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DOES IT ENABLE COLLUSION OR COMPETITION: EXAMINING THE EFFECTS OF IT ON SERVICE PRICING IN MULTIMARKET MULTIHOSPITAL SYSTEMS[1]

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In the U.S., multihospital systems (MHSs) charge significantly higher prices for hospital services than stand-alone hospitals. Rivalry restraint theory suggests that MHS with multimarket contact (MMC) can tacitly collude and mutually forebear from price competition to keep their prices above competitive levels. We posit that the success of such MMC-induced rivalry restraints (the truce) is affected by two conflicting roles of IT at the corporate level and market unit levels, respectively. The corporate parent seeks to standardize IT applications enterprise-wide to coordinate market units as a means of jointly implementing the rivalry restraint strategy and keeping prices high enterprise-wide. However, market units, i.e., the member hospitals of MHS clustered in geographic patient markets, face competitive pressures to reduce their service costs. Market units seek to use differentiated IT applications to achieve cost reductions, which then fuel price competition in local markets, jeopardize the sustainability of the truce, and weaken the enterprise-wide price effects of the corporate parent's rivalry restraint strategy. In a longitudinal study of 195 multihospital systems in the U.S. in the 2005-2013 time period, we found support for these ideas. The corporate-wide standardization of the operational IT of MHS complements the rivalry restraint strategy to increase enterprise-wide prices. Market units' use of differentiated analytical IT reduces costs in local markets and weakens the price effects of the rivalry restraint strategy. The study advances IS research and practice by theorizing how the corporate-level and the market unit-level IT of a multi-unit, multimarket (MUMM) organization can have opposing moderating effects on the link between MMC and the average prices charged by the MUMM organization.

Keywords: Tacit collusion, rivalry restraint, multimarket competition, multi-unit multimarket firm, enterprise-wide coordination, information technology, data analytics, multihospital health system, process of care quality, service prices

Introduction

The practical motivation for this study is to understand why hospital service prices in the U.S. are so high. On average, U.S. hospitals charge 3.4 times the actual cost of providing services (Bai & Anderson, 2015), and hospitals owned by multihospital systems (MHSs) charge significantly higher prices than stand-alone hospitals (Dranove et al., 1996; Melnick & Keeler, 2007). As MHSs own more than 67% of nonfederal hospitals in the U.S. (https://www.aha.org/statistics/fast-facts-us-hospitals) it is important to understand the mechanisms by which MHSs are able to charge higher prices.

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The theoretical motivation for this study stems from a possible explanation offered by rivalry restraint theory: rival MHSs with multimarket contact (MMC) might be tacitly colluding with each other (i.e., making a truce) to mutually forbear from price competition in order to keep their enterprise-wide prices above competitive levels (Schmitt, 2018). In the hospital industry, however, such a truce is challenging to establish and sustain because market units face competitive pressures to reduce prices. Thus, it is difficult for the corporate parent of an MHS to secure the full cooperation of its market units in implementing its rivalry restraint strategy. A market unit refers to MHS member hospitals clustered in a geographic patient market.[2] Facing price reduction pressures from local rivals, insurance firms, and the government, market units may wish to reduce the costs of their services. If market units compete on the cost of services locally, the corporate parent cannot effectively implement its rivalry restraint strategy. The goal misalignment between the corporate parent and its market units thus motivates our research question: *Under what conditions can an MHS use a rivalry restraint strategy to keep the overall, enterprise-wide prices charged for hospital services high despite market units' need to reduce the cost of their services in local markets?* We posit that the answer depends on certain IT mechanisms at both the corporate level and the market unit level.

At the corporate level, an MHS needs an enterprise-wide coordination mechanism to implement its rivalry restraint strategy across its market units. We propose the cross-unit *standardization of operational IT (SOIT)* as a corporate-level IT mechanism that the MHS can use to implement its rivalry restraint strategy. At the market unit level, we explain why market units' use of *differentiated analytical IT (DAIT)* can reduce market units' costs of services and serve as a market unit-level IT mechanism that provides the market units with cost-based advantages over rivals in their local markets. However, market units competing on the cost of services locally would inhibit the corporate parent's ability to keep prices high through its rivalry restraint strategy.

We posit that the corporate parent's use of cross-unit *SOIT* can complement the MMC-induced rivalry restraint strategy to reinforce its price effects. In contrast, market units' use of *DAIT* can lead to cost-based differentiation in services and dampen the price effects of the rivalry restraint strategy by fostering competition on the cost of services. We found support for these ideas in a sample of 5,660 observations of 195 MHSs competing in 592 geographic patient markets between 2005 and 2013. SOIT positively moderates the enterprise-wide price effects of MMC-induced rivalry restraint whereas DAIT negatively moderates this relationship.

The study contributes to rivalry restraint theory (RRT) by explaining how and why corporate-level and market unit-level IT mechanisms (SOIT and DAIT) have opposing moderating effects on the link between MMC and price. This study also contributes to information systems (IS) theories on firm profitability. The majority of IS studies focus on the role of IT in competitive advantage-based theories of firm profitability (Bhatt & Grover, 2005; Mata et al., 1995; Melville et al., 2004; Wade & Hulland, 2004). Collusion-based theories of firm profitability, such as RRT, have received much less attention in the IS literature. A few exceptions have conducted MMC studies in IT industries: e.g., personal computers (Kang et al., 2010), enterprise software (Chellappa et al., 2010), and IT services (Ruckman et al., 2015). However, these studies did not theorize or test the roles of IT mechanisms in implementing an MMC-induced rivalry restraint strategy. A couple of other IS studies controlled for the extent of MMC when studying competitive action (Chi et al., 2010) and within-industry diversification (Tanriverdi & Lee, 2008). However, they did not theorize about MMC-induced rivalry restraint strategy or the roles of IT mechanisms in such a strategy. Chari et al. (2008) called for new research to address this research gap: "Multipoint competition requires sophisticated [IT] systems to supply information necessary to make decisions in one business based on competitive situations in another. It will be useful to study the information system profiles of successful multipoint competitors" (p. 232). Drnevich and Croson (2013) reinforced this by stating: "Given that IT investments may affect post-entry rivalry in an unusual direction (with investments intended to increase competition sometimes dampening it, and vice versa), the empirical evaluation of such IT investments becomes problematic without an underlying theory of how the technology affects marketplace competition" (p. 491). Our study responds to these calls by theorizing how corporate-level and unit-level IT mechanisms moderate the link between MMC and price.

Background on Rivalry Restraint Theory ∎

The Logic of the Rivalry Restraint Theory (RRT)

RRT applies to multi-unit multimarket (MUMM) firms such as multihospital systems operating hospitals in two or more geographic patient markets. RRT argues that MUMM firms seek multimarket contact (MMC) with other MUMM firms to create spheres of influence vis-à-vis each other. MMC is defined as the extent to which two MUMM firms face each

[2] A geographic patient market is a geographic area with a grouping of hospitals that are within the commuting distance of patients (Douglas & Ryman, 2003; Dranove & White, 1994).

other as rivals in multiple markets (Korn & Rock, 2001). Sphere of influence, a concept adapted from international politics, is defined as an MUMM firm's claim to exclusive or predominant control over some markets (Gimeno, 1999). RRT expects a higher extent of MMC to give MUMM rivals broader spheres of influence to force each other into tacit collusion and mutual forbearance from competition in the markets where they overlap (Sengul & Dimitriadis, 2015).

MMC-induced rivalry restraint is a form of collusion. Antitrust laws ban collusive behavior (Berenson, 2015; Bond & Syropoulos, 2008; Hannan & Prager, 2004). Thus, MUMM firms cannot explicitly communicate their tacit collusion strategies to their market units or to outsiders. This creates measurement challenges for rivalry restraint studies. In previous studies, scholars have considered the reduced magnitude of some competitive actions to be potential measures of tacit collusion among MMC rivals: e.g., making R&D investments that seek to differentiate the cost or the quality of services, entering into each other's markets, lowering prices, etc. (Sengul & Dimitriadis, 2015; Yu & Cannella, 2013). Many of these competitive actions are difficult to observe. For example, a firm's internal R&D initiatives seeking to reduce costs or increase the quality of services are often confidential and difficult to observe from the outside. Market entry might be challenging to observe in industries where entry behavior is rare or infrequent (Gimeno & Woo, 1999). A relatively easier-to-observe measure of MMC-induced rivalry restraint is the prices charged by MMC rivals in overlapping markets. Using average price levels as a measure of rivalry restraint, many studies have found support for MMC-induced rivalry restraint in numerous industries (for a review, see Yu & Cannella, 2013). Thus, we also adopt price as an observable measure of rivalry restraint.

The Assumptions of RRT

RRT makes four key assumptions about organizational and market conditions under which MMC-induced rivalry restraint is likely to emerge and be sustained (Sengul & Dimitriadis, 2015). We first explicate these assumptions and then explain how and why the proposed corporate-level IT (SOIT) and the market unit-level IT (DAIT) mechanisms are likely to enable or inhibit the satisfaction of these assumptions and, accordingly, moderate the link between MMC and price.

Assumption #1—Enterprise-wide coordination mechanism: Based on RRT, an MMC-induced rivalry restraint is likely to emerge and be sustained if an MUMM firm can effectively coordinate the pricing behaviors of its market units in implementing the strategy and collect timely and accurate information about the adherence of market units to the strategy (Golden & Ma, 2003; Schmitt, 2018; Sengul & Dimitriadis, 2015). This assumption requires an enterprise-wide coordination mechanism to implement and enforce the rivalry restraint strategy across the firm's market units. However, theoretical or empirical MMC research has not yet theorized such a coordination mechanism: "The theoretical and empirical exploration of the link between multimarket contact and other dimensions of organizational design … remains an open area for future research" (Sengul & Dimitriadis, 2015, p. 27). To address this gap, we propose cross-unit SOIT as an enterprise-wide coordination mechanism (e.g., Du, 2015; Tanriverdi, 2005, 2006; Tanriverdi & Uysal, 2011; Tippins & Sohi, 2003) for implementing and enforcing the rivalry restraint strategy across market units to reinforce the price effects of the strategy.

Assumption # 2—Goal alignment between corporate parent and market units: Based on RRT, it is assumed that the corporate parent and market units of an MUMM firm have goal alignment when implementing an MMC-induced rivalry restraint strategy (Golden & Ma, 2003; Sengul & Gimeno, 2013). However, the research on multi-unit organizations has documented major goal misalignment problems between corporate parents and market units (Eisenhardt & Piezunka, 2011). In the specific context of a rivalry restraint strategy, due to regulatory bans on tacit collusion, the corporate parent cannot explicitly use strategic communication to inform its market units that they should tacitly collude with rivals to mutually forebear from price competition. Instead, the corporate parent uses policies to implicitly force the market units to follow the strategy. For example, the parent sends pricing instructions to the market units without justifying why prices are kept above competitive levels. The vagueness of strategic communications can increase the goal misalignment problems between the corporate parent and the market units. Not knowing why they need to keep prices above competitive levels, the market units can deviate from the corporate parent's pricing instructions to jeopardize the sustainability of the truce and weaken the price effects of the corporate parent's rivalry restraint strategy.

Among the few exceptions in the literature, Golden and Ma (2003) discuss the importance of establishing incentive systems and integration mechanisms to coordinate market units; Sengul and Gimeno (2013) discuss how the corporate parent can strategically manipulate decision rights delegation and resource allocation to prevent market units from defying the rivalry restraint instructions of the corporate parent through, for example, pricing instructions. Beyond such administrative mechanisms, we explain how a corporate parent can use cross-unit SOIT as a mechanism to monitor whether market units are implementing pricing instructions or disregarding the truce and bring the defectors back into compliance.

Assumption #3—In overlapping markets, there are only MUMM rivals: Based on RRT, MMC-induced rivalry restraint is likely to emerge and be sustained in oligopolistic markets in which there are only MUMM rivals (Makadok, 2010, 2011). While RRT assumes away single-unit or single-market (SUSM) players (Sengul & Dimitriadis, 2015), in reality, there are also SUSM rivals in the overlapping markets of MUMM firms. For example, 323 of the 592 geographic patient markets in our study sample (54.6%) had stand-alone hospitals or a single-market MHS, and some SUSM players compete on the costs of services and put competitive pressure on the market units of MHSs to reduce the costs of their services. The IS literature suggests that differentiated IT capabilities can enable firms to cope with such competitive pressures (Bhatt & Grover, 2005; Mata et al., 1995; Melville et al., 2004; Wade & Hulland, 2004). For instance, hospitals develop data analytical IT capabilities to gain competitive advantage (Mueller-Peltzer et al., 2020; Son et al., 2020; Zolbanin et al., 2022; Zolbanin & Delen, 2018). We posit that market units' use of DAIT could differentiate their hospital services, motivate them to compete with local rivals rather than complying with the corporate parent's rivalry restraint instructions, and weaken the price effects of the rivalry restraint strategy.

Assumption #4—Resources, products, and services of MUMM rivals are homogenous: Based on RRT, rivalry restraint is likely to emerge and be sustained if MUMM rivals have similar resources and homogeneous services (Bernheim & Whinston, 1990; Makadok, 2010). This assumption is important for forcing MUMM rivals into tacit collusion and mutual forbearance from price competition. If rivals have no differentiation in their resources and services, market units will have incentives to avoid competition and keep prices above competitive levels. If some market units use DAIT to differentiate their services in terms of cost or quality, they might prefer to use the competitive advantages of differentiation to compete with rivals (Bharadwaj, 2000). The ensuing competition could jeopardize the sustainability of the truce established by the rivalry restraint strategy and weaken its price effects.

