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Hospital-physician Integration and Physician Collaboration: Implications for Care Efficiency and Outcomes

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I am submitting herewith a dissertation written by Hui Jia entitled "Hospital-physician Integration and Physician Collaboration: Implications for Care Efficiency and Outcomes." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Management Science.

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Abstract

This thesis focuses on healthcare operations management and consists of two essays that investigate empirically how the relationship between physicians and hospitals and the relationship between peer physicians, respectively, affect clinical care outcomes and care efficiency.

In the first essay, I study hospital-physician integration as a type of organization-service provider relationship. Many prior studies have provided insights into the benefits of a tight collaboration between hospitals and physicians. However, neutral and even negative effects of this relationship on healthcare performance have been observed and discussed in the literature. This mixed evidence points to a need for further study to elucidate the implications of hospital-physician integration for healthcare performance. This essay adopts an activity-based approach to operationalization of hospital-physician integration, referred to as ABI. I utilize patient-visit level information for patients who have been treated with coronary artery bypass graft (CABG) surgery to demonstrate a U-shaped association between ABI and clinical outcomes such as patient length of stay (LOS), in-hospital mortality risk, and readmission risk. I also find that hospital teaching status and bed utilization suppress the effect of ABI on patient LOS. The results suggest that a medium level of integration could be desirable, since a strategy of high integration trades off potentially higher patient volumes and knowledge ossification for suboptimal care outcomes.

In the second essay, I study collaboration between physicians working in emergency department (ED), a horizontal relationship between peer service providers. More specifically, I use measures of physician familiarity and a physician's level of exposure to different peer partners, referred to as partner exposure, to denote peer collaboration. Using data on patient visits to hospital emergency departments in the U.S. state of Florida, I build econometric

models to evaluate empirically the relationship between peer collaboration and care efficiency, as measured by a patient's time spent in the ED and the number of procedures received. My investigation shows that both physician familiarity and level of partner exposure help improve care efficiency, with the associated effects being stronger for patients with severe conditions. Besides the main hypotheses, we provide several post-hoc analyses which further reveal that physicians' single-siting status complements and enhances the relationships between physician familiarity and partner exposure, respectively, and care efficiency.

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Chapter 1

Introduction

Healthcare is a complex, knowledge intensive service industry in which both individuals and organizations rely on repetitive practice and lengthy training to deliver better performance and reach higher productivity. Meanwhile, the US faces a potential shortage of between 37,800 and 124,000 physicians in the next 12 years, based on a report released by the Association of American Medical Colleges (AAMC) (of American Medical Colleges, 2021). This projected shortage challenges each member in the healthcare system to cooperate and find multi-faceted solutions. In particular, physician shortages lead to a greater need for physicians multisiting, i.e., physicians who work for different hospitals where the demand for medical care is larger than the supply. This care setting complicates the relationship between hospitals, physicians and patients, and translates into additional challenges for care providers. This dissertation provides an empirical examination of different relationships between care providers, namely between physicians and hospitals and between peer physicians, with the intent of highlighting how these relationships can affect operational performance in different healthcare work environments. Thus, this dissertation contributes to the healthcare operations management literature a better understanding of the underlying mechanisms that explain the observed causal linkages between provider relationships and care outcomes, while also delivering practical insights for healthcare decision makers and managers.

The first important and debated set of research questions that I focus on relate to hospital-physician integration. Hospital-physician integration has emerged as an area of intense focus for hospital managers and healthcare researchers alike, especially as U.S. hospitals are transitioning from a volume-based to a value-based healthcare system. Hospital-physician integration motivates hospitals and physicians to work together to achieve the triple aim of improving care outcomes, lowering costs, and, ultimately, driving up patient satisfaction and value by more actively aligning the objectives of physicians and hospitals. This alignment and the expected improved ability to deliver against the triple aim should position hospitals to improve their profitability by maximizing their CMS reimbursements under the reformed payment models.

Although improvements in healthcare performance are not always observed in association with increased integration, there is still a growing trend in the healthcare industry to more strongly integrate hospitals and physicians, as this model is believed to lead to better care quality and lower costs. Extant research appears to support this trend, as increased provider familiarity and the relevant experience brought about by integration are found to be important factors in improving care performance through learning by doing (Huckman and Pisano, 2006) To reveal the underlying mechanisms that explain how hospital-physician integration impacts service quality, this essay leverages the lens of individual and organizational learning capabilities to theorize and demonstrate empirically a non-linear association between integration and hospital operational performance. The activity-based approach measuring integration, introduced in this essay, affords a more granular examination of integration (at the level of a specific cardiac procedure–coronary artery bypass graft, CABG), thus avoiding potentially imprecise generalizations that previous studies investigating integration at the hospital level were forced to make.

The second essay is set in an emergency department (ED) context and investigates physician familiarity and levels of partner exposure as distinct dimensions of a physician's professional relationships and collaboration. The ED remains the dominant conduit for the hospital inpatient admission of urgent and complex cases. ED teams work together towards the common goal of achieving positive health outcomes for patients, and provider collaboration is a foundational requirement of delivering successful emergency care. We observe that although collaboration in healthcare settings is an active research area, peer collaboration among physicians, has received less attention, especially in an ED setting. This study contributes several novel findings. First, physician familiarity is beneficial for care efficiency in the ED, as measured by less time spent by patients in the ED and a lower number of procedures received. Second, an ED physician's level of partner exposure has benefits for care efficiency, as also measured by less time spent by patients in the ED and a lower number of procedures received. These benefits are observed regardless of the team role played by individual physicians. Meanwhile, our results indicates that care efficiency improved through handling by paired physicians with both high partner exposure or with experience of working in different emergency rooms. This finding is particularly interesting, as previous studies have predominantly focused on partner exposure from the perspective of an individual working independently, with less attention given to the level of partner exposure for members of a team. Third, the care efficiency benefits of physician familiarity and levels of partner exposure are stronger for patients with severe conditions. The findings of the second study not only advance existing literature on the care benefits of physician collaboration, but offer guidance to hospital schedulers who are advised to incorporate physician collaboration patterns as inputs into the ED shift scheduling process.

