)	(10)	(11)
Intercept	−3.751***	−3.720***	−3.792***	−3.675***
log(*LGSINFRA*)	−0.098**	−0.055*	−0.103**	−0.056*
log(*CLINICREQ*)	0.089*	0.106+	0.095*	0.101+
SYSAFF_DUMMY	−0.015	−0.009	–	–
SYSAFF = *1*	–	–	−0.076	0.024
SYSAFF = *2*	–	–	−0.056	−0.055
SYSAFF = *3*	–	–	0.009	0.001
SYSAFF_DUMMY × log(*LGSINFRA*)	0.070*	–	–	–
SYSAFF_DUMMY × log(*CLINICREQ*)	–	−0.027	–	–
SYSAFF = *1* × log(*LGSINFRA*)	–	–	0.204**	–
SYSAFF = *2* × log(*LGSINFRA*)	–	–	0.024	–
SYSAFF = *3* × log(*LGSINFRA*)	–	–	0.072	–
SYSAFF = *1* × log(*CLINICREQ*)	–	–	–	−0.129
SYSAFF = *2* × log(*CLINICREQ*)	–	–	–	−0.040
SYSAFF = *3* × log(*CLINICREQ*)	–	–	–	0.102
CONTROLS	Yes	Yes	Yes	Yes

$+p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

	(12)	(13)	(14)	(15)
Intercept	−1.787***	−1.764***	−1.845***	−1.718***
log(*LGSINFRA*)	−0.127***	−0.073**	−0.132***	−0.073**
log(*INVCLINICREQ*)	0.070+	0.096	0.075+	0.094
SYSAFF_DUMMY	−0.112	−0.099	–	–
SYSAFF = *1*	–	–	−0.246*	−0.111
SYSAFF = *2*	–	–	−0.125	−0.115
SYSAFF = *3*	–	–	−0.061	−0.065
SYSAFF_DUMMY × log(*LGSINFRA*)	0.101**	–	–	–
SYSAFF_DUMMY × log(*CLINICREQ*)	–	−0.043	–	–
SYSAFF = *1* × log(*LGSINFRA*)	–	–	0.276***	–
SYSAFF = *2* × log(*LGSINFRA*)	–	–	0.045	–
SYSAFF = *3* × log(*LGSINFRA*)	–	–	0.099*	–
SYSAFF = *1* × log(*CLINICREQ*)	–	–	–	−0.150
SYSAFF = *2* × log(*CLINICREQ*)	–	–	–	−0.052
SYSAFF = *3* × log(*CLINICREQ*)	–	–	–	0.070
CONTROLS	Yes	Yes	Yes	Yes

+$p < 0.10$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Propensity score LMM results with random intercepts for each hospital and each county and random slope for each hospital; Model (16) dependent variable: log(Inventory to Operating Expenses); Model (17) dependent variable: log(Inventory to Operating Revenue); Model (18) dependent variable: log(Inventory to Supply Chain Expenses); N = 284, hospitals = 141, counties = 32.

	(16)	(17)	(18)
Intercept	−2.810***	−2.983***	−0.915
log(*LGSINFRA*)	−0.116*	−0.110*	−0.134**
log(*CLINICREQ*)	0.145*	0.117+	0.117
SYSAFF = *1*	−0.112	−0.090	−0.302**
SYSAFF = *1* × log(*LGSINFRA*)	0.212**	0.216**	0.296***
CONTROLS	Yes	Yes	Yes

+$p < 0.10$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

LMM results with random intercepts for each hospital and each county and random slope for each hospital; Dependent variable: log(Inventory to Operating Expenses); N = 878, hospitals = 307, counties = 55.

	(19)	(20)	(21)
Intercept	−3.644***	−3.716***	−3.603***
log(*LGSINFRA*)	−0.067*	−0.109**	−0.062*
log(*CLINICREQ*)	0.099**	0.103**	0.113*
SYSCENT	0.072	0.073	0.076
SYSAFF = *1*	0.026	−0.074	0.014
SYSAFF = *2*	−0.086	−0.088	−0.092
SYSAFF = *3*	0.061	0.052	0.040
SYSAFF = *1* × log(*LGSINFRA*)	–	0.184**	–
SYSAFF = *2* × log(*LGSINFRA*)	–	0.025	–
SYSAFF = *3* × log(*LGSINFRA*)	–	0.064	–
SYSAFF = *1* × log(*CLINICREQ*)	–	–	−0.143
SYSAFF = *2* × log(*CLINICREQ*)	–	–	−0.048
SYSAFF = *3* × log(*CLINICREQ*)	–	–	0.110
CONTROLS	Yes	Yes	Yes

+$p < 0.10$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

LMM results with random intercepts for each hospital and each county and random slope for each hospital; Dependent variable: log(Inventory to Operating Expenses); N = 878, hospitals = 307, counties = 55.

	(22)	(23)	(24)
Intercept	−3.734***	−3.798***	−3.727***
log(*LGSINFRA*)	−0.065*	−0.101**	−0.069**
log(*CLINICREQ*)	0.106**	0.110**	0.122*
$SYSAFF_{LAG} = 1$	0.037	−0.055	0.030
$SYSAFF_{LAG} = 2$	−0.037	−0.039	−0.032
$SYSAFF_{LAG} = 3$	0.059	0.053	0.042
$SYSAFF_{LAG} = 1 \times$ log(*LGSINFRA*)	–	0.174**	–
$SYSAFF_{LAG} = 2 \times$ log(*LGSINFRA*)	–	0.022	–
$SYSAFF_{LAG} = 3 \times$ log(*LGSINFRA*)	–	0.055	–
$SYSAFF_{LAG} = 1 \times$ log(*CLINICREQ*)	–	–	−0.151
$SYSAFF_{LAG} = 2 \times$ log(*CLINICREQ*)	–	–	−0.050
$SYSAFF_{LAG} = 3 \times$ log(*CLINICREQ*)	–	–	0.109
CONTROLS	Yes	Yes	Yes

+$p < 0.10$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

GLM logistic results; Dependent variable: *SYSAFF* = 1; *Inventory Costs* operationalized as inventory to operating expenses; N = 878.

	(25)
Intercept	−3.887*
log(*LGSINFRA*)	0.103
log(*CLINICREQ*)	−0.314
log(*Inventory Cost*)	0.134
CONTROLS	Yes

+$p < 0.10$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

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