Conceptual Underpinnings of the Corporate-Level and Market Unit-Level IT Mechanisms

We ground the proposed corporate-level SOIT and market unit-level DAIT mechanisms in the IS literature. IS research and practice distinguish between: (1) enterprise-wide, IT-enabled coordination mechanisms of multi-unit organizations (e.g., Du, 2015; Tanriverdi, 2005, 2006; Tanriverdi & Uysal, 2011; Tippins & Sohi, 2003) and (2) differentiated IT capabilities of business units that can differentiate the cost or quality of services (e.g., Gregory et al., 2015).

Some IS studies have conceptualized the IT-enabled, enterprise-wide coordination mechanism of a multi-unit firm as the use of common IT systems across the units (Tanriverdi, 2005, 2006; Tanriverdi & Uysal, 2011). In the enterprise IT architecture literature, scholars have conceptualized the IT-enabled, enterprise-wide coordination mechanism as the use of standardized IT infrastructure technologies, applications, business processes, and data across the units of a multi-unit firm (Ross et al., 2006). In the MHS context, Du (2015) conceptualized the enterprise-wide standardization of operational IT (SOIT) as a source of parenting advantage that enables the corporate parent to integrate acquired units and exchange resources between existing and newly acquired units (Du, 2015). Building on these conceptualizations, we adopt the cross-unit SOIT as an MHS's enterprise-wide, IT-enabled, cross-unit coordination mechanism.

At the market unit level, the IS literature has recognized that the units of a firm can adopt differentiated IT capabilities to reduce the costs or increase the quality of their services to gain competitive advantages over local rivals (Bhatt & Grover, 2005; Mata et al., 1995; Melville et al., 2004; Wade & Hulland, 2004). During the time frame of our study (2005-2013), hospitals sought to adopt the emerging data analytical IT capabilities to differentiate the cost and quality of hospital services (Mueller-Peltzer et al., 2020; Son et al., 2020; Zolbanin et al., 2022; Zolbanin & Delen, 2018). Thus, we adopt the use of differentiated analytical IT (DAIT) as an IT mechanism that can provide market units with competitive advantages and motivate them to compete with local rivals rather than complying with the corporate parent's rivalry restraint instructions to weaken the price effects of the rivalry restraint strategy.

Hypotheses

In this section, we fully develop and justify our hypotheses in the context of the hospital industry. We theorize how and why the corporate-level and the market unit-level IT mechanisms of an MHS would moderate the link between the extent of MMC and the average prices charged by the MHS in a geographic patient market. In Appendix A, we use a real-life example to illustrate our key concepts such as MHS, market units, MMC with rival MHS, and patient markets.

Reinforcing Rivalry Restraint with Corporate-Level IT Mechanisms

To implement the rivalry restraint strategy, the corporate parent of an MHS needs to instruct its market units on how to set prices for their hospital services based on the tacitly agreed-upon price levels with the rival MHS. If a rival MHS defects from the truce, the corporate parent also needs a coordination mechanism to simultaneously lower the prices charged by all its market units in the overlapping markets with the defecting MHS to coordinate a retaliation attack to punish the defector. IS studies on multi-unit firms suggest that the cross-unit standardization of operational IT can create an enterprise-wide mechanism for communication, coordination, and knowledge exchange across the units (e.g., Du, 2015; Tanriverdi, 2005, 2006; Tanriverdi & Uysal, 2011; Tippins & Sohi, 2003).

We define an *MHS's cross-unit standardization of operational IT (SOIT)* as the degree to which the MHS standardizes the operational IT applications of its market units enterprise-wide. MHSs often come into being through the mergers and acquisitions of hospitals (Du, 2015) and thus inherit the existing IT systems of the acquired hospitals. Some MHSs strive to standardize the IT systems of the acquired hospitals (Tanriverdi & Du, 2011). Others leave the IT systems of the acquired hospitals as stand-alone silos (Du, 2015).

At a low level of SOIT, each MHS member hospital has its own silo of operational IT applications (Tanriverdi & Du, 2011). Business processes and data generated by different operational IT applications are also different across member hospitals. Compatibility, interoperability, and integration problems are pervasive across the silos of member hospitals' operational IT. For example, during our study time frame, some hospitals were still using the 9th version of the International Classification of Diseases codes (ICD-9), which consists of about 14,000 diagnoses and 4,000 procedures, while other member hospitals were using the 10th version (ICD-10), which contains nearly 70,000 diagnoses and 72,000 procedures (Khera et al., 2018). Electronic medical record systems rely on ICD codes to document provided hospital services. Likewise, billing applications cite ICD codes in submitting insurance claims. Pricing of the same hospital service could exhibit differences across the member hospitals of an MHS simply due to the differences in the ICD codes used. The lack of standardization of ICD codes in operational IT systems can inhibit the corporate parent's ability to implement the tacitly agreed-upon price uniformly across all of its market units. Due to the lack of standardization, the corporate parent may not even be able to collect pricing data from its member hospitals, make prices comparable, or assess whether the market units are implementing the tacitly agreed-upon prices or deviate from the truce.

At a high level of SOIT, there are few operational IT silos across the member hospitals of an MHS. A standardized operational IT foundation serves all the member hospitals, allowing the hospitals to code and price their services consistently (Tanriverdi & Du, 2011). It becomes easier for the corporate parent to implement its rivalry restraint instructions consistently in market units. Thus, SOIT is likely to complement the MMC-induced rivalry restraint strategy and reinforce its effects on the average prices charged by an MHS in a patient market:

H1a: *An MHS's cross-unit standardization of operational IT (SOIT) positively moderates the link between the MMC and the MHS's average hospital service prices in a patient market.*

Once the MMC-induced rivalry restraint (truce) is in place, one challenge for the corporate parent is to enforce the truce among its market units. The goal alignment assumption of RRT implies that the corporate parent needs to detect any deviations of its market units from the corporation's rivalry restraint strategy and bring the defectors back into compliance with the truce. Hospital service prices in a market unit can change for reasons other than hospitals' attempts to defect from the truce. For example, insurance carriers and employer organizations negotiate with hospitals to reduce hospital service prices (Reinhardt, 2006); however, such price reductions do not necessarily signal hospitals' intentional defection from the truce. IS studies have argued that analytical IT capabilities can increase a firm's capacity to detect such signals and make sense of them (Roberts et al., 2012). The corporate parent of an MHS can use analytical IT capabilities to sense price changes in overlapping markets with MMC rivals and assess whether the pattern of price changes implies a rival's defection from the truce.

We define an *MHS's cross-unit standardization of analytical IT (SAIT)* as the degree to which the MHS uses standardized analytical IT applications across its market units. The SAIT can serve as an enterprise-wide analytical platform for collecting and analyzing pricing data from the local markets of its member hospitals. It can increase the corporate parent's sensemaking capacity in determining whether price-change patterns indicate a defection from the truce.

At a low level of SAIT, the MHS does not use any standardized, common, shared analytical IT applications across its market units. For example, individual hospitals commonly use revenue management applications to optimize medical coding, pricing, patient throughput, and cost allocation decisions (Qi & Han, 2020). Some of these analytical IT applications can help hospitals assign ICD codes and diagnoses related group (DRG) classifications to their hospital services, with the objective of increasing insurance carriers' likelihood of accepting the insurance claims and paying out the maximum amounts claimed (Dafny & Dranove, 2009; Dafny, 2005). When different hospitals use different analytical IT applications for revenue management and financial decision-making, the discrepancies could lead to differences in the pricing of the same hospital service across different member hospitals in a patient market and make it challenging for the corporate parent to decide whether those differences signal a purposeful defection from the truce or not.

At a high level of SAIT, the member hospitals of an MHS operate on a shared, common analytical platform. The corporate parent faces fewer challenges in analyzing and making sense of pricing changes, as the pricing data collected from market units are more consistent and comparable. A high level of SAIT would enable the corporate parent to have better visibility of the prices charged by its market units for hospital services, allowing it to better assess whether they signal defection from the truce. Detecting the defections in a timely manner could enable the corporate parent to take timely action to bring the defecting units back into compliance to sustain the truce and reinforce the price effects of the rivalry restraint strategy.

H1b: *An MHS's cross-unit standardization of analytical IT (SAIT) positively moderates the link between MMC and the MHS's average hospital service prices in a patient market.*

Weakening Rivalry Restraint with Market Unit-Level IT Mechanisms

Based on RRT, the rivalry restraint strategy of an MUMM firm is most effective in oligopolistic markets in which there are only MUMM rivals (Makadok, 2010, 2011). However, MHSs also face SUSM rivals such as stand-alone hospitals, health systems that own a single hospital, multihospital systems that operate in a single market, etc. Some SUSM rivals could compete on cost and pressure market units of MHSs to reduce the costs of their services. As health IT studies have shown, hospitals turn to innovative operational and analytical IT applications to differentiate the costs and the quality of their hospital services (Agarwal et al., 2010; Dranove et al., 2014; Fichman et al., 2011). If certain innovative IT applications are relatively rare in the hospital industry, hospitals that are early adopters can potentially use them to differentiate their IT capabilities and gain competitive advantages.

We define *market unit-level use of differentiated operational IT (DOIT)* as the degree to which market units adopt relatively new operational IT applications whose adoption rates are low in the hospital industry. DOIT can potentially differentiate the costs of hospital services by enabling market units to improve the efficiency of their clinical and administrative processes (Menon et al., 2009). DOIT can also potentially differentiate the process-of-care quality metrics by encoding best-practice medical recommendations and procedures in IT systems. Various IS studies have found evidence that using differentiated operational IT systems reduces hospitals' deviations from recommended medical standards (Lin et al., 2019), shortens patients' length of stay (Oh et al., 2018), and prevents patient safety events (Hydari et al., 2019). When market units use DOIT to achieve such differentiation in their hospital services, they violate RRT's assumption about the homogeneity of MMC rivals' resources and services. If local rivals such as SUSM firms start to compete on cost, the market units of an MHS would be tempted to compete via the cost-based advantages provided by differentiation instead of complying with the corporate parent's rivalry restraint instructions. Thus, market units' use of DOIT can negatively moderate the link between MMC-induced rivalry restraint and hospital service prices.

H2a: *The market unit-level use of differentiated operational IT (DOIT) negatively moderates the link between MMC and the MHS's average hospital service prices in a patient market.*

We define *market unit-level use of differentiated analytical IT (DAIT)* as the degree to which market units of an MHS in a patient market use relatively new analytical IT applications whose adoption rates are low in the hospital industry. IS studies have shown that business intelligence and analytics differentiate hospital services to enhance hospital revenues (Qi & Han, 2020) and improve performance (Anand et al., 2020). Differentiated analytical capabilities improve the effectiveness and efficiency of operational, financial, and clinical decision-making. They also improve environmental scanning, historical information processing, predictive modeling, scenario planning, etc. (Anand et al., 2020). These improvements can differentiate the cost and quality of hospital services. When market units gain competitive advantages through such differentiation, they have strong incentives to compete with local rivals by offering competitive pricing rather than complying with the corporate parent's instructions to keep prices above competitive levels. Thus, market units' use of DAIT threatens the sustainability of the truce between MMC rivals and weakens the price effects of the MMC-induced rivalry restraint.

H2b: *The market unit-level use of differentiated analytical IT (DAIT) negatively moderates the link between MMC and the MHS's average hospital service prices in a patient market.*

Methods

Data Sources and Sample Construction

We tested our hypotheses in the U.S. hospital industry in the 2005-2013 time period. To construct our research data set and measure study variables, we combined six archival data sources. First, we obtained data on hospitals' affiliations with MHSs and hospitals' use of health IT systems from the Healthcare Information and Management Systems Society's analytics database (HIMSS Analytics). Second, we obtained data on the financial and operational metrics of hospitals from the Healthcare Cost Report Information System (HCRIS) database. Third, we obtained data on the quality of care delivery processes of hospitals from the Hospital Compare Database. Fourth, we obtained data on hospitals' medical service offerings from the Provider of Services (POS) database. Fifth, we obtained data on the concentration of health insurance markets from the annual insurance market reports published by the American Medical Association (AMA). Finally, we manually coded MHSs' investments into corporate-wide IT and analytics initiatives from the Factiva news archive and other public sources.[3] After dropping observations with missing data, we retained a final sample of 195 multimarket multihospital systems, operating, on average, 8.94 hospitals in 5.38 geographic patient markets.

Our unit of analysis is *MHS-in-market-in-year*. That is, each market unit of a given MHS in a given year serves as one observation. The 195 MHSs retained in our final sample operated hospitals in 592 geographic markets and generated a total of 5,660 *MHS-in-market-in-year* observations for 1,062 *MHS-in-market* units (i.e., market units for short) between 2005 and 2013.

Measurement of Dependent Variable

As in previous MMC studies (e.g., Gimeno & Woo, 1999), we used the average hospital service price charged by an MHS in a local patient market as an indicator of the rivalry faced by the MHS in that market.[4] Higher average prices charged indicate a lower level of rivalry or a higher level of rivalry restraint.

To compute the average prices charged by an MHS in a patient market, we started with the *list prices* of hospital services as published in the chargemasters of the MHS's member hospitals in that market. Building on prior studies (e.g., Keeler et al., 1999), we used the *average revenue-per-patient-day* as an estimate of the average prices charged, calculated as the gross revenue from patient services divided by severity-adjusted patient days.