The remainder of this dissertation is structured as follows. Chapter two develops the framework of activity based hospital-physician integration and studies the associated effects of activity based hospital–physician integration on cardiac surgery outcomes. Chapter three explores econometric models for physician collaboration with different familiarity and partner exposure levels on care efficiency in an emergency department setting. Chapter four briefly concludes this dissertation.

Chapter 2

Hospital–physician Integration and Cardiac Surgery Outcomes: A U-shaped Relationship?

2.1 Abstract

Hospital-physician integration has been increasingly considered as a potential solution for the underlying challenges hospitals face as they are adapting to value-based healthcare services. This study adopts an activity-based measure of integration (ABI) to investigate the association between integration and care outcomes. Integration is defined as the proportion of physicians who concentrate all their activity in a single hospital. We utilize patient-visit level information for Florida patients hospitalized for coronary artery bypass graft (CABG) between 2011 and 2014 to test hypotheses that posit a U-shaped association between ABI and patient clinical outcomes such as patient length of stay (LOS), in-hospital mortality risk, and readmission risk. Our econometric analysis indicates that patient LOS and mortality risk are minimized at ABI tipping points of 49% and 43%, respectively. We also find that hospital teaching status and bed utilization suppress the effect of ABI on patient LOS. Our results suggest that a medium level of integration could be desirable, since a strategy of high integration trades off potentially higher patient volumes and revenues for suboptimal care outcomes. Overall, this study offers new insights for theory and practice, as the non-linear association between integration and care outcomes has not been investigated previously.

Keywords: healthcare, hospital-physician integration, patient care outcomes, single-site operations, econometric modeling.

2.2 Introduction

The growing integration between hospitals and physicians has emerged as an area of intense focus for hospital managers and healthcare researchers alike, especially as U.S. hospitals are transitioning from a volume-based to a value-based healthcare system. The changing industry backdrop is making hospitals and physicians realize that, in order to adapt and succeed in the new healthcare system, they have to work together toward a common, unified set of goals. However, prior research has portrayed the hospital-physician relationship as labile and capricious, since the two parties usually have different priorities, with one party (i.e., hospitals) looking to maximize benefits and the other (i.e., physicians) insisting on autonomy and ethical responsibility to patients (Shortell et al., 2000; Budetti et al., 2002; Hurst et al., 2005). Despite these conflicting interests, it is hoped that the revamped, value-based healthcare system can offer an economic environment in which hospitals and physicians have a renewed motivation to work together to achieve the triple aim of improving care outcomes, lower costs, and, ultimately, drive up patient satisfaction and value (VanLare and Conway, 2012; Bishop et al., 2016).

Despite the growing trend among hospitals to integrate physicians, the question of whether it is possible to both improve quality of care and increase efficiency, or lower costs, through tighter hospital-physician integration is still an active area of research. A significant number of recent studies have adopted an employment-based lens to examine hospital-physician integration, whereby integration is defined as the percentage of physicians who are either employed by, or are under contract with, the hospital (e.g., Nyaga et al., 2015; Dobrzykowski and McFadden, 2020; Zepeda et al., 2020, etc.). However, this stream of literature provides mixed views on the benefits of employment-based hospital-physician integration (EBI) for hospital performance. Some studies uncover benefits, such as better supply chain efficiency (Nyaga et al., 2015; Abdulsalam et al., 2018), better conformance quality (Zepeda et al., 2020) and patient satisfaction (Dobrzykowski and McFadden, 2020). However, other studies find drawbacks, such as higher prices and spending (Baker et al., 2014), or no significant relationship between EBI and patient care outcomes, including mortality risk, 30-day readmission risk, and length of stay (Madison, 2004; Scott et al., 2017; Machta et al., 2019). With the literature still divided on the implications of EBI for care outcomes, there continues to be a need for research that clarifies the benefits of integration. We seek to contribute to this literature by attempting to reconcile some of these mixed findings.

An alternative arrangement that characterizes a hospital's level of integration with its physicians is the concentration of physicians' activity in that hospital (e.g., Wholey and

Burns, 1991; Burns and Muller, 2008). Even though this activity-based approach has been one of the earlier operationalizations of hospital-physician integration documented in the literature (e.g., Wholey and Burns, 1991; Burns and Wholey, 1992; Burns and Muller, 2008), it has received limited attention in the healthcare operations management (HOM) literature. The activity- and employment-based approaches to defining integration are related, potentially overlapping measures, yet not identical. For example, physicians concentrating their activity in one hospital may be employees of the hospital, may be independent professionals, or may be part of a physician group with admitting privileges at that hospital. At the same time, some physicians are employed by hospital systems and integrated delivery systems or networks that include multiple hospitals within one ownership structure. As employees of the health system, these physicians could still practice in different hospital locations within the same system. While such contractual arrangements still promote physician alignment with a specific employer, the level of alignment and integration with specific hospitals within the system is unclear, especially when hospitals retain their autonomy and distinct culture (KC and Tushe, 2021). As such, while a physician's concentration of activity in a single hospital does not imply physician employment by that hospital, this arrangement is still likely to offer compelling incentives to physicians to support and participate in their hospital's performance improvement initiatives (Wholey and Burns, 1991; Burns and Wholey, 1992). According to Burns and Muller (2008), activity concentration, just like physician employment, represents one form of economic hospital-physician integration, and is a proxy for a physician's trust, loyalty and commitment to a specific hospital. As physicians decide to concentrate their inpatient activity in one facility, they balance their preference for professional independence with their preference for convenience and income maximization (e.g., Wholey and Burns, 1991). Physicians choosing to fully concentrate their activity in one facility clearly show a preference for the latter, and they have limited incentives to deviate frequently from this arrangement (Wholey and Burns, 1991; Huckman and Pisano, 2006; KC and Tushe, 2021).

An activity-based measure of hospital-physician integration (henceforth referred to as ABI) can be constructed from more readily available patient claims data, relative to the EBI approaches currently used in the literature. The ABI approach affords measuring integration at more granular levels of investigation, such as specific hospital departments, disease categories, or procedures. A higher level of granularity is often preferred, reflecting the reality that physician activity or employment typically varies significantly from department to department within a hospital (Singleton and Miller, 2015). The reliance on hospital-level averages when measuring integration, a common approach adopted by the EBI literature (e.g., Nyaga et al., 2015; Young et al., 2016; Scott et al., 2017; Abdulsalam et al., 2018; Mishra et al., 2020), may help explain some of the mixed findings identified earlier on the implications of EBI. In this study, we leverage the distinctive features of the ABI approach to examine the relationship between integration and care outcomes. Our approach to measuring ABI is facilitated by a dataset that combines patient-level data from the State Inpatient Database (SID) for the state of Florida, spanning 2011-2014, with hospital-level data from the Centers for Medicare and Medicaid Services (CMS) annual cost reports. We are able to observe and track the activity of individual physicians across hospitals, thus enabling us to distinguish physicians who only work in one hospital location from physicians who work in multiple hospitals over a given period of time. We define physician ABI at the level of a specific cardiovascular surgery procedure, coronary artery bypass graft (CABG), and correlate it with care outcomes for patients undergoing CABG.

Previous related studies argue for a positive linear association between EBI and care outcomes. However, this association may be more complex, as we articulate in this paper. Leveraging the lenses of individual and organizational learning theories, we argue that while ABI generally enables learning, high levels of ABI correlate with a paucity of exploration activities, which hinders the preservation of requisite knowledge variety at the organizational level (e.g., Choi and Thompson, 2005; Fang et al., 2010), and increased physician workload and hospital volume, which inhibit individual learning (e.g., KC and

Terwiesch, 2009). These side effects could slow or suppress the accumulation of benefits resulting from ABI, particularly in hospitals with already high levels of integration. Taken together, the seemingly contradictory positive and negative implications of ABI for patient-level outcomes could point to plausible diminishing returns for ABI, or even a U-shaped relationship between ABI and care outcomes. Thus, there could exist an ABI tipping point, such that for values of ABI below the tipping point performance improves with ABI, whereas for values of ABI beyond the tipping point the benefits of ABI diminish considerably, or are even outweighed by its drawbacks and, as a result, performance declines with ABI.

Building on these research opportunities, this study makes two primary contributions to the HOM literature. First, we reaffirm and support the effectiveness of ABI as a proxy for the economic alignment between hospitals and physicians. Our ability to measure ABI at the level of a specific cardiac procedure complements and extends related studies that measure integration at the hospital or clinical unit levels. This higher level of granularity allows us to minimize concerns related to potential variation in both care outcomes and levels of integration, not only across different units of a hospital but also across different procedures in the same hospital unit, such as CABG in cardiovascular services. This approach enables our study to offer a potential explanation for the mixed findings identified previously vis-à-vis the benefits of employment-based integration.

Our second contribution pertains to theorizing and testing empirically a U-shaped relationship between ABI and patient care outcomes. Our results offer support to this non-linear association between ABI and patient length of stay (LOS) and in-hospital mortality risk, whereas no association is detected, neither linear nor non-linear, between ABI and readmission risk. Further, we estimate the ABI tipping point to be around 49% for LOS and 43% for in-hospital mortality. These results indicate that a medium level of ABI for target procedure yields highest hospital benefits. We infer that our finding that care outcomes improve initially as ABI increases, but start declining once ABI exceeds a certain tipping point, may help explain some of the mixed evidence identified by prior research about the role of integration. Thus, from a theoretical standpoint, our findings pertaining to the non-linear relationship between ABI and care outcomes shed new light on the implications of integration and are consistent with theoretical lenses relating to individual and organizational learning, physician workload and capacity utilization.

At the same time, our investigation offers a fresh perspective to researchers and hospital administrators alike on the benefits of hospital-physician integration, and suggests that a "middle-ground" approach may be superior to an "all or nothing" approach when deciding the extent of integration, echoing, and offering further support to, statements made in Zepeda et al. (2020). Given the significant financial commitment required of hospitals seeking to increase integration, our findings can be construed as "good news" for hospital administrators seeking better clinical outcomes through integration, since the journey to the tipping point of integration, i.e., where the clinical benefits of alignment top out, appears to be shorter. Moreover, our findings suggest that hospital administrators seeking a strategy of high integration may have to trade off potentially higher patient volumes and revenues for lower, suboptimal care outcomes.

2.3 Literature Review and Hypotheses Development

2.3.1 Literature Review

Our study relates to two streams of literature. One stream adopts a physician-level perspective and investigates the performance of physicians operating at single versus multiple hospital sites. The other stream adopts a hospital-level perspective and investigates the implications of employment-based hospital-physician integration. According to the first literature stream, Huckman and Pisano (2006) and KC and Tushe (2021) find that the quality of a cardiovascular physician's performance, represented by mortality rates, likelihood of complications, and patient LOS, is better when the physician works at a single hospital. These studies argue that a significant portion of a physician's experience is dependent on site-specific characteristics, and does not easily transfer across different locations. Working consistently in a single facility, physicians accumulate a deep level of familiarity with the personnel, operating procedures, tools, and resources available at that facility (KC and Tushe, 2021; Shroyer et al., 2018; Choi and Thompson, 2005). This minimizes the detrimental effects of switching from one environment to another, reorienting and adapting to different teams, routines, systems, which are typically associated with multi-siting (e.g., KC and Tushe, 2021).

However, some of the above studies point out that working at multiple hospitals can offer a number of counterbalancing benefits as well. One such benefit is knowledge transfer among care providers having diverse experiences and levels of expertise, potentially contributing to a stimulating work environment which fosters individual learning, dissemination of best practices, creativity, and, ultimately, higher productivity and better care outcomes (Thomas-Hunt et al., 2003; Choi and Thompson, 2005; KC et al., 2013; KC and Tushe, 2021). Prior research has shown that the benefits of learning are not limited to multi-site workers only, but may spread to the entire organization, or site, thanks to spillover effects (Argote and Fahrenkopf, 2016; Thomas-Hunt et al., 2003). We note that while prior research argues that single-siting (or conversely, multi-siting) exhibits both positive and negative ramifications for physician performance, the benefits outweigh the drawbacks, such that single-siting is generally recommended for physicians seeking to maximize the quality of their clinical performance (e.g., Huckman and Pisano, 2006; KC and Tushe, 2021, etc.). However, the literature has not investigated the extent to which these physician-level findings hold when single-siting is measured in aggregate at the organizational or hospital levels. This research seeks to bridge this knowledge gap by investigating the extent to which the advantages and disadvantages of single-siting balance out, when single-siting is measured as a group- or hospital-level behavior, which is used as a proxy for activity-based hospital-physician integration in this study.