In the U.S. hospital industry, most patients do not pay the list prices in the chargemaster. For insured patients, prices are negotiated by patients' insurance companies and they obtain contractual discounts. Likewise, uninsured patients often receive discounts or charity write-offs. Thus, we also considered the *realized price,* i.e., the price actually collected by a hospital, which is the net patient revenue (gross revenue minus allowances and discounts).

As list prices are easier to observe for MMC rivals (Schmitt, 2018), we chose them in computing our primary dependent variable. We conducted a robustness check with realized prices and found qualitatively similar results. Appendix B1 presents the formulas and procedures used for both price measures. Model B2 of Table 1 presents the results of the robustness check.

Measurement of the Primary Independent Variable

We built on previous MMC studies (e.g., Baum & Korn, 1999; Kang et al., 2010) to measure the extent of MMC faced by the MHS in a given market, calculated as the average of MMC scores across all the dyads between the focal MHS and its MMC rivals in a given market. We calculated a dyadic MMC score as a weighted count of the overlapping markets between a pair of MMC rivals. Appendix B2 presents the detailed procedures and mathematical formulas used for the MMC measure.

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[3] To address potential media bias (underreporting or overreporting of IT announcements), we supplemented systematic keyword searches on Factiva news archives with searches on MHS websites, annual reports, PR announcements, and press releases. For publicly traded MHSs, we also reviewed the 10K statements. In addition, we checked if any MHSs in our sample appeared in the annual lists of "Most Wired Hospitals or Health Systems" and, if they did, we checked to see whether this recognition was due to enterprise-wide analytical investments. Media bias is a concern—primarily for small and medium-sized organizations that do not have enough analyst coverage or for organizations trying to hide bad news. These concerns are less likely for our sample and measures. All MHSs in our sample owned at least two hospitals and operated in at least two geographic patient markets. Therefore, they were all large organizations with good media coverage. In addition, our measures focus on large, enterprise-wide IT and analytics investments of MHSs, which serve as positive indicators that the MHSs are unlikely to try to hide from the public eye.

[4] In the MMC literature, some studies measure rivalry (or the lack thereof) based directly on competitive actions and reactions. However, such measurement would require high visibility of such actions and reactions at the level of dyads of competitors. The U.S. hospital industry is highly regulated and slow-paced, with relatively infrequent market entries and exits or other publicized competitive moves, which prevented us from directly measuring rivalry based on actions and reactions. The choice of using average price levels to measure rivalry restraint is common in prior MMC studies. For example, Gimeno and Woo (1999) similarly developed their hypotheses around rivalry restraint and then measured it using price. They argue that "although rivalry entails a pattern of competitive actions and reactions, its outcome is commonly reflected in decreased prices for the services provided by a firm." (p. 246).

Measurement of Moderating Variables

We measured the four IT-based moderating variables at two levels. At the MHS level, we measured both the standardization of operational IT (**MHS_SOIT**) and the standardization of analytical IT (**MHS_SAIT**). At the market unit level, we measured market units' use of differentiated operational IT (**Unit_DOIT**) and differentiated analytical IT (**Unit_DAIT**). Prior studies examining IT standardization versus IT differentiation (e.g., Gregory et al., 2015) provide conceptual guidance for our measurement of these variables.

To begin our measurement procedure, we profiled hospitals based on their use of IT applications. Specifically, for hospitals owned by the MHSs in our sample, we obtained lists of the IT applications they were using from the HIMSS Analytics database. Then, we classified these applications as either operational or analytical applications. Operational IT applications are defined as IT applications that support the day-to-day operation of a hospital's administrative and clinical work processes (Menon et al., 2009; Peng et al., 2019; Qi & Han, 2020; Setia et al., 2011). Analytical IT applications are defined as IT applications that are used to analyze data regarding services, internal business operations, customers (e.g., patients, payors), competitors, and the external market conditions of a hospital to generate insights for executive decision-making (Anand et al., 2020; Chen et al., 2012; Saldanha et al., 2017).

Then, building on previous studies (e.g., Du, 2015), we used entropy-based measures for computing MHS_SOIT and MHS_SAIT. In computing Unit_DOIT and Unit_DAIT, we used weighted counts of respective IT applications to capture the extensiveness and rareness of the operational and analytical IT applications in use. We then weighed this count variable using an adoption rate-based variable indicating the application's rareness in the industry. Appendix B3 presents the computation details of these four IT-based moderating variables.

Measurement of Control Variables

To rule out alternative explanations and account for other known factors in the MMC literature that could confound MMC effects, we included a total of 22 controls at three levels: (1) MHS market unit, (2) Market, and (3) MHS. Appendix B4 presents the definitions, operationalizations, and rationales of the controls. We also controlled for *year effects.* Appendix B5 reports descriptive statistics and pairwise correlations of the study variables.

As reported in Appendix B5, the correlations among a few study variables are relatively high. We calculated the variance inflation factors (VIF) of all the predictor variables. Two of them have VIF scores greater than 10. We ran a series of robustness checks by (1) dropping all variables with a VIF of greater than 10, (2) dropping all variables with VIFs greater than 8, (3) dropping seven selected control variables so that no pair of control variables had correlations greater than 0.5, or (4) dropping the same seven control variables plus the two IT variables with insignificant moderating effects. We note that for variables retained in the fourth robustness check, no pair of any predictor variables, including the multiplicative terms, had correlations greater than 0.5, and their VIF scores were all below 5. Our main results remain robust to all of these checks. Thus, overall, it does not appear that the high correlations among some study variables significantly influenced our main results. Because the control variables are borrowed from the MMC literature and included for theoretical consideration, as explained in Appendix B4, we chose to retain all the variables. The results of the fourth robustness check above are presented in Model B1 of Table 1.

Model Specification

Our data consists of an unbalanced panel of cross-sectional time-series observations. Thus, we estimated panel data models by including fixed effects at the market unit level.[5] Our primary estimation model is as follows:

$$Price_{imt} = \beta_0 + \beta_1 MMC_{imt} + \beta_2 MHS\_SOIT_{it} + \beta_3 MHS\_SAIT_{it} + \beta_4 Unit\_DOIT_{imt} + \beta_5 Unit\_DAIT_{imt} + \beta_6 MMC_{imt} \times MHS\_SOIT_{it} + \beta_7 MMC_{imt} \times MHS\_SAIT_{it} + \beta_8 MMC_{imt} \times Unit\_DOIT_{imt} + \beta_9 MMC_{imt} \times Unit\_DAIT_{imt} + Controls + MU_{im} + Year_t + \varepsilon_{imt},$$

Where *Controls* denote the vector of all control variables; MU_{im} denotes the fixed effects of the market units of MHS *i* in market *m*; $Year_t$ denotes a set of binary variables for year fixed effects; and ε_{imt} denotes the error term. We mean-centered MMC and IT moderating variables for the convenience of interpreting the results of their interaction relationships.

[5] We ran Hausman's specification tests to compare coefficient estimates of the fixed-effects and random-effects models. The results reject the null hypothesis that the two models have no systematic differences and support our choice of a fixed-effects model (Greene, 2002).

Table 1. The Effects of MMC, MHS-Level IT, and Unit-Level IT on Price

Dependent variable (DV): Price	Primary models (list price as DV)						Robustness checks				
Model specification	**Fixed effects panel data models**						**Multi-collinearity**	**Realized price as DV**	**Fixed-effect IV**	**System GMM**	**Multilevel mixed effects**
Variables	***Model A1***	***Model A2***	***Model A3***	***Model A4***	***Model A5***	***Model A6***	***Model B1***	***Model B2***	***Model B3***	***Model B4***	***Model B5***
Multimarket contact (MMC)	0.766 (0.522)	0.752 (0.516)	0.770 (0.487)	0.993+ (0.548)	0.996+ (0.519)	1.115+ (0.576)	0.923+ (0.509)	0.229 (0.211)	0.996+ (0.576)	1.384 (2.113)	0.944* (0.475)
Cross-unit standardization of operational IT (MHS_SOIT)		-1.657*** (0.397)	-1.622*** (0.392)	-1.709*** (0.398)	-1.675*** (0.394)	-1.650*** (0.406)	-0.669* (0.274)	0.163 (0.157)	-1.675*** (0.409)	-3.557*** (0.825)	-1.663* (0.764)
Cross-unit standardization of analytical IT (MHS_SAIT)		0.646* (0.298)	0.664* (0.298)	0.651* (0.298)	0.667* (0.298)	0.631* (0.307)		-0.079 (0.094)	0.667* (0.304)	2.881*** (0.779)	0.669 (1.031)
Market units' differentiated operational IT (Unit_DOIT)		0.051* (0.023)	0.049* (0.022)	0.043+ (0.023)	0.042+ (0.023)	0.041+ (0.023)		0.003 (0.007)	0.042+ (0.024)	-0.069 (0.065)	0.031 (0.033)
Market units' differentiated analytical IT (Unit_DAIT)		-0.083 (0.108)	-0.074 (0.108)	-0.078 (0.107)	-0.070 (0.108)	-0.071 (0.109)	-0.043 (0.116)	0.037 (0.037)	-0.070 (0.078)	-0.420 (0.320)	-0.087 (0.150)
MMC × MHS_SOIT			2.162* (0.860)		1.917* (0.827)	2.413+ (1.424)	2.235* (0.874)	0.622* (0.305)	1.917* (0.851)	5.357+ (3.053)	2.303** (0.760)
MMC × MHS_SAIT						-0.064 (0.181)					
MMC × Unit_DOIT						-0.049 (0.097)					
MMC × Unit_DAIT				-0.804** (0.275)	-0.757** (0.268)	-0.726** (0.273)	-0.614** (0.225)	-0.283** (0.096)	-0.757** (0.235)	-1.870* (0.842)	-0.712** (0.219)
Control variables	included	Included	included	included	included	included		included	included	included	included
Year fixed effects	included	Included	included	included	included	included		included	included	included	included
Constant	16.311* (7.370)	20.247* (7.850)	20.869** (7.901)	20.443** (7.818)	20.982** (7.858)	20.940** (7.809)	14.301*** (3.301)	9.099** (3.082)	20.982*** (3.278)	40.437* (15.808)	27.621** (9.329)
R-squared	0.392	0.395	0.396	0.396	0.397	0.397	0.381	0.163	N/A	N/A	N/A

Note: $+p < 0.10$; $*p < 0.05$; $**p < 0.01$; $***p < 0.001$; two-sided tests when applicable; standard errors reported in the parentheses; all models are based on analyses of 5,660 observations from 1,062 market units of 195 MHS. Fixed-effect models all specify fixed effects at the market unit level. MMC, MHS_SOIT, MHS_SAIT, Unit_DOIT, and Unit_DAIT are first mean-centered and then multiplied for convenient interpretation of regression coefficients of interaction items; we omit the results of control variables and year fixed effects here for space limit. Appendix C presents the detailed results of our control variables from selected models of this table.

Results

Table 1 presents the results. Models A1-A6 report the results with or without moderating effects. Models B1-B5 present the results of the robustness checks. In order to fit the main results into Table 1, we moved the results on the control variables to Appendix C.

In Model A6, we report the full results with all four potential moderating effects between our IT variables (operational vs. analytical IT at the MHS vs. market unit level). The coefficient of MMC × MHS_SOIT (as in H1a) is statistically significant at the level of 0.1, whereas the coefficient of MMC × Unit_DAIT (as in H2b) is statistically significant at the level of 0.01. The coefficients of the other two moderating effects, MMC × MHS_SAIT (as in H1b) and MMC × Unit_DOIT (as in H2a), are insignificant.

Because of the high correlation between MHS_SOIT and MHS_SAIT (corr. = 0.876), the inclusion of all four moderating items in Table A6 introduces collinearity concerns. We also note that the R^2 for Model A6 does not show any noticeable improvement over the R^2 of Model A5. Based on the principle of parsimony, i.e., Occam's razor, we chose to rely on Model A5 as our primary model to interpret the results, run robustness checks, and draw conclusions, with the acknowledgment that H1b and H2a are not supported.

The results of Model A5 support H1a and H2b. We further note, based on the results of Model A3-A6 and Model B1, that our conclusions regarding MMC × MHS_SOIT (H1a) and MMC × Unit_DAIT (H2b) remain qualitatively similar whether included individually (Models A3 and A4), simultaneously (Model A5), together with the other moderating items (Model A6), or when the other insignificant IT moderators are completely removed (Model B1).

The Main Effects of MMC on Price

As reported in Model A5 of Table 1, MMC has a positive and marginally significant effect on price (β_1= 0.996, p-value < 0.1) when the two moderators are at their mean values. To further investigate the significance of the MMC price effects, we conducted regions of significance analyses (Aiken &

West, 1991) to examine the statistical significance of the MMC effects on price when the values of the two moderators vary. Specifically, we ran significance tests on the MMC price effects at all the observed values of MHS_SOIT and Unit_DAIT in our sample. The results show that at a significance level of 0.05, the regions in which the MMC price effects are significant cover approximately 40.5% of the overall observed regions of MHS_SOIT and Unit_DAIT values. As reported in Model A1 of Table 1, MMC does not show significant price effects when the moderating roles of the IT mechanisms are not taken into account.

The Main Effects of the IT Mechanisms on Price

While not explicitly hypothesized, we observe that some IT mechanisms have significant main effects on price. For instance, the operational IT mechanisms at the corporate (MHS) level and the market unit level have significant effects on price in Models A2-A6.

At the corporate level, we found that the cross-unit standardization of operational IT across market units (MHS_SOIT) significantly reduced prices. This main effect is consistent with prior IS studies finding that MHSs can achieve economies of scale in order to reduce hospital service prices by standardizing the IT resources of its member hospitals (Du, 2015). At the market unit level, our findings indicate that the use of differentiated operational IT (Unit_DOIT) increased the cost of hospital services, at a significance level of 0.1. This effect is also supportive of the use of IT to support competition—i.e., hospitals engage in an “arms race” (Morrisey, 2001) by investing in advanced technologies and then charging premium prices for their services.

Regarding analytical IT, we found that the corporate-level analytical IT mechanism, i.e., the cross-unit standardization of analytical IT across market units (MHS_SAIT), significantly increased hospital prices, as supported invariantly in Model A2-A6. This finding is consistent with prior IS research, which found that the use of analytical IT capabilities for revenue management boosted revenues from patient services (Qi & Han, 2020). The enterprise-wide standardization of analytical IT might enable MHSs to engage in such revenue management at scale to boost its overall revenues from all hospital services across its market units. At the level of individual market units, we did not observe any significant price effects for a market unit’s use of differentiated analytical IT (Unit_DAIT). Together, the two results indicate that performing analytics at the MHS scale might be critical for the MHS’s ability to boost revenues from hospital services.

The Interaction Effects of MMC and IT Mechanisms on Price

We found evidence in support of the moderating roles of MHS-level cross-unit standardization of operational IT (MHS_SOIT) and market unit-level use of differentiated analytical IT (Unit_DAIT) on the price effects of MMC. In Model A5 of Table 1, MHS_SOIT significantly amplified the positive effects of MMC on price ($\beta_6 = 1.917$, p-value < 0.05), while Unit_DAIT significantly attenuated these effects ($\beta_9 = -0.757$, p-value $<$ 0.01).

Figure 1 further depicts the interaction effects by plotting the relationship between MMC and price when a given moderator, either MHS_SOIT (Figure 1a) or Unit_DAIT (Figure 1b), takes on low versus high values (the 25th and 75th percentiles of their values in the sample), while the other moderator is fixed at its median value. We also included error bars to illustrate the 95% confidence intervals of the estimated prices when MMC varies.

In Figure 1a, the slope of the line between MMC and price increases when MHS_SOIT changes from low to high levels, while in Figure 1b, the slope of the line between MMC and price decreases when Unit_DAIT changes from low to high levels. Overall, the results in Table 1 and Figure 1 are consistent with our hypotheses H1a and H2b regarding the moderating effects of MHS_SOIT and Unit_DAIT on the link between MMC and price.

As noted, both the main effects and the moderating effects of the IT mechanisms affect price. MHS_SOIT has a negative main effect on price and a positive moderating effect on the link between MMC and price. In Figure 1a, the MMC-Price line for low MHS_SOIT is at a higher level than the MMC-Price line for high MHS_SOIT, although the slope of the line increases when MHS_SOIT increases from a low to a high level. The 95% confidence intervals of the two lines do not overlap, suggesting that when MHS_SOIT is high, *price* is statistically significantly lower than *price* when MHS_SOIT is low. These results suggest that MHS might be using the coordination mechanism created by the cross-unit standardization of operational IT to support both competition and collusion. The use of this IT-enabled coordination mechanism for competition reduces price while the use of the same mechanism for tacit collusion amplifies the price effects of the tacit collusion strategy.

In Figure 1b, the two MMC-Price lines at low and high levels of Unit_DAIT intersect near the medium level of MMC. The 95% confidence intervals of the two lines always overlap. Thus, we cannot determine whether market units’ low or high usage levels of differentiated analytical IT capabilities would have overall positive or negative net effects on price. Our results only allow us to conclude that Unit_DAIT negatively moderates the link between MMC and prices by flattening their relationship line.

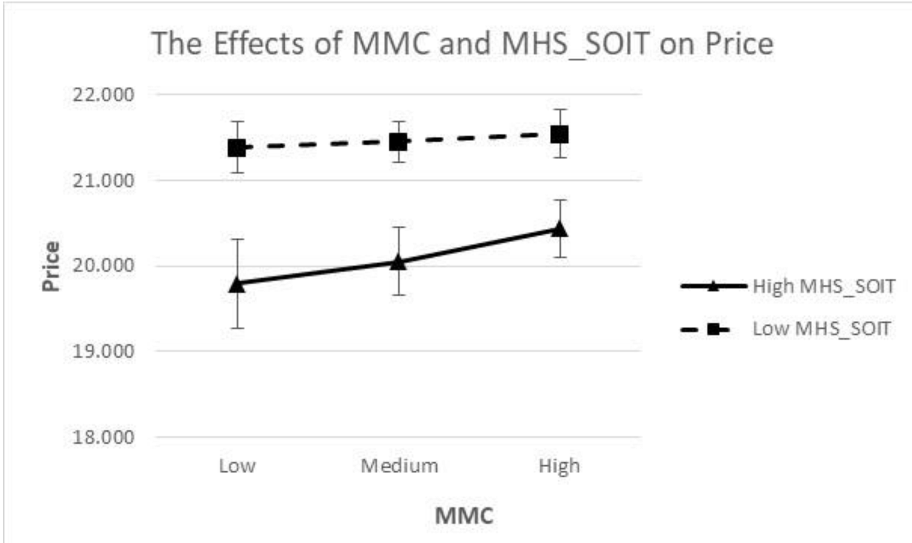

Figure 1(a). Effects of MMC and MHS_SOIT on Price

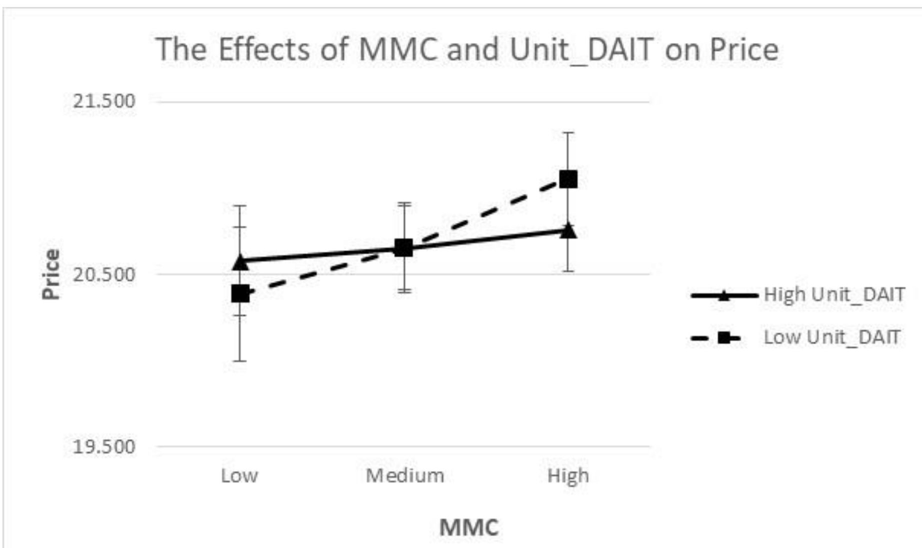

Figure 1(b). Effects of MMC and Unit_DAIT on Price

Figure 1. Visual Illustration of Interaction Effects

Endogeneity and Identification

Sensitivity to Omitted Confounding Variables

To address endogeneity concerns, we first assessed the sensitivity of our results to potentially omitted confounding variables. In particular, we relied on the impact threshold for the confounding variable (ITCV) analysis, developed by Frank and colleagues (Frank, 2000; Frank et al., 2013). ITCV enables researchers to investigate questions such as: "How much bias must there have been due to uncontrolled preexisting differences to make the inference invalid?" (Frank et al., 2013, p. 438). It quantifies a threshold, or a "switch point," such that the estimated effect of interest can be considered robust to the risk of omitted confounding variables if the estimated effect size exceeds the switch point. Using the online tool developed by Rosenberg et al. (2018), we examined the estimated effects of MHS_SOIT and Unit_DAIT as in Model A5 of Table 1. Our analyses suggest that our results are robust to possibly omitted confounding variables.

Fixed Effect 2SLS Models

IT investments and standardization can all be endogenous decisions of MHS and their member hospitals, as certain unknown factors might simultaneously influence both IT decisions and price. To address this concern, we used a set of four instrumental variables to account for the endogeneity concerns of MHS_SOIT, MHS_SAIT, Unit_DOIT, and Unit_DAIT as analyzed in Model A5 of Table 1.

The instrumental variables we used are the national and state-level average levels of IT standardization and differentiation, which represent the national and local trends of IT development. They qualify as a valid instrument variable because health organizations often succumb to peer influence when making IT development decisions (Angst et al., 2010; Salge et al., 2015), but national or statewide health IT trends should not have a direct effect on the focal hospital's pricing of health services.

In particular, we applied the same formula as defined in Appendix B3 to calculate annual MHS_SOIT and MHS_SAIT for all MHSs in the U.S. and then took the national averages as two instrumental variables. We similarly calculated annual hospital-level DOIT and DAIT for all the hospitals in the same state of the focal MHS's market unit and then took the statewide average to measure the other two instrumental variables. Because we used cross-sectional time-series panel data, we specified fixed-effect two-stage least squares models (FE2SLS) (Semykina & Wooldridge, 2010; Wooldridge, 2010). Model B3 of Table 1 reports the results based on the FE2SLS model. Our main results and conclusions remain qualitatively the same.

System GMM Models

Because of the limited availability of instrumental variables, we cannot fully account for the endogeneity biases with FE2SLS models if additional variables are also potentially endogenous. We thus used system GMM (generalized method of moments) models as an alternative estimation method for robustness checks (e.g., Bardhan et al., 2013; Salge et al., 2015). Specifically, we estimated the Arellano-Bover (1995) / Blundell-Bond (1998) system GMM models, which use the lagged values of both levels and the first differences of endogenous variables as instrumental variables. We considered all variables under the direct control of an MHS or its market units as potentially endogenous, including our primary independent variables, all market unit-level control variables, and all MHS-level control variables other than the age of the MHS. Then, building on the established system GMM specification procedures (Roodman, 2009) and previous studies with a similar data setup (e.g., Bardhan et al., 2013), we specified the two-step GMM estimator by using the second and deeper lags of all the potentially endogenous variables as well as their first differences as the instrumental variables. Following previous studies (e.g., Aral et al., 2012; Bardhan et al., 2013), we also included a Windmeijer finite-sample correction (Windmeijer, 2005) to correct for potential downward biases in the two-step covariance matrix of the parameter estimates.

Model B4 of Table 1 reports the results based on system GMM models. These results indicate that our main conclusions regarding the roles of MHS_SOIT and Unit_DAIT remain qualitatively unchanged at a significance level of 0.1.

Multilevel Mixed Effects Models

As reported earlier, our primary model specification uses unit-level fixed effects and year fixed effects and assumes that any unobserved MHS-level effects are unrelated to our independent variables and invariant across time and MHS market units. As another robustness check, we relaxed this assumption by specifying a mixed-effect panel data model with two random effects, one at the corporate level of the MHS and the other one at the unit level as *MHS-in-market*, in addition to the fixed effects for years. Model B5 of Table 1 reports the results based on the multilevel mixed effects models. The main results remain qualitatively the same with this new model specification.

Discussion and Conclusion

The findings address the motivating questions of the study as follows: Regarding the practice-oriented question of how MHSs are able to charge higher average prices for hospital services, we found that MHSs use the MMC-induced rivalry restraint strategy to tacitly collude and forbear from price competition to keep their prices above competitive levels. Regarding the theoretical question of how MHSs implement the rivalry restraint strategy when their market units face pressures to compete on cost, we found that the use of cross-unit SOIT positively interacts with the strategy to reinforce price effects. In addition, the study explained why and how market units' use of DAIT reduces the effectiveness of the rivalry restraint strategy. The proposed theory and findings contribute to academic and practitioner conversations on the strategic roles of IT in alternative theories of firm profitability.

Contributions to Research

Contribution to the Strategic Roles of IT in Theories of Firm Profitability

The majority of IS studies examining the strategic roles of IT build on the resource-based view of firm profitability (Bhatt & Grover, 2005; Mata et al., 1995; Melville et al., 2004; Wade & Hulland, 2004). The dominant perspective within this view argues that IT can improve firm profitability by increasing the firm's competitive action repertoire and serving as a source of competitive advantage (e.g., Chi et al., 2010; Vannoy & Salam, 2010). A less prominent perspective draws attention to the possibility that multimarket competition can create opportunities for tacit collusion with rivals and calls for research on the IT profiles of successful multimarket competitors (Chari et al. 2008). This study responds to this call by theorizing a specific IT mechanism (SOIT) by which MUMM firms implement a rivalry restraint strategy to collude with MMC rivals and keep their prices above competitive levels. We found that SOIT positively interacts with MMC to increase the cost of hospital services. This finding provides evidence that MHSs use SOIT to support a tacit collusion strategy. This finding strengthens the less prominent perspective described above by explaining how IT could contribute to firm profitability through tacit collusion with rivals rather than fueling a cycle of competitive action and reaction among the rivals.

The study also theorizes and validates why market units' use of differentiated analytical IT (DAIT) weakens the price effects of the rivalry restraint strategy. Differentiated resources such as the early adoption of emerging analytical IT capabilities, and consequently lower-cost or higher-quality hospital services, violate the assumptions of RRT for sustaining tacit collusion. Indeed, we found that DAIT negatively interacts with MMC to significantly dampen the price effects of the tacit collusion strategy. Our analyses in Appendix D further indicate that DAIT and MMC together significantly reduce the costs of hospital services and also marginally but significantly improve the quality of care delivery. When MMC rivals in overlapping markets observe that the market units of the focal MHS are differentiating the cost and quality of hospital services, they may also start to invest in their own cost efficiency and/or quality, thus further fostering service heterogeneity, thereby breaking the truce and weakening the price effects of the corporate-level rivalry restraint strategy.