According to the second literature stream, the level of hospital-physician integration is defined as the proportion of fully employed physicians. Among these studies, Mishra et al. (2020) reports that physician contracting emphasis (i.e., the inverse of employment-based integration) is positively associated with higher operational margins but longer LOS. Zepeda et al. (2020) shows that higher levels of employ-based integration are associated with better and more consistent levels of conformance quality for cardiovascular services, whereas Abdulsalam et al. (2018) points out that higher integration can improve supply management efficiency. Overall, these studies confirm the positive contribution of employment-based hospital-physician integration to increased hospital productivity and profitability, as integration strengthens hospital governance and enhances the level of trust and alignment between physicians and hospitals (Dobrzykowski and McFadden, 2020). Other studies investigate the effect of integration on patient care quality. For example, Scott et al. (2017) and Short and Ho (2019) find either no association, or even a negative association, between hospital-physician integration and measures of care quality including risk-adjusted mortality rates, 30-day readmission rates, and length of stay. Contrasting the positive association between integration and hospital cost efficiency with the non-significant or negative association between integration and care outcomes reported in the extant literature yields a mixed picture on the implications of integration for hospital performance. Seeking to explain these mixed results, several studies have identified a number of hospital characteristics, such as hospital capacity utilization, teaching intensity, or specific hospital core capabilities (Everson et al., 2016; Mishra et al., 2020; Zepeda et al., 2020) that moderate the relationship between integration and hospital performance. These findings provide evidence on the complexity of the relationship between integration and performance and on contextual elements that can influence it. However, none of these studies investigated the possibility of a non-linear relation between integration and performance.

2.3.2 Hypotheses Development

Knowledge acquisition and diffusion across members of an organization are critical for that organization's ability to make consistent performance improvements and sustain a competitive advantage (Argote and Ingram, 2000; Thomas-Hunt et al., 2003; Kane et al., 2005; Fang et al., 2010). Organizations learn to the extent to which their individual constituent members, i.e., people, learn. For some specialized members, such as surgeons, who require years of specialized training and continued practice to accurately diagnose a patient's condition and deliver an effective treatment, continuous individual learning is a key factor for delivering high performance. We next explore potential linkages between ABI and individual and organizational learning by drawing from the extensive related literature on learning (e.g., Huckman and Pisano, 2006; KC and Staats, 2012; KC et al., 2013; Ch'ng et al., 2015; Miedaner and Sülz, 2020, etc.).

Different hospitals, even members of the same hospital system, likely differ with respect to clinical personnel, operating procedures, processes and routines, equipment, materials and supplies, technology, culture, management, etc. (e.g., Huckman and Pisano, 2006; Dobrzykowski and Tarafdar, 2015; KC and Tushe, 2021). As a result, multi-site physicians who go back and forth between hospitals are subject to switching costs, as they have to constantly readjust to the specific environment of each hospital. This physician switching between hospitals is associated with a longer patient length of stay and a higher risk of complications (KC and Tushe, 2021). The amount of time between hospital switches amplifies the switching cost, as learning depreciation and forgetting effects are getting stronger as tasks are performed less frequently (Ramdas et al., 2018). Further compounding the negative ramifications of multisiting, Huckman and Pisano (2006) finds that the experience of cardiac surgeons is "firm specific" and not portable across hospitals. Thus, a surgeon's volume of work performed at other hospitals does not yield improvements in the surgeon's performance at the focal hospital. In contrast, a physician working in a single hospital should be less exposed to the aforementioned interruptions in, and forgetting and depreciation of, individual learning (Bailey, 1989). Working full time in a single hospital is more conducive to a stable environment that promotes individual learning and continuous improvement. Prior literature supports the advantages of single-siting, whereby physicians concentrate all their activity in a single hospital, over multi-siting, whereby physicians split their activity across multiple hospitals, and indicates that care outcomes are better for patients treated by single-site physicians (Huckman and Pisano, 2006; KC and Staats, 2012; Shroyer et al., 2018; KC and Tushe, 2021). The benefits of this learning mechanism are illustrated in the left panel of Figure 1.

As hospitals are increasingly relying on single-site physicians, there is also an observed increase in the number of cases handled and the number of claims submitted per physician (e.g., Kralewski et al., 2013; Koch et al., 2017). We observe a similar positive association between single-siting and physician workload in our dataset (correlation = 0.213, $p < 0.01$, see Table 2). This association yields effects and consequences that are distinct from the ones presented earlier. Such dynamics are partly attributable to the financial thrust behind a physician's concentration of activity in a single hospital, consisting of higher patient volume, higher productivity, and ultimately higher revenue (e.g., Coughlin and Gerhardt, 2013; Baker et al., 2014; Tormoehlen and Unrath, 2018). However, these benefits may not be sustainable when physician workload increases and leads to overwork (e.g., Williams et al., 2007; KC and Terwiesch, 2009; Tan and Netessine, 2014, etc.). For example, Berry Jaeker and Tucker (2017) found a non-linear relationship between clinician workload and performance measures including length of stay and mortality rates, indicating that clinicians initially speed up to cope with the increasing workload, however, long, sustained periods of overwork are counterproductive and lead to adverse outcomes. Hospital bed utilization is also shown to have a U-shaped relationship with patient mortality risk (Kuntz et al., 2015). More generally, the non-linear association between workload and throughput times is well documented in the queuing literature, which establishes that, as utilization increases and approaches 100%, queue length and throughput times explode (Berry Jaeker and Tucker, 2017). At the same time, physicians may attempt to multitask in order to cope with the increasing workload. Whereas limited multitasking may initially help, an increase in multitasking or workload will ultimately have negative effects on physician performance and clinical outcomes (KC, 2014), as illustrated in the left panel of Figure 1.