Interestingly, within MUMM firms, the two strategic roles of IT could be simultaneously at work. We find evidence that the corporate-level IT mechanism (SOIT) supports firm profitability through tacit collusion with rivals whereas the market unit-level IT mechanism (DAIT) supports firm profitability through competitive advantage. The two IT roles conflict with each other and dampen each other's effects on firm profitability. These findings suggest that scholars should pay attention to both mechanisms. For example, IS studies focusing on how business units of a firm use IT for competitive actions may wish to control for the corporate parent's use of an enterprise-wide IT coordination mechanism to implement and enforce tacit collusion with multimarket rivals.

There is seemingly conflicting empirical evidence on whether IT softens competition (Drnevich & Croson, 2013; Shambaugh et al., 2018) or intensifies competition (McAfee & Brynjolfsson, 2008; Nan & Tanriverdi, 2017). The proposed theory explains why these seemingly conflicting sets of arguments and empirical evidence might be simultaneously valid. IT is a multipurpose technology. A firm can use IT to enhance its competitiveness and capacity to take competitive actions, but it can also use IT to restrain rivalry. Different IT-enabled mechanisms at different organizational levels may play different roles in enhancing or restraining competition, as revealed by our results.

In our empirical context, the corporate parents of MHSs have a clear corporate goal in investing in SOIT: i.e., coordinate market units to adhere to the tacit collusion strategy with MMC rivals. Similarly, market units have a clear strategic goal in investing in DAIT: i.e., differentiate services in terms of cost and quality in order to gain competitive advantages in their local markets. The goal misalignment between the corporate parent and the market units might explain why MUMM firms often invest in the two conflicting IT mechanisms simultaneously and dampen each mechanism's profitability benefits. Drnevich and Croson (2013) also raise the possibility that IT investments may have unintended effects: e.g., an IT investment intended to increase competition might inadvertently constrain competition and vice versa. Further research is required to theorize why the two conflicting IT mechanisms might be used simultaneously despite the profitability trade-offs. This study provides a theoretical foundation and a set of IT constructs for further theorizing the strategic roles of IT in competitive advantage-based and collusion-based theories of firm profitability.

Contribution to Coordination Mechanisms of the Rivalry Restraint Theory (RRT)

Based on RRT, MUMM firms need to have effective enterprise-wide coordination mechanisms to implement and enforce the rivalry restraint strategy across their market units (Sengul & Gimeno, 2013). The extant literature focuses on conventional coordination mechanisms such as task forces, boundary spanners, the use of incentives, and the allocation of decision rights (Golden & Ma, 2003; Sengul & Gimeno, 2013). The effectiveness of these coordination mechanisms is rather limited. They provide only partial solutions to the coordination problems of MUMM firms (Sengul & Gimeno, 2013). This study theorizes a corporate-level, IT-based coordination mechanism (SOIT) and validates that SOIT-enabled MUMM firms reinforce the price effects of the rivalry restraint strategy. The introduction of SOIT extends RRT's explanatory mechanisms regarding the implementation and enforcement of a rivalry restraint strategy across the market units of MUMM firms. The extended RRT can open up new avenues of research for strategy and for IS scholars seeking to understand how MUMM firms achieve profitability through the use of collusion-based strategies.

RRT also requires MMC rivals to have undifferentiated resources and services in order to sustain the truce established by the rivalry restraint strategy. This study proposes a market unit-level IT mechanism that violates this assumption and reduces the effectiveness of the rivalry restraint strategy. Specifically, this study theorizes how and why market units' use of differentiated analytical IT capabilities (DAIT) reduces the cost of services and motivates market units to engage in competition rather than adhering to the corporate parent's instructions to keep prices high. The integration of DAIT extends RRT's explanatory processes regarding the sustainability of the rivalry restraint strategy. The extended RRT opens up new avenues of research for strategy and for IS scholars seeking to understand how the corporate-level and market unit-level IT mechanisms affect the interactions between collusion-based and competition-based strategies and their profitability outcomes.

Contribution to the Sensing Mechanisms of RRT

Based on RRT, MUMM firms need to have mechanisms to track the prices charged by MMC rivals and can sense if there is defection from the truce. In the hospital industry, insurance carriers and employer organizations negotiate hospitals' list prices to obtain lower realized prices. Dynamic changes in realized prices are not directly observable. This creates a major challenge for MHSs to track the realized prices and sense whether changes in patterns imply defection from the truce established by the rivalry restraint strategy. Model B2 of Table 1 indicates that MMC does not have a significant effect on the realized prices. This finding suggests that MHSs, in general, are not able to keep realized prices high despite MMC-induced rivalry restraints. However, when MMC interacts with SOIT, they jointly have a positive effect on the realized prices. This finding suggests that SOIT enables MHSs to better track dynamically changing realized prices, detect defections from the truce, and bring defectors back into compliance with tacit collusion to keep realized prices high. In contrast, MHSs with low levels of SOIT cannot keep the realized prices high despite having multimarket contact with rival MHSs. The introduction of IT constructs such as SOIT into RRT can open up new avenues of research on how firms use IT to achieve profitability through collusion-based strategies.

Contribution to Industrial Organization View of MUMM Firms

Health economists and strategists have taken the industrial organization (IO) perspective to argue that multihospital systems might be able to increase prices by increasing their bargaining powers in local markets. To account for these explanations, we controlled for the concentration of hospitals, on the one hand, and the concentration of buyers (insurance firms) on the other. The results in Appendix C indicate that hospital concentration has a positive and marginally significant effect on hospital prices whereas insurance concentration does not have a significant effect. After controlling for these IO-based measures, we found that rivalry restraint through MMC still significantly increased hospital prices. These findings inform the scholarly conversations in the IO literature, indicating that IO forces, per se, may not be as influential in affecting hospital prices as assumed in the literature. However, it is possible that IT mechanisms might interact with IO forces to amplify or dampen their effects. Future research may wish to explore how MHSs' IT mechanisms might interact with IO forces to affect hospital prices.

Contributions to Practice

Implications for Regulators

Collusion among rivals violates antitrust regulations. Although MHSs have been under scrutiny from regulatory agencies for their price inflation behaviors (Gaynor & Vogt, 2000), regulators face significant challenges in detecting tacit collusion (Berenson, 2015). In reviewing the MMC literature, Yu and Cannella (2013) warned policy makers about the policy implications of MMC, especially from the perspective of consumer welfare. They note: "There are significant but widely ignored ethical concerns that arise from the emergence of mutual forbearance. It is, after all, a form of collusion" (Yu & Cannella, 2013, p. 104). The current antitrust laws focusing on individual markets as the unit of antitrust analysis may not be effective in addressing the tacit collusion arising from multimarket contact (Bond & Syropoulos, 2008; Hannan & Prager, 2004). To develop future policy solutions, a better understanding of when MMC is likely to lead to tacit collusion may be needed. Our study informs regulators that the ability of an MHS to effectively implement an MMC-induced tacit collusion strategy is contingent on the MHS's enterprise-wide coordination capabilities. Our study reveals that MHSs that achieve high levels of SOIT are rare, but they are the types of MHSs who are likely to effectively coordinate the implementation and enforcement of an MMC-induced tacit collusion strategy to keep prices above competitive levels. Thus, regulators may wish to prioritize scrutinizing MHSs with high levels of SOIT.

Implications for Executives of MHS

This study informs MHS executives that the use of a rivalry restraint strategy can enable them to keep prices above competitive levels. However, market units facing competitive pricing pressures in their local markets can ignore the parent's pricing guidance and deviate from the tacit collusion strategy. Our results suggest that an IT-enabled, enterprise-wide coordination mechanism might enable the corporate parent to implement and enforce its pricing guidance to keep the prices charged by market units high. The study also informs MHS executives that market units' analytical IT capabilities weaken the price inflation effects of the rivalry restraint strategy. Overall, these results indicated that pulling the levers of both tacit collusion and competition simultaneously may not be feasible. The use of IT to support one of these strategies might reduce the effectiveness of the other strategy or vice versa.

Limitations and Future Research

One limitation of the study is that it defined markets geographically and focused on multimarket contact across geographic markets. The empirical study focused on the average price of hospital services offered by an MHS in a given geographic patient market. Our findings do not explain the prices charged for specific hospital services at a granular level. The proposed theory, however, could potentially also apply at the finer-grained level of hospital services. To test the validity of this proposition, future studies could define markets at a more granular level, such as specific hospital services, and examine how MMC in hospital service markets would affect the price of specific hospital services, such as cardiovascular surgery or knee replacement.

Another limitation is that the study focused only on the interactions between the rivalry restraint strategy and IT-based mechanisms. There could also be interactions between this strategy and other factors, especially external market structure factors or internal organizational design factors. MMC scholars have called for a better understanding of the various contingencies that make MMC-induced rivalry restraint more likely to emerge and be sustained (Sengul & Dimitriadis, 2015; Yu & Cannella, 2013). Future research opportunities include theorizing and testing additional interactions.

We developed and validated our theory in the context of U.S. hospitals. We posit that the same theoretical mechanisms, with proper contextualization, might also apply to MMC-induced rivalry restraint in other industries. We acknowledge that multihospital systems may not have the same level of tight governance and control over their market units as MUMM firms in other industries. Future studies could test the generalizability of the proposed theory in other contexts.

The IS literature has extensively studied the roles of IT in competitive advantage-based theories of firm profitability such as the resource-based and knowledge-based views of the firm (Bhatt & Grover, 2005; Mata et al., 1995; Melville et al., 2004; Wade & Hulland, 2004). As we seek to better understand the roles of IT in alternative theories of firm profitability (e.g., Drnevich & Croson, 2013; Makadok, 2010; Makadok, 2011), we call for further theorizing on the roles of IT in collusion-based theories of firm profitability. While we theorized the two-way interactions between MMC and corporate-level IT and MMC and unit-level IT, a fruitful next step would be to theorize the three-way interactions among MMC, corporate-level IT, and unit-level IT mechanisms.

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Appendix A

An Illustrative Example of MHS and MMC in the U.S. Hospital Context

Definitions of Key Terms

Table A1. Definitions

Term	Definition
Patient Market	A patient market is a geographic area with a grouping of hospitals that are within the commuting distance of patients (Douglas & Ryman, 2003; Dranove & White, 1994). We measure geographic patient markets using core-based statistical areas (CBSA). The Office of Management and Budget of the U.S. federal government defines a CBSA as an urban center and its adjacent areas with a population of at least 10,000 people who are socioeconomically connected to the urban center by commuting.
Multimarket, multihospital systems	In the U.S. hospital industry, multihospital systems (MHS) are defined as "two or more hospitals owned, leased, sponsored, or contract managed by a central organization" (https://www.aha.org/statistics/fast-facts-us-hospitals) We further define multimarket multihospital systems as multihospital systems that operate hospitals in at least two CBSA-based geographic patient markets.
Market unit of multimarket MHSs	We define an MHS market unit as the MHS's cluster of member hospitals in a geographic patient market. An MHS market unit contains one or more member hospitals. For instance, MHSs may have a flagship hospital and several satellite community hospitals that refer patients to flagship hospitals and share resources with them.
Multimarket contact (MMC)	Multimarket contact (MMC) refers to the situation in which two MHSs compete with each other in more than one market. We then define an MHS's extent of MMC with another MHS as the number of geographic patient markets in which the two MHSs compete, i.e., the number of overlapping patient markets of the two MHSs.

An Illustrative Example

We used Trinity Health (www.trinity-health.org/) as an example of a multimarket, multihospital system (MHS) in our sample. As of 2013, Trinity Health operated a total of 40 hospitals organized into 23 market units in 23 CBSA-based patient markets. Some market units had more than one hospital. For example, within one CBSA-based patient market near Philadelphia, PA., Trinity Health's market unit had a total of seven hospitals as of 2013.[6] Figure A1 visually illustrates the geographic dispersion of Trinity Health and the multimarket contact it had with a selective sample of three rival MHSs as of 2013. Figure A1 shows that Trinity Health (**T**) had multimarket market contact (MMC) with Select Medical (**S**) in eight of its 23 patient markets, with Kindred Healthcare (**K**) in six markets, and with Ascension Health (**A**) in four markets. Trinity Health competed with all three MMC rivals in two patient markets, competed with two MMC rivals in four additional patient markets, and competed with one MMC rival in another four patient markets. Thus, considering only these three other MHSs, Trinity Health competed against MMC rivals in 10 out of its 23 patient markets.

[6] In 2013, Trinity Health operated a total of seven hospitals in the CBSA of Philadelphia-Camden-Wilmington: (1) Lourdes Medical Center of Burlington County, (2) Mercy Fitzgerald Hospital, (3) Mercy Suburban Hospital, (4) Nazareth Hospital, (5) Our Lady of Lourdes Medical Cente, (6) St. Francis Hospital, and (7) St. Mary Medical Center.

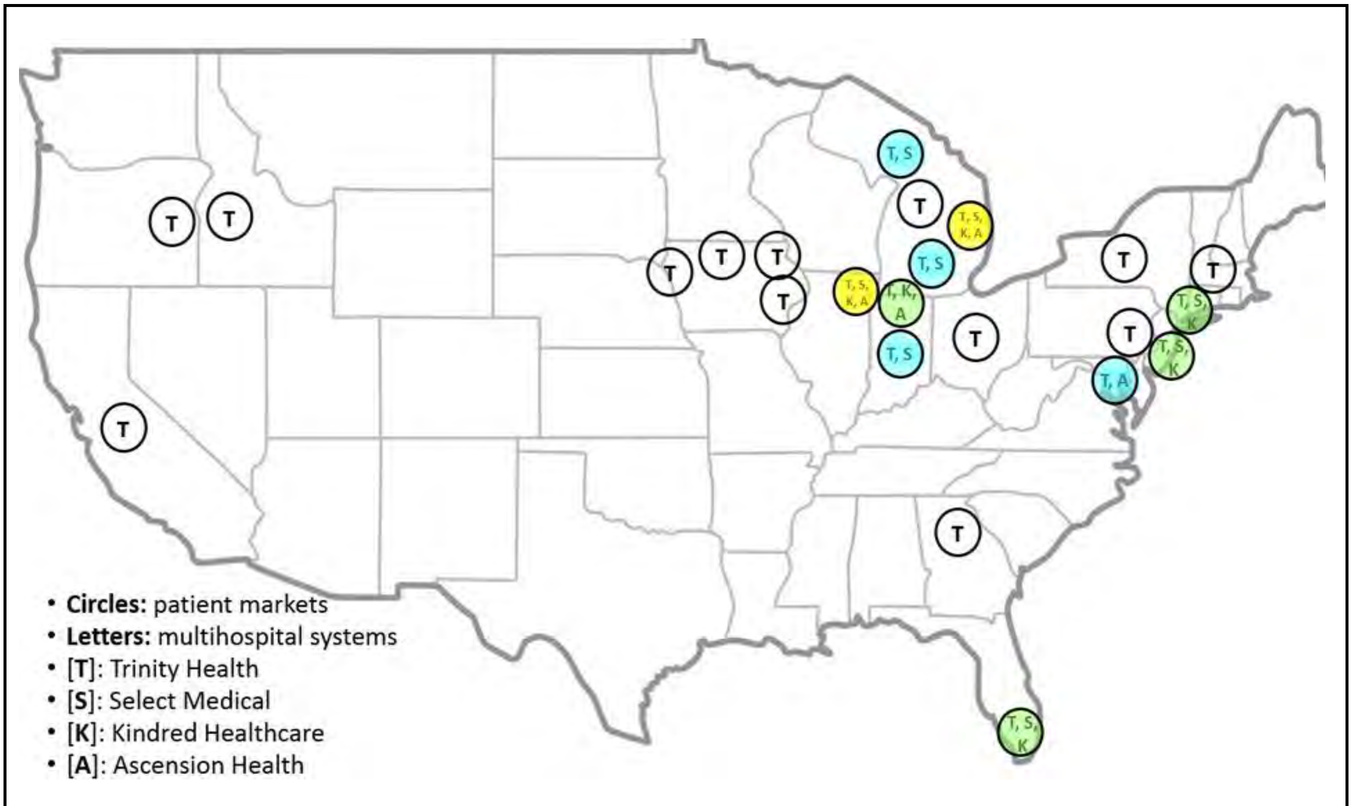

Figure A1. Illustration of MMC among Multihospital Multimarket Systems (MHS)

Appendix B

The Data and Measurement of Study Variables

Notation

We use the following notations throughout Appendix B.

- The dataset consists of N multihospital systems (MHS), M CBSA-based patient markets, and T years, with MHS indexed as i, markets indexed as m, and years indexed as t.

- Each MHS i operates in a total of M_{it} markets in year t (i.e., MHS i has a total of M_{it} market units)

- In each market unit m, MHS i operates a total number of D_{imt} hospitals in year t, with hospitals indexed as d

List Price / Realized Price Charged by Patient Services[7]

The list or realized price level (measured as revenue-per-patient-day) charged by hospital d of MHS i in market m in year t ($LPrice_{imdt}$ *or* $RPrice_{imdt}$) is defined as:

$$LPrice_{imdt} = \frac{GrossPRev_{imdt}}{Pday_{imdt} \times CMI_{imdt}}$$

$$RPrice_{imdt} = \frac{NetPRev_{imdt}}{Pday_{imdt} \times CMI_{imdt}},$$

where $GrossPRev_{imdt}$ is the hospital's annual gross revenue from patient services in year t; $NetPRev_{imdt}$ is the hospital's annual net revenue from patient services (i.e., gross revenue from patient services minus allowances and discounts on patient accounts) in year t; $Pday_{imdt}$ is the total number of days patients spent in the hospital d in year t; and CMI_{imdt} is the hospital's case-mix index in year t. Hospitals' CMI data are from the CMI data file published by the Centers for Medicare & Medicaid Services (CMS) and all other financial and operational data are from CMS' HCRIS database.

Then, for the market unit m of an MHS i in year t, its overall list or realized price level ($ListPrice_{imt}$ or $RealPrice_{imt}$) is defined as the weighted average of hospital-level prices:

$$ListPrice_{imt} = \frac{\sum_{d=1}^{D_{imt}}(LPrice_{imdt} \times Bed_{imdt})}{\sum_{d=1}^{D_{imt}}(Bed_{imdt})}$$

$$RealPrice_{imt} = \frac{\sum_{d=1}^{D_{imt}}(RPrice_{imdt} \times Bed_{imdt})}{\sum_{d=1}^{D_{imt}}(Bed_{imdt})},$$

where Bed_{imdt} is the total number of staffed beds operated by the hospital d in year t. Note that, based on these price formulas, if a market unit m of an MHS i in year t only operates one hospital, then $D_{imt}=1$, and the average price level of a market unit would be the same as the price calculated for this single member hospital.

[7] Hospitals sometimes report extreme financial values. For example, one hospital reported only 71 patient days in a year with a revenue of $135 million. We do not have further evidence indicating whether these extreme cases are due to reporting errors or other unusual circumstances. To mitigate the influence of such extreme cases, when calculating relevant variables, we excluded hospitals whose list or realized prices were either in the top or the bottom 0.1% of the distribution of the entire hospital population in our study time frame. Other studies using similar empirical contexts have made similar decisions: e.g., an MMC study winsorized the data of hospital prices at the 5% and 95% levels (Schmitt, 2018).

Multimarket Contact (MMC)

We build on the formula developed by Baum and Korn (1996) to measure MMC at the level of MHS-in-market units (market units). The original formula of Baum and Korn (1996) is adapted to take into consideration the relative importance of the overlapping markets to the focal firm, as recommended by other MMC studies (e.g., Baum & Korn, 1999; Kang et al., 2010). Specifically, we measure the MMC level of an MHS *i* in market *m* in year *t* as follows:

$$MMC_{imt} = \frac{\sum_{j \neq i} \sum_m (P_{imt} \times P_{jmt} \times Bed_{imt})}{\sum_m (P_{imt} \times Bed_{imt}) \times N_{MMCt}}, for\ all\ j\ when \sum_m (P_{imt} \times P_{jmt}) > 1,$$

where P_{imt} and P_{jmt} are binary variables indicating whether MHS *i* and *j* have presence in market *m* in year *t* (1 = present; 0 otherwise); Bed_{imt} is the count of staffed beds operated by MHS *i* in market *m* in year *t*; N_{MMCt} is the total number of MHS that contact the focal MHS *i* in market m in year *t* and also contact MHS *i* in one or more additional markets in the same year *t*. Thus, $\frac{\sum_m (P_{imt} \times P_{jmt} \times Bed_{imt})}{\sum_m (P_{imt} \times Bed_{imt})}$ is the ratio of the weighted count of overlapping markets between MHS *i* and *j* to the total number of MHS *i*'s markets, with the share of beds operated by MHS *i* in market *m* over its total beds across all the markets as the weight. The condition $\sum_m (P_{imt} \times P_{jmt}) > 1$ ensures that MHS *i* and *j* have multimarket contact. The overall formula calculates the average level of multimarket contact between MHS *i* and all its multimarket competitors that contact the focal MHS *i* in market m in year *t*. This measure takes on values from zero to one. Specifically, $MMC_{imt} = 0$ when MHS *i* does not engage any multimarket competitors in market *m* in year *t*. $MMC_{imt} = 1$ when MHS *i* engages each and every one of the multimarket competitors it engages in market *m* in year *t* also in all of its other markets.

Corporate-Level and Market Unit-Level IT Constructs

Profiling hospitals' health IT applications: To measure the proposed corporate-level and unit-level IT constructs, we follow previous studies in constructing the health IT profiles of all the hospitals in the sample based on the HIMSS Analytics database (e.g., Du, 2015). HIMSS Analytics annually tracks the use of a variety of health IT applications for U.S. hospitals. We selected all 69 health IT applications that had been tracked by HIMSS Analytics in all years in our study time frame in order to ensure the comparability of our measures across the years. We then categorized these 69 health IT applications into two types: (1) operational IT applications and (2) analytical IT applications. We identified 59 operational IT applications in 13 categories and 10 analytical IT applications in three categories, as listed in Table B1 below.

Measuring MHSs' cross-unit standardization of operational IT (MHS_SOIT) and analytical IT (MHS_SAIT): We respectively measured MHS_SOIT and MHS_SAIT based on the average standardization levels of operational IT and analytical health IT applications used across an MHS's member hospitals. First, following previous studies (e.g., Du, 2015), we adopted an entropy-based measure to capture the standardization level of an IT application in an MHS. We indexed different health IT applications (such as EMR systems) by *k*, and the specific brands of software products (such as Cerner or Epic) by *j*, then the standardization level of an application k in MHS *i* in year *t* (STD_{ikt}) as:

$$STD_{ikt} = -\sum_{j=1}^{M_{ikt}} \left(\frac{Bed_{jkt}}{Bed_{it}} Ln \frac{Bed_{it}}{Bed_{jit}}\right)$$

where Bed_{it} is the total count of staffed beds operated by MHS *i* in year *t*, Bed_{jkt} is the total count of staffed beds of hospitals that implement the j^{th} software product of this application *k*, and M_{ikt} is the total number of different brands of software products used in MHS *i* in year *t* for this application *k.* The negative sign of the formula ensures that a larger value represents a higher level of standardization.

After calculating the standardization level of each and every health IT application, we define the overall operational and analytical IT standardization levels of an MHS *i* in year *t* (MHS_SOIT_{it} and MHS_SAIT_{it}) as the average standardization levels of all the operational or analytical IT applications used in this MHS, calculated as:

$$MHS\_SOIT_{it} = \frac{\sum_{k\_op} STD_{ikt}}{n\_Op}$$

$$MHS\_SAIT_{it} = \frac{\sum_{k\_An} STD_{ikt}}{n\_An},$$

where *k_Op* and *k_An* are the two sets of different operational or analytical IT applications used in MHS ***i*** in year ***t**, and* ***n_Op*** *and* ***n_An*** are their respective counts.

Table B1. The List of Health IT Applications Used for Measuring IT Constructs

Operational IT applications		Analytical IT applications
(1) Cardiology & PACS 1. Cardiology – Cath lab 2. Cardiology – CT (computerized tomography) 3. Cardiology – Echocardiology 4. Cardiology – Intravascular ultrasound 5. Cardiology – Nuclear cardiology 6. Cardiology information system **(2) Radiology & PACS** 7. Radiology information system 8. Radiology – Angiography 9. Radiology – CR (computed radiography) 10. Radiology – CT (computerized tomography) 11. Radiology – DF (digital fluoroscopy) 12. Radiology – Mammography 13. Radiology – DR (digital radiography) 14. Radiology – MRI (magnetic resonance imaging) 15. Radiology – Nuclear medicine 16. Radiology – U.S. (ultrasound) **(3) Electronic medical record** 17. Clinical data repository 18. Clinical decision support system (CDSS) 19. Computerized practitioner order entry (CPOE) 20. Order entry (includes order communications) 21. Physician documentation **(4) Health information management** 22. Dictation 23. Dictation with speech recognition 24. Encoder 25. Chart deficiency 26. Chart tracking/locator 27. Abstracting **(5) Laboratory information system** 28. Blood bank 29. Anatomical pathology 30. Microbiology 31. Laboratory information system	**(6) Clinical information systems** 32. Emergency department information system (EDIS) 33. Intensive care 34. Obstetrical systems (labor and delivery) 35. Operating room (surgery) – post-operative 36. Operating room (surgery) – Pre-operative 37. Respiratory care information system 38. OR scheduling **(7) Nursing information systems** 39. Nursing documentation 40. Patient acuity 41. Nurse staffing/scheduling 42. Electronic medication administration record (EMAR) **(8) Pharmacy information systems** 43. Pharmacy management system **(9) Transcription** 44. In-house transcription **(10) General financial systems** **General ledger** 45. Accounts payable **(11) Human resources systems** 46. Personnel management 47. Benefits administration 48. Time and attendance 49. Payroll 50. Staff scheduling **(12) Revenue cycle management systems** 51. Enterprise master person index (EMPI) 52. Patient billing 53. Patient scheduling 54. Electronic data interchange (EDI) – Clearing house vendor 55. Credit/collections 56. ADT/registration **(13) Supply chain management systems** 57. Enterprise resource planning 58. Materials management	**(1) Financial decision support** 1. Financial modeling 2. Budgeting 3. Contract management 4. Cost accounting 5. Data warehousing/mining – Financial 6. Executive information system **(2) Utilization review/risk management** 7. Case mix management 8. Data warehousing/mining – Clinical 9. Outcomes and quality management **(3) Clinical & business intelligence** 10. Business intelligence – Financial

Measuring a market unit's use of differentiated operational IT (Unit_DOIT) and analytical IT (Unit_DAIT): We computed the Unit_DOIT and Unit_DAIT measures in four steps. First, we respectively counted all unique operational or analytical IT applications used by a hospital d of MHS i in market m in year t. Then, we measured the rareness of a given IT application in year t as follows. We computed the adoption rate of the IT application in the U.S. hospital industry, as tracked by the HIMSS Analytics database. We calculated the rarity of an IT application in year t as one minus its adoption rate in the U.S. hospital industry in that year. Then, in the third step, we replaced the simple count-based measure described in the first step with a weighted count measure. We used the rarity of an IT application as its weight. This step led to a weighted count-based measure of operational or analytical IT at the hospital level (IT_Op_{imdt} and IT_An_{imdt}).