Complementing individual learning, an organization's environment further impacts knowledge acquisition and diffusion across its members, and has critical implications for organizational performance (e.g., Argote and Ingram, 2000; Fang et al., 2010, etc.). Building on theoretical concepts from organizational learning, we position ABI as a potential lever that can disrupt the balance between exploration and exploitation in hospitals. Scholars have used exploitation to refer to the use, improvement, and propagation of existing solutions, whereas exploration refers to the search for, and discovery of, new solutions (March, 1991; Fang et al., 2010). Exploitation is expected to provide more certain, immediate, incremental returns, whereas exploration is regarded as enabling the discovery of profoundly novel solutions (Holland et al., 1992). In order to thrive, organizations need a well-balanced mix of exploitation and exploration initiatives that are carefully tailored to the organizations' individual characteristics (March, 1991; Fang et al., 2010).

Consistent with this theoretical context, physicians who work in a hospital can be construed to represent an organizational subgroup. Depending on the extent of linkages and exchanges with physicians from outside the organizational boundaries, physician subgroups can operate in isolation, semi-isolation, or as fully open. As such, a group of physicians who concentrate their activity in a single hospital and require minimal connections to other hospitals and external organizations to deliver care, can be considered an isolated group. Such a group could enjoy high levels of familiarity and harmony, and could spend significant time and effort on exploitation-type activities centered on continuous improvement of existing processes. However, such an isolated group would have relatively limited exposure to outside practices and ideas, some potentially innovative, and lack the know-how and motivation to engage in changes that may disrupt the status quo. Such groups run the risk of knowledge ossification and obsolescence, as they stop being infused with new knowledge and ideas from external sources (e.g., Berman et al., 2002). As a result, prior research has argued that isolated groups risk becoming less adaptable to environmental factors and getting trapped in local optima (e.g., March, 1991; Fang et al., 2010).

In contrast, a group composed entirely of physicians who operate at multiple facilities can be considered a totally open group that can benefit from direct, constant exposure to a wide range of exploration-type existing and emerging practices used across the industry. However, the challenge for such open groups is to select, adhere to, and promote across the organization a set of coherent, optimal practices that can promote individual learning and help distinguish that organization in the marketplace. As a consequence of operating in an environment with diverse information and knowledge, individuals develop fewer, more superficial connections to the organization and may have less incentive to share their knowledge with others and contribute to organizational improvement (Thomas-Hunt et al., 2003). As such, a fully open hospital would face difficulty in identifying and enacting mechanisms for sharing the relevant knowledge acquired by its individual members. Such hospitals could become trapped in a permanent state of change, inefficiency, and suboptimal performance. Building on these arguments and holding fully open groups at one end and isolated groups at the other end, we argue that semi-isolated groups represent a middle-ground approach where a hospital relies on some proportion of both physicians who operate exclusively in that hospital and physicians who operate at multiple hospitals. The organizational learning literature argues that semi-isolated groups can more effectively balance the exploitation-exploration trade-off, allowing them to stay open to outside knowledge and opportunities, while also nurturing a focus on distilling best practices into procedures that are to be exploited consistently throughout the organization (March, 1991; Fang et al., 2010). The performance trade-off between exploration and exploitation is captured in the middle panel of Figure 1.

In sum, the complementary lenses of individual and organizational learning, considered either separately or together, suggest a nonlinear relationship between ABI and clinical outcomes. More specifically, according to both individual learning (due to the interplay between learning and workload management complexity mechanisms) and organizational learning (due to the dynamics of open, semi-isolated, and fully-isolated groups), performance initially increases with ABI, when ABI is low, but then performance stagnates and declines when ABI increases beyond a certain threshold, as shown in Figure 1. In this study we employ several clinical outcomes as performance proxies for healthcare quality and efficiency. One such outcome is in-hospital patient mortality risk. Mortality is the most widely used measure of care quality for benchmarking the performance of hospitals and physicians, is objective and reliably tracked via death certificates, and is an outcome that occurs relatively more frequently in patients undergoing CABG surgery (Huckman and Pisano, 2006; KC and Terwiesch, 2009; KC and Staats, 2012). Mortality has also been investigated in the context of physician-level splitting behavior (Huckman and Pisano, 2006), whereas our focus here is at the level of a cardiac procedure. Thus, we hypothesize that

H1a. *Activity-based integration has a U-shaped association with patient in-hospital mortality risk.*

Notwithstanding its importance as a measure of care quality, mortality is just one dimension of hospital operational performance. Another measure of care quality widely recognized in the literature is patient readmission risk (e.g., KC and Terwiesch, 2012; Senot et al., 2016; Oh et al., 2018, etc.). The U.S. Centers for Medicare and Medicaid Services (CMS) impose financial penalties for hospitals with excessive readmission rates for certain target conditions via the Hospital Readmissions Reduction Program (HRRP), which came into effect in 2012. The HRRP underscores the critical importance of readmissions as a measure of care quality and has motivated hospitals to implement quality improvement initiatives aimed at reducing the incidence of readmissions. The importance of readmissions is also reflected in a growing operations literature that investigates potential operational levers that can help curb readmissions (Senot et al., 2016; Oh et al., 2018). ABI is one such lever that has the potential to relate to readmission risk through the learning mechanisms described above. As such, we hypothesize that

H1b. *Activity-based integration has a U-shaped association with patient 30-day readmission risk.*