As the last step, we aggregated these individual hospital-level IT measures to the market unit level of MHS if a market unit operated more than one hospital. For the market unit m of MHS i in year t, $Unit\_DOIT_{imt}$ and $Unit\_DAIT_{imt}$ are computed as weighted averages of their corresponding hospital-level values:

$$Unit\_DOIT_{imt} = \frac{\sum_{d=1}^{D_{imt}}(IT\_Op_{imdt} \times Bed_{imdt})}{\sum_{d=1}^{D_{imt}}(Bed_{imdt})}$$

$$Unit\_DAIT_{imt} = \frac{\sum_{d=1}^{D_{imt}}(IT\_An_{imdt} \times Bed_{imdt})}{\sum_{d=1}^{D_{imt}}(Bed_{imdt})},$$

where Bed_{imdt} is the total number of staffed beds operated by the hospital d in year t.

Control Variables

Table B2 summarizes definitions, measurements, and the rationales of the control variables. It follows the notations presented above unless specified otherwise.

Table B2. Control Variables

Control variables	Measurement	Rationale for inclusion
Controls for market unit-level characteristics of MHS i in market m in year t		
Unit's process-of-care quality	Measured as the weighted average of the process-of-care quality scores of the member hospitals of MHS *i* in market *m* in year *t*. The total number of staffed beds operated by a hospital is used as the weight for hospitals. The process-of-care quality scores of a hospital is calculated as the average quality scores of 20 quality indicators reported by Hospital Compare (Du, 2015).	In the health care context, greater quality in care delivery will confer competitive advantages on an MHS and improve its financial performance. Strong operational capabilities may also interfere with firms' use of MMC-induced rivalry restraint strategies (Makadok, 2010).
Unit's medical service scope	Measured as the count of different medical services offered by the member hospitals of the market unit *m* of MHS *i* in year *t*. We generated a list of 46 common hospital medical services as tracked by CMS Provider of Services (POS) database during our study time frame and then checked whether each of these services was offered by at least one member hospital of a given MHS in a given market. We log-transformed this variable before entering it in regression models.	The number of different services may confer economies of scope on the organization, which could potentially interfere with the rivalry restraint effects of MMC and affect performance (Gimeno & Woo, 1999; Li & Greenwood, 2004).
Unit's medial service overlap with MMC rivals	Measured as the average of dyad-level service overlap between the focal MHS *i* and every MMC rivals this MHS faces in market *m* in year *t*. We first measured this variable at the dyad level as follows: out of the total 46 hospital medical services as identified above for the prior variable, we counted the services provided both by the focal MHS and its given MMC rival. To reduce the impacts of missing data, we further divided this count of overlapped services by the total count of overlapped and known non-overlapped services between the dyad. Then, we took the average of dyad-level service overlap scores across all the dyads between the focal MHS and all its MMC rivals in market *m* in year *t*.	Medical service overlap could be another source of multimarket contact in the hospital context in which rivals compete with each other in multiple product markets in addition to geographic markets (Boeker et al., 1997). While our study is focused on the level of geographic markets, we controlled for the medical service overlap within each market to account for the influence of this other type of MMC.

Unit's capacity share in market	The capacity share of an MHS *i* in market *m* in year *t* is defined as the number of staffed beds operated by the hospitals of MHS *i* in market *m* in year *t*, divided by the total number of staffed beds from all hospitals in that market *m* in year *t*, including both stand-alone hospitals and MHS-affiliated hospitals.	Firms with larger capacity share in a market have higher monopoly power in both setting prices and competing against rivals (Gimeno and Woo, 1999).
Unit's Medicare and Medicaid patient percentage	For a hospital *d* of MHS *i* in market *m* in year *t*, we define $MRatio_{imdt}$ as the number of Medicare and Medicaid patients of a hospital divided by the total number of patients of this hospital. Then, at the level of MHS *i* in market *m* in year *t*, this variable is calculated as the weighted average across all MHS *i*'s member hospitals in this market *m*, as $$MRatio_{imt} = \frac{\sum_{d=1}^{D_{imt}}(MRatio_{imdt} \times Bed_{imdt})}{\sum_{d=1}^{D_{imt}}(Bed_{imdt})}$$ where Bed_{imdt} is the annual total number of staffed beds operated by the hospital *d* in year *t*.	The price for services to Medicare/Medicaid patients is not negotiated but instead predetermined by the CMS at the diagnosis level. Individual hospitals have limited influence on the pricing offered to these groups of patients.
Unit's capacity share in parent MHS	The capacity share of the m^{th} market unit in the whole MHS *i* in year *t* is defined as the number of staffed beds operated by the hospitals of MHS *i* in market *m* in year *t*, divided by the total number of staffed beds operated by all the hospitals of MHS *i* in year *t* across all the markets it has presence.	A market unit that accounts for a larger share capacity of its parent MHS has more power and influence against its corporate parent and its sibling market units; thus, they can better mobilize other market units to act and react in coordinated ways.
Unit operating teaching hospitals	A binary variable indicating whether MHS *i* operates a teaching hospital in market *m* in year *t* [1 = yes]	Teaching hospitals have different cost structures because they conduct research and train medical residents and their physicians are involved in research, teaching, and practice. In addition, teaching hospitals generally have a higher reputation for their medical expertise, which affects price premiums.
Unit operating specialty hospitals	A binary variable indicating whether MHS *i* operates a specialty hospital in market *m* in year *t* [1 = yes]	MHS with specialty hospitals (e.g., children's hospital, psychiatric hospital, cancer hospital) may have economies of scope that can influence both the pricing and the functioning of the MMC mechanism.
Unit's number of ambulatory care facilities	The log-transformed count of ambulant care delivery facilities owned by MHS *i* in market *m* in year *t*.	An MHS controlling more clinics in the same market will have a more steady patient inflow and thus gain more bargaining power in the market. Because physicians are commonly affiliated with clinics rather than hospitals, controlling clinics also enables an MHS to gain an advantage in the factor market of physicians.
Controls for market-level characteristics of market m in year t		
Concentration (HHI) of the focal hospital markets	Measured as the Herfindahl–Hirschman Index (HHI_{jt}) of a market *m* in year *t*, which is defined as $HHI_{mt} = \sum_{j=1}^{N_t} S_{jt}^2$ Where S_{jt} represents the market share of the j^{th} MHS or stand-alone hospital in market *m* in year *t*, and N_t is the total number of health care providers, including both MHS and stand-alone hospitals in this market.	Highly concentrated markets are less competitive, which may enhance the effect of MMC.

Concentration (HHI) of the focal health insurance markets	Measured as Herfindahl-Hirschman Index (HHI) of a health insurance market. Health insurance markets are defined by the AMA (American Medical Association) at the levels of both states and metropolitan areas. We matched metropolitan areas defined by AMA with our CBSA-based markets. If there was a match, we directly used the AMA-reported HHI value; otherwise, we used the AMA-reported HHI value of the state for unmatched CBSA markets in our sample.	Highly concentrated commercial health insurers imply greater bargaining power for insurers, which can put health providers at a disadvantage in price negotiations.
Market share of single-market competitors in the focal market	The ratio of patient discharges from either stand-alone hospitals or hospitals controlled by non-multimarket MHS, divided by total patient discharges from all hospitals in a given market *m* in year *t*.	Single-market competitors are not threatened by possible retaliation in multiple markets, which could thus put more competitive pressure on multimarket firms.
Market's bed utilization rate	Measured as the total patient-days of all hospitals in a market *m* in year *t*, divided by the total available bed days in that market in the same period. The variable captures the degree to which a market is saturated.	Firms in saturated markets face greater competitive pressure, which could impact change their pricing and competition behaviors.
Controls for MHS-level characteristics of MHS i in year t		
MHS-wide initiatives for operational IT MHS-wide initiatives for analytical IT	Measured through manual coding of news releases about each MHS in our sample. These two variables were coded as 1 if we were able to find news articles that publicly discussed the focal MHS's strategic intent to start system-wide initiatives regarding either operational or analytical IT; they were coded 0 otherwise.	In addition to standardizing the operational IT systems of their member hospitals, MHSs could invest in their own operational and analytical systems. These initiatives may not be fully captured by our MHS-level IT standardization variables but nevertheless still have influences on the MHS's financial performance.
The MHS's cross-hospital variance in service offerings	Measured as the average coefficients of variation (standard deviation divided by mean value) of all the medical services across member hospitals of an MHS (Dranove & Shanley, 1995). The measurement procedure had three steps. First, in the same process we used to measure prior service-based variables, we identified whether a given MHS offered a certain medical service or not in a given market in a given year. Then, we calculated the coefficients of variation for each service across all MHS market units. Lastly, we took the average of coefficients of variation across all the services.	Previous studies suggest that different MHSs have different levels of "systemness," which may affect both their operating performance and their competitive behaviors (Dranove & Shanley, 1995).
MHS-level IT investment decision-making (two binary variables)	We used this set of two binary variables to account for an MHS's IT investment decision-making models. Specifically, we leveraged the information of MHS decision-making authorities in terms of capital IT expenditure approval, as tracked by the HIMSS Analytics database, to infer decision-making modes. Based on the HIMSS Analytics database, we identified three different types of decision-making scenarios: (1) shared decision-making—the MHS uses certain committees, such as the IT steering committee, to review and approve certain IT investment expenditures; (2) individual decision-making—the MHS delegate all the IT investment decision rights to individual roles such as CFO or CIO; and (3) the involvement of MHS in its hospitals' IT investment decisions is unknown in the database (due to either no involvement or not reporting to HIMSS Analytics). We used the third scenario as the reference category and included two binary control variables for the first two scenarios.	The subsidiaries of an MMC rival often have incentives to pursue their own best interest and may consequently deviate from overall rival restraint strategies as set by their corporate parents. The parents may impose certain governance mechanisms, such as limiting subsidiaries' decision rights and resources, in order to control them (Sengul & Gimeno, 2013). We include this set of variables to account for the different governance mechanisms an MHS adopts to regulate its member hospitals.
MHS's geographic diversification	Measured as the log-transformed count of geographic markets in which the focal MHS *i* has a presence in year *t*	Geographically diversified MHS has more opportunities to share resources across markets but also more challenges to coordinate across different markets.
Size of MHS	The log-transformed count of total staffed beds owned by an MHS *i* in year i	Larger MHSs may potentially have greater bargaining powers and economies of scale.

Age of MHS	The number of years of an MHS since the firm was formed.	Older MHSs may have more experience in dealing with competitors and developing and exploiting their own capabilities.
For-profit status of MHS	A binary variable indicating whether an MHS *i* is for-profit or not-for-profit in year *t* [1 = for-profit]. In our sample, six MHSs changed their for-profit status during our study time window, which allows the variable to be included in our fixed-effect models.	For-profit hospitals face higher pressures in generating revenue and thus have greater incentives to behave strategically when choosing between competing and colluding.

Descriptive Statistics and Pairwise Correlations

Table B3 presents the descriptive statistics of our study variables and their pairwise correlations.

Table B3. Descriptive Statistics and Pairwise Correlations (*N* = 5,660; listwise deletion)

		1	2	3	4	5	6	7	8	9	10	11	12	13	14
1.	Price														
2.	Multimarket contact (MMC)	-.018													
3.	Cross-unit operational IT standardization (MHS_SOIT)	-.044**	.147***												
4.	Cross-unit analytical IT standardization (MHS_SAIT)	-.004	.149***	.876***											
5.	Market unit's use of differentiated Op. IT (Unit_DOIT)	-.164***	.174***	.208***	.107***										
6.	Market unit's use of differentiated An. IT (Unit_DAIT)	-.057***	.089***	.080***	.046***	.423***									
7.	Unit's process-of-care quality	.166***	.086***	-.122***	-.100***	.089***	.213***								
8.	Unit's medical service scope	-.074***	.253***	-.068***	-.109***	.222***	.214***	.335***							
9.	Unit's medial service overlap with MMC rivals	-.011	.614***	-.089***	-.047***	.128***	.140***	.126***	.372***						
10.	Unit's capacity share in market	-.014	-.405***	.106***	.037**	-.049***	-.123***	-.030*	-.146***	-.603***					
11.	Unit's Medicare and Medicaid patient percentage	-.054***	-.289***	.019	.002	-.125***	-.143***	-.221***	-.264***	-.333***	.294***				
12.	Unit's capacity share in parent MHS	-.108***	.426***	.353***	.266***	.209***	-.029*	.005	.295***	.140***	.038**	-.130***			
13.	Operating teaching hospitals (1 = Yes)	-.063***	.318***	.020	.019	.166***	.047***	.015	.241***	.198***	-.123***	-.122***	.383***		
14.	Operating specialty hospitals (1 = Yes)	-.179***	-.065***	-.000	.031*	.001	-.012	-.026+	.036**	.016	.026*	-.064***	-.036**	-.314***	
15.	Unit's number of ambulatory care facilities	-.059***	.351***	.059***	-.008	.303***	.129***	.232***	.505***	.273***	-.085***	-.238***	.452***	.329***	.015
16.	HHI of the focal hospital market	.036**	-.499***	.126***	.064***	-.129***	-.155***	-.080***	-.268***	-.664***	.911***	.319***	-.055***	-.169***	-.020
17.	HHI of the focal health insurance markets	-.096***	-.059***	-.017	-.015	.032*	-.083***	-.092***	-.021	-.059***	.065***	.191***	.002	-.022	.077***
18.	Market share of single-market players	-.043**	.103***	-.074***	-.053***	.061***	.127***	-.027*	.107***	.116***	-.676***	-.093***	-.034*	.091***	-.013
19.	Market's bed utilization rate	-.174***	.305***	-.003	.011	.280***	.119***	-.074***	.175***	.357***	-.502***	-.209***	.217***	.226***	.028*
20.	MHS-wide IT (1=present)	.014	.007	-.076***	-.057***	-.065***	-.085***	.089***	.005	-.014	.078***	.044**	-.002	.049***	-.003
21.	MHS-wide analytics (1=present)	-.018	.039**	-.109***	-.162***	.093***	.072***	.063***	.074***	.037**	.014	-.024+	.027*	-.005	-.015
22.	MHS's cross-hospital variance in service offerings	.008	-.289***	-.440***	-.258***	-.193***	-.085***	-.206***	-.239***	-.032*	-.062***	.113***	-.490***	-.159***	.128***
23.	MHS-level IT decision-making—Executive	.035**	-.101***	-.130***	-.100***	-.156***	-.143***	.051***	.015	-.059***	.056***	.030*	-.006	-.047***	.040**
24.	MHS-level IT decision-making—Committee	.053***	.052***	.039**	-.079***	.017	.029*	-.007	.013	-.033*	.018	.047***	.097***	-.006	-.090***
25.	MHS's geographic diversification	.033*	-.307***	-.598***	-.426***	-.187***	.020	-.011	-.064***	.052***	-.116***	.032*	-.585***	-.184***	.150***
26.	MHS's size (bed counts)	-.028*	-.148***	-.562***	-.390***	-.023+	.208***	.066***	.057***	.163***	-.182***	-.044***	-.575***	-.081***	.151***
27.	MHS's age	-.014	-.001	.239***	.231***	.098***	.007	.024+	.038**	-.043**	.086***	-.009	.132***	.090***	-.077***
28.	MHS's for-profit status (1 = for-profit)	.044***	-.194***	-.191***	.007	-.307***	-.047***	-.088***	-.129***	.020	-.140***	.058***	-.318***	-.124***	.169***
	Mean	10.9	.216	-.661	-.494	9.68	2.47	.935	3.22	.222	.464	.569	.144	.0744	.93
	Std. Dev.	10.1	.268	.499	.501	3.6	1.14	.071	.281	.215	.368	.133	.22	.262	.256

		15	16	17	18	19	20	21	22	23	24	25	26	27	28
15	Unit's number of ambulatory care facilities														
16	HHI of the focal hospital market	-.189***													
17	HHI of the focal health insurance markets	-.009	.044**												
18	Market share of single-market players	.053***	-.589***	-.022+											
19	Market's bed utilization rate	.228***	-.490***	-.029*	.371***										
20	MHS-wide IT (1=present)	.057***	.074***	.002	-.071***	-.076***									
21	MHS-wide analytics (1=present)	.142***	-.002	.051***	.007	.019	.019								
22	MHS's cross-hospital variance in service offerings	-.332***	-.039**	.059***	.021	-.032*	.014	-.089***							
23	MHS-level IT decision-making—Executive	.010	.067***	-.003	-.046***	-.091***	.097***	.052***	.077***						
24	MHS-level IT decision-making—Committee	.004	.008	-.015	-.004	.031*	-.028*	.010	-.189***	-.150***					
25	MHS's geographic diversification	-.282***	-.115***	.056***	.052***	-.045***	-.033*	-.094***	.804***	.069***	-.151***				
26	MHS's size (bed counts)	-.157***	-.211***	.031*	.114***	.061***	-.052***	-.047***	.648***	-.025+	-.157***	.888***			
27	MHS's age	.100***	.076***	-.018	-.056***	-.027*	-.071***	-.061***	-.152***	.026*	-.017	-.157***	-.123***		
28	MHS's for-profit status (1 = for-profit)	-.366***	-.091***	.064***	.065***	-.060***	-.031*	-.304***	.569***	.030*	-.144***	.668***	.521***	-.141***	
	Mean	1.38	.339	.314	.282	.585	.259	.255	1.08	.227	.0716	2.7	8.15	37.6	.381
	Std. Dev.	1.13	.393	.125	.296	.137	.438	.436	.436	.419	.258	1.06	1.33	29.5	.486

Note: +$p < 0.10$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$;

Appendix C

Results of Control Variables for Table 1

Table C1. Results of Control Variables for Table 1

DV: Price	Primary models		Robustness checks				
	Model A5	*Model A6*	*Model B1*	*Model B2*	*Model B3*	*Model B4*	*Model B5*
MHS's market unit level characteristics							
Unit's process-of-care quality	2.983	2.968	2.735	-0.218	2.983*	-3.642	3.163
	(1.874)	(1.874)	(1.690)	(0.698)	(1.291)	(10.865)	(2.308)
Unit's medical service scope	-1.314+	-1.308+	-1.584+	-0.548+	-1.314***	-5.910***	-1.571*
	(0.780)	(0.776)	(0.874)	(0.305)	(0.386)	(1.514)	(0.750)
Unit's medial service overlap with MMC rivals	-1.036	-1.074		0.039	-1.036	11.005	-1.098
	(0.779)	(0.776)		(0.290)	(0.699)	(7.907)	(0.844)
Unit's capacity share in market	-14.814+	-14.781+		-0.532	-14.814***	-5.632	-10.320+
	(8.896)	(8.882)		(3.446)	(1.473)	(4.282)	(6.073)
Unit's Medicare and Medicaid patient percentage	0.308	0.324	0.405	-0.055	0.308	-2.501	0.171
	(1.197)	(1.200)	(1.242)	(0.486)	(0.862)	(2.816)	(1.337)
Unit's capacity share in parent MHS	0.245	0.186		0.041	0.245	3.556	-3.668
	(2.162)	(2.198)		(0.727)	(1.647)	(5.989)	(3.082)
Operating teaching hospitals (1 = yes)	1.539**	1.542**	1.251**	0.139	1.539**	0.732	1.130**
	(0.473)	(0.472)	(0.423)	(0.187)	(0.508)	(1.501)	(0.429)
Operating specialty hospitals (1 = yes)	-0.776	-0.797	-1.156+	-0.310	-0.776	-3.584*	-1.815*
	(0.718)	(0.727)	(0.599)	(0.272)	(0.554)	(1.650)	(0.749)
Unit's number of ambulatory care facilities	-0.008	-0.007		0.047	-0.008	-0.326	-0.061
	(0.108)	(0.108)		(0.043)	(0.112)	(0.312)	(0.140)
Market-level characteristics							
HHI of the focal hospital market	5.993+	5.979+	-0.210	-0.247	5.993***	7.140	4.957+
	(3.624)	(3.622)	(1.296)	(1.369)	(0.839)	(6.109)	(2.939)
HHI of the focal health insurance markets	-0.083	-0.080	-0.193	-0.140	-0.083	-1.979	-0.329
	(0.517)	(0.518)	(0.527)	(0.188)	(0.721)	(3.235)	(0.472)
Market share of single-market players	-0.121	-0.119	1.573*	0.360	-0.121	6.379	-0.614
	(1.250)	(1.246)	(0.666)	(0.481)	(0.682)	(4.515)	(1.369)
Market's bed utilization rate	-5.710***	-5.691***	-6.005***	-3.009***	-5.710***	-24.195*	-7.252***
	(1.635)	(1.647)	(1.600)	(0.625)	(1.072)	(10.056)	(1.176)
MHS-level characteristics							
MHS-wide IT (1 = present)	-0.044	-0.041	-0.065	0.050	-0.044	-0.572	-0.060
	(0.096)	(0.095)	(0.097)	(0.045)	(0.133)	(0.401)	(0.138)
MHS-wide analytics (1 = present)	0.361**	0.355**	0.409**	0.057	0.361*	0.047	0.368*
	(0.127)	(0.127)	(0.135)	(0.053)	(0.143)	(0.256)	(0.186)
MHS's cross-hospital variance in service offerings	0.001	-0.008	-0.038	0.227*	0.001	0.362	0.019
	(0.261)	(0.259)	(0.239)	(0.093)	(0.256)	(0.839)	(0.393)
MHS-level IT decision-making—Executive	0.068	0.068	-0.047	-0.006	0.068	0.528	0.123
	(0.169)	(0.170)	(0.182)	(0.068)	(0.184)	(0.786)	(0.270)
MHS-level IT decision-making—Committee	-0.074	-0.077	-0.140	0.089	-0.074	1.815	0.194
	(0.307)	(0.307)	(0.357)	(0.122)	(0.326)	(2.197)	(0.366)
MHS's geographic diversification	-0.509	-0.512		0.324	-0.509	0.991	-0.286
	(0.648)	(0.648)		(0.244)	(0.574)	(1.068)	(0.878)
MHS's size (bed counts)	-0.235	-0.230		-0.396	-0.235	-0.321	-0.971
	(0.791)	(0.786)		(0.289)	(0.350)	(0.859)	(1.281)
MHS's age	-0.014+	-0.014+	-0.010*	-0.003	-0.014	0.024	-0.011+
	(0.008)	(0.008)	(0.005)	(0.003)	(0.013)	(0.018)	(0.006)
MHS's for-profit status (1 = for-profit)	1.149	1.179		0.232	1.149	-1.144	0.688
	(1.069)	(1.059)	-0.065	(0.353)	(1.746)	(1.645)	(1.392)
R^2	0.397	0.397	0.381	0.163	N/A	N/A	N/A

Note: Results of the primary independent variables are reported in Table 1 in the body text and omitted here. +p < 0.10; *p < 0.05 ;**p < 0.01; ***p < 0.001; Standard errors reported in the parentheses; Year dummy variables are included in the regression but results are omitted here.

Appendix D

Additional Exploratory Analyses on Cost and Quality of Care

We argue that market units' use of differentiated operational IT or analytical IT could differentiate the costs and/or the quality of their hospital services, violate RRT's assumption of undifferentiated services, and weaken the price effects of MMC-induced rivalry restraint. To further assess the validity of this explanation, we explore if the use of differentiated IT applications by market units actually differentiates hospital services. Specifically, we used the cost of hospital services and the process-of-care quality metrics of hospital services as the dependent variables of interest. We kept the independent variables of the study the same as in our price models. We measured cost as hospitals' operating expenses per patient-day, then aggregated it to the level of market units by using the same aggregation procedure we used for the price measure. Quality was measured as a market unit's process-of-care quality, which served as a control variable whose details are presented in Table B2. The results of this analysis are presented in Table D1.

Table D1. The Effects of MMC, MHS-level IT, and Unit-level IT on Price on Cost and Quality of Hospital Services

	Cost		Quality	
Variables	**Model C1**	**Model C2**	**Model D1**	**Model D2**
Multimarket contact (MMC)	0.298+ (0.163)	0.357+ (0.182)	-0.004 (0.008)	-0.001 (0.009)
Cross-unit operational IT standardization (MHS_SOIT)	0.048 (0.145)	0.057 (0.150)	-0.010 (0.008)	-0.012+ (0.007)
Cross-unit analytical IT standardization (MHS_SAIT)	-0.019 (0.082)	-0.032 (0.086)	-0.004 (0.005)	-0.002 (0.005)
Market unit's use of differentiated operational IT (Unit_DOIT)	0.004 (0.007)	0.004 (0.007)	0.001 (0.000)	0.001 (0.000)
Market unit's use of differentiated analytical IT (Unit_DAIT)	0.012 (0.024)	0.011 (0.023)	-0.002 (0.001)	-0.002 (0.001)
MMC × MHS_SOIT	0.264 (0.266)	0.455 (0.449)	0.039*** (0.011)	0.011 (0.019)
MMC × MHS_SAIT		-0.180 (0.377)		0.035* (0.017)
MMC × Unit_DOIT		-0.025 (0.029)		-0.002* (0.001)
MMC × Unit_DAIT	-0.269*** (0.080)	-0.253** (0.078)	0.006 (0.004)	0.007+ (0.004)
Control variables	included	included	included	included
Fixed year effects	included	included	included	included
Constant	9.772** (3.189)	9.749** (3.165)	0.715*** (0.061)	0.710*** (0.061)
Number of observations	5,657	5,657	5,660	5,660
R^2	0.299	0.300	0.720	0.721

Note: +p < 0.10; *p < 0.05 ; **p < 0.01; ***p < 0.001; two-tailed t-tests; standard errors reported in the parentheses; All modes are fixed-effect panel data models with fixed effects at the level of market units of MHS. MMC, MHS_SOIT, MHS_SAIT, Unit_DOIT, and Unit_DAIT are mean-centered; we omit the results of control variables and year fixed effects here due to space considerations.