Inpatient length of stay (LOS) is another commonly-used metric to evaluate hospital performance and is largely considered a proxy of both care quality and care delivery efficiency (McDermott and Stock, 2007; KC and Terwiesch, 2011; Nair et al., 2013). For example, a low LOS could be indicative of care quality, suggesting that patients recover faster and with fewer complications (McDermott and Stock, 2007). A low LOS may also reflect operational efficiency, represented by a hospital's ability to treat patients faster, with fewer delays and less waiting time (McDermott and Stock, 2007; Nair et al., 2013). Yet other studies have positioned LOS as a process related measure of quality that, in turn, can affect other care outcomes such as mortality (KC and Terwiesch, 2009) and readmission risks (Oh et al., 2018). Thus, a premature discharge, that is a short LOS, is associated with higher risks of mortality and readmision, respectively (KC and Terwiesch, 2009; Oh et al., 2018). These findings suggest that LOS is a distinct measure of performance from mortality and readmission risks, justifying treating LOS as a separate care outcome. Consistent with prior literature findings that learning is a process of seeking, selecting, and adapting new "routines" to improve performance (Pisano et al., 2001), it is likely that ABI is related to LOS, a comprehensive measure of performance, considering the linkages we established earlier between ABI and learning. Consequently, we hypothesize that

H1c. *Activity-based integration has a U-shaped association with patient in-hospital length of stay.*

Effects of teaching status and bed utilization

Teaching hospitals play a pivotal role in the healthcare system and are responsible for creating a learning environment conducive to training resident physicians and medical school students, supporting research and providing a wide variety of patient services (Blumenthal et al., 1997; Dimick et al., 2004). As a result, teaching hospitals offer a different learning environment and a wider range of learning opportunities, face different operational challenges, and require different operations strategies compared to non-teaching hospitals (Melo and Beck, 2015; Mishra et al., 2020). Teaching hospitals tend to attract a large share of patients with complex, acute conditions and comorbidities who often require specialized, non-routine care and treatment (Iezzoni et al., 1990; Senot et al., 2016). As such, teaching hospitals foster an environment where physicians can also engage in research activities, with a focus on adopting novel treatment approaches for complex conditions (Shahian et al., 2012). Physicians practicing in teaching hospitals thus have more abundant opportunities to get exposure not only to a broad range of treatment approaches, but also to novel, cutting-edge techniques and therapies. This exposure reduces knowledge barriers and accelerates learning and knowledge dissemination (Sheng et al., 2013). As a locus of knowledge creation and application in healthcare delivery, highly integrated teaching hospitals should be less affected by the attenuation of knowledge sharing specific to integrated, isolated-group hospitals. As teaching hospitals are able to attract more talented physicians with deep expertise in specialty areas (Ayanian and Weissman, 2002; Theokary and Ren, 2011) and proactively promote inter-hospital communication and collaboration, highly integrated teaching hospitals should still be able to maintain their technological and knowledge edge.

As teaching hospitals offer a variety of services to various patient demographics, they face high levels of clinical practice variation (Dobrzykowski et al., 2016; Mishra et al., 2020). In an effort to reduce this variation and improve the consistency of care outcomes, hospitals have been adopting process improvement initiatives, such as lean, and have been working to develop, validate, implement, and monitor standardized care pathways (Dobrzykowski et al., 2016). The hoped benefit of such initiatives is the development of a shared understanding among care providers regarding the streamlined set of steps and actions that are needed to treat specific illnesses effectively and efficiently (Dobrzykowski et al., 2016; Mishra et al., 2020). Studies have shown that teaching hospitals are more likely to adopt standardized care pathways (Darer et al., 2002), suggesting that teaching hospitals with low levels of ABI can still coordinate effectively with multi-site physicians and maintain a consistent level of performance. In summary, it is plausible that a hospital's involvement in teaching activities can attenuate the effects of ABI on hospital performance, at both low and high levels of integration. Therefore, we posit that

H2. *A hospital's teaching status suppresses the relationship between activity-based integration and hospital performance, as measured by (a) in-hospital mortality risk, (b) 30-day readmission risk, and (c) patient length of stay.*

Capacity utilization has come under increased scrutiny from hospital administrators seeking higher economies of scale, higher resource efficiency, and ultimately lower care delivery costs. Bed capacity is the primary metric used to define hospital capacity, as staffing and other resources are usually determined as a function of the number of beds (Kuntz et al., 2015; Mishra et al., 2020). While high levels of bed utilization yield ample financial benefits (Green and Nguyen, 2001), one has to consider the impact of this strategy on all service providers in the hospital. For example, high levels of bed utilization are associated with long delays and waiting times for beds, especially in the presence of high clinical practice variation (Green and Nguyen, 2001). Whereas physicians are the mainstay in a medical team, the timely and precise contribution of multiple care providers (such as various specialized nurses, anesthesiologists, perfusionists, radiologists, lab technicians, etc.) is essential for the successful delivery of care. As physicians and other care providers work together as a team to deliver care, the final service delivered is impacted by the member of the team with the lowest capacity, who is acting as a bottleneck (Avgerinos and Gokpinar, 2017a). The bottleneck limits the capacity of the team and may hinder a timely sharing of information and knowledge, ultimately impacting the performance and productivity of the entire team (Avgerinos and Gokpinar, 2017a). The presence and limiting impact of bottlenecks are further exacerbated in a high utilization environment by the observed tendency of clinicians to multitask and switch more often between patients (KC and Terwiesch, 2009; KC, 2014), which increases the frequency of service interruptions and leads to delays and potential complications (KC, 2014; Laxmisan et al., 2007). Clinicians facing excessive workloads also risk developing work-related stress, which disrupts both individual and team performance and is detrimental to teamwork (Kuntz et al., 2015). Consequently, an environment of high capacity utilization predisposes clinicians to fire-fighting behaviors (Tucker et al., 2020) and disrupts knowledge creation and knowledge sharing, thus blunting the effects of integration. Therefore, we posit that

H3. *High levels of bed utilization suppress the relationship between activity-based integration and hospital performance, as measured by (a) in-hospital mortality risk, (b) 30-day readmission risk, and (c) patient length of stay.*

2.4 Data Description and Econometric Models

2.4.1 Research Data

To test our hypotheses, we use patient-visit level data from the State Inpatient Database (SID) for patients undergoing CABG procedures in the state of Florida from 2011 to 2014. Thus, our observations are at the patient-visit (hospitalization) level. Each hospitalization contains patient demographic information (i.e., age, gender, race, and insurance coverage type), admission type (emergency or elective), and information on medical diagnosis, such as the number of co-morbid conditions, etc. The primary condition is identified by the International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) codes. We focus on the CABG procedure, since it is the most common and risky cardiac surgery performed worldwide with annual volumes of approximately 200,000 cases in the US alone (D'Agostino et al., 2018). It is a costly surgery that leads to tens of millions of dollars in costs for hospitals and patients (Eisenberg et al., 2005; Feng et al., 2018). Moreover, CABG patients are considered relatively homogeneous, and therefore have been used as a study cohort extensively in the literature (e.g., Huckman, 2003; Huckman and Pisano, 2006; KC and Terwiesch, 2011; Feng et al., 2018; Lu and Rui, 2018; Shroyer et al., 2018; Adida and Bravo, 2019, etc.). CABG is also one of the six conditions targeted by the CMS HRRP. Finally, in order to be able to control for various hospital-level characteristics, such as hospital bed size, teaching status, patient days, and ownership status (for-profit, not for-profit), we also linked our patient-visit level data with hospital data from the CMS cost reports.

Before conducting our analysis, we removed index hospitalizations that had missing patient information, hospitalizations occurring in hospitals that either had insufficient information available in the CMS cost reports or handled less than 25 CABG cases annually (e.g., Senot et al., 2016), and hospitalizations where patients were transferred to other short-term acute care hospitals in LOS and Readmission model. These latter patient visits were removed from consideration, since it doesn't represent the true length of hospitalization and is not clear how to differentiate the causes of readmission between the sender and the receiving hospitals (Krumholz et al., 2020). Finally, we remove hospitalizations with LOS that exceed 28 days (99th percentile), as these can be considered long term care hospitalizations. Our final dataset comprises 33,505[1] index hospitalizations handled by 979 physicians in 71 hospitals, when studying mortality risk as an outcome, and 32,678 index hospitalizations handled by 956 physicians in 71 hospitals, when studying readmission risk and LOS as outcome variables.

2.4.2 Outcome Variables

We study three patient care outcomes, namely in-hospital mortality (MORT), 30-day all-cause readmission (ReAd), and patient length of stay (LOS). MORT is an indicator variable that takes value "1" if the patient died during the index hospitalization, and "0" otherwise; ReAd is an indicator variable that takes value "1" if the patient was admitted to any hospital, for any condition, within 30 days post discharge from the index hospital, and "0" otherwise.

[1] Since we use 1-year lagged endogenous variable as the instrumental variable, the sample size for the fitted models is smaller at 24,105 hospitalizations.

An elective (planned) visit does not qualify as a readmission visit. LOS represents the length of stay (in days) of an index hospitalization.

2.4.3 Independent Variable

Our main independent variable is ABI_{ht}, which measures the level of ABI corresponding to hospital h during year t and is defined as the fraction of CABG physicians whose activities are exclusively in hospital h during year t. Physicians are deemed "CABG physicians" if they performed at least one CABG procedure during year t. The SID contains all inpatient hospitalizations in a state during a given year. The dataset also contains a unique identification number for each physician, allowing us to track physician activity across hospitals and years. We can thus measure physician workload at each hospital and determine if a physician works full time in a single hospital (i.e., all physician's inpatient activities, CABG and otherwise, are in a single hospital), so that the physician is de facto integrated with the hospital. More formally, let $NumCABGPhysicians_{ht}$ represent the total number of qualified CABG physicians during year t at hospital h, and let $NumCABGFull_{ht}$ represent the number of CABG physicians whose inpatient service activities during year t were rendered exclusively at hospital h. Then, we define

$$ABI_{ht} = NumCABGFull_{ht}/NumCABGPhysicians_{ht}.$$

2.4.4 Control Variables

We control for several commonly used patient- and hospital-level variables that have been shown to have an effect on hospital performance (Huckman and Pisano, 2006; KC and Terwiesch, 2011; Ding, 2014; Zepeda et al., 2020). The patient-level variables include patient demographics such as age, gender, race, as well as information related to the hospitalization such as length of stay, number of diagnoses, number of procedures performed during the hospitalization, payer type, admission type, and frequent comorbidities associated with

CABG. We also control for several hospital-level variables such as teaching status, hospital ownership, bed utilization, hospital bed size, and average physician workload. Previous studies have shown that teaching hospitals have better patient care outcomes (Theokary and Ren, 2011). Hospital ownership is represented in this study by for-profit and not for-profit hospitals. Prior research has shown that as a result of their profit-driven strategies, for-profit hospitals are more likely to cherry pick patients, in an effort to reduce their readmission rates, mortality rates or LOS (Ding, 2014; Scott et al., 2017). Not for-profit hospitals benefit from various tax exemptions and provide uncompensated care (Ding, 2014; Bishop et al., 2016). Therefore, it is important to control for hospital ownership when evaluating the effects of hospital-physician integration on care outcomes.

Consistent with prior literature (e.g., Mishra et al., 2020), bed utilization is defined as the ratio of total inpatient days to total hospital bed days, which in turn is defined as the number of bed times 365. A high level of bed utilization is indicative of high capacity utilization, and has been shown to be associated with hospital performance, namely shorter LOS and higher readmission rates (Kuntz et al., 2015; Berry Jaeker and Tucker, 2017). Finally, we categorize hospital bed size into three levels, as previous studies observed a non-linear association between hospital size and patient care outcomes (e.g., McDermott and Stock, 2007). Following the Healthcare Cost and Utilization Project (HCUP) Statistical Briefs (Elixhauser and Wier, 2006), we categorize hospital size as small, medium and large, conditional on location and teaching status. For hospitals located in rural areas, those with less than 40 beds are considered small, and those with more than 75 beds are considered large. For non-teaching hospitals located in urban areas, those with less than 100 beds are considered small, and those with more than 100 beds are considered large. For teaching hospitals located in urban areas, those with less than 250 beds are considered small, and those with more than 450 beds are considered large. We also control for the average physician workload, defined as the average caseload of the CABG physicians in a given hospital and given year and measured at the hospital level. Finally, we control for physician experience, defined as the cumulative cardiovascular caseload handled by individual CABG physicians between 2011 and the year of the current hospitalization, measured at the physician level.

2.4.5 Summary Statistics

Table 1 reports summary statistics for the patient-level variables, and Table 2 reports summary statistics for, and pair-wise correlations among, hospital-level variables. We note that the average patient age in our data is 66 years, 75.6% of the patients are male, 78% are white, 57.5% were admitted either as emergency or urgent hospitalizations, and Medicare is the payer for 65.1% of the patients. We see that 82.5% of the patients have hypertension, 14.7% have renal failure, and 24% have chronic pulmonary disease. The average LOS is 9.1 days, the overall in-hospital mortality rate is 1.3%, and the overall readmission rate is 12.3%. From Table 2, we see that the average ABI is 0.27, 43.84% of the hospitals in our study are for profit, and 47.46% are teaching hospitals. The physician experience variable, the only physician-level variable in our data, has a mean of 269 and a standard deviation of 265. All continuous variables are normalized before the models are estimated.

2.4.6 Econometric Models

Let y_{ipht} represent one of the three patient care outcome measures (i.e., LOS, MORT, ReAd) corresponding to index hospitalization i treated by physician p in hospital h at time t. To test our hypotheses, we use the following regression model

$$f(y_{ipht}) = \alpha_0 + \alpha_1 ABI_{ht} + \alpha_2 ABI_{ht}^2 + \beta_1^\top H_{ht} + \beta_2^\top P_{iht} + \beta_3 PE_{ipt} + T_t + \epsilon_{ipht}, \tag{2.1}$$

where $f(.)$ is a known link function that will be specified for each of the three outcomes, ABI_{ht} represents the activity-based integration level corresponding to hospital h at time t, H_{ht} is a vector of hospital-level control variables corresponding to hospital h at time t (see Table 2), P_{iht} is a vector of patient-level control variables (see Table 1), PE_{ipt} is the caseload experience up to time t for the physician who handles hospitalization i, T_t represents year-fixed effects, and ϵ_{ipht} represents a visit-level error term. Coefficients α_1 and α_2 capture the relationship between ABI and the patient care outcomes, and are used to test the hypothesized U-shaped relationships. When we study LOS, we set the link function to be the log-link, i.e., $f(y_{ipht}) = \log(y_{ipht})$, and when we study MORT or ReAd, we set the link function to be the logit-link, i.e., $f(y_{ipht}) = ln\big(\frac{P(y_{ipht}=1)}{1-P(yipht=1)}\big)$.

If ABI is an exogenous variable, then model (2.1) yields unbiased estimates of the coefficients α_1 and α_2. However, there is a reasonable concern that the variable is endogenous. For example, the profitability level of a hospital, its management strategy or culture may affect both patient outcomes and the propensity of physicians to concentrate all their activity in that hospital. A hospital with lower or even negative revenues would be a less attractive integration target for physicians and its management would have a weaker motivation to increase integration, since the labor cost of full-time physicians is large (Baker et al., 2014). Moreover, budgetary constraints or different business strategies may also confound the effects of ABI, such that a hospital may choose to invest in, for example, healthcare information technology (HIT) or latest medical equipment rather than promoting physician integration. For example, Zepeda et al. (2020) show that the presence of HIT in a hospital substitutes for physician employment, with respect to its effect on conformance quality. Since we do not possess information on hospitals' strategic and budgetary priorities, our key independent variable, i.e., ABI, is likely to be endogenous in model (2.1). More specifically, the level of hospital-physician integration, represented by ABI_{ht} and ABI^2_{ht}, may be correlated with the error term, ϵ_{ipht}, since the latter partly accounts for unmeasured confounders (e.g., management style, budgetary priorities, etc.). In fact, a Hausman test based on model (2.1) yields a test statistic of 32.2 ($p < 0.001$), suggesting that ABI is indeed an endogenous variable.

2.4.7 Instrumental Variables and 2SRI Estimation

To account for this potential endogeneity bias, we use an instrumental variable (IV) approach to estimate model (2.1). The IV method aims to circumvent the estimation bias caused by endogeneity by introducing an external variable, i.e., the instrumental variable, into the estimation process (Wooldridge, 2002). An IV is a variable that is correlated with the endogenous variable of interest (the *relevance* condition), but is uncorrelated with the error term in the model (the *exclusion restriction* condition). Since the endogeneity of the linear term (ABI_{ht}) implies the endogeneity of the quadratic term (ABI_{ht}^2), we instrument both terms. While the idea of IV estimation is compelling in theory, it is often difficult to find valid instrumental variables in practice, i.e., variables that only affect hospital-physician integration but not hospital performance. For this reason, we resort to a commonly used strategy of adopting lagged values of the endogenous variable(s) of interest as instrumental variables (Kesavan et al., 2014; Tan and Netessine, 2014; Sharma et al., 2016). More specifically, we instrument ABI_{ht} and ABI_{ht}^2 via their one-year lagged values, i.e., ABI_{ht-1} and ABI_{ht-1}^2, respectively. The F-statistics for the test of relevance from our regression models (2.2) and (2.3) are 14,687.8 and 10,246.6 ($p < 0.001$), respectively, indicating that the instruments are strong. However, considering that we have more than one endogenous variable in our model, ABI_{ht} and ABI_{ht}^2, the usual tests for weak instruments might be unreliable. Therefore, we also run the Cragg-Donald test (Cragg and Donald, 1993), which is suitable for multiple endogenous variables, and found the corresponding F-statistic to be 1,997.8 ($p < 0.001$), further confirming that our instruments satisfy the relevance condition.

We expect these lagged values of the endogenous variable to be exogenous because the integration levels from previous year should not be directly related with the (potential) unobserved factors that determine the patient care outcomes (i.e., MORT, ReAd, LOS) during the current year. In other words, the lagged variables are not contemporaneously correlated with the disturbance terms ϵ_{ipht}, so they should satisfy the exclusion restriction assumption of a valid instrument. Admittedly, lagged integration may not be an ideal instrument in the event of unobserved factors that are correlated over time. However, these factors can be thought of as trends which are controlled for in our models with year fixed effects, thus lessening this potential concern (e.g., Tan and Netessine, 2014; Kesavan et al., 2014).

When the instrumental variables are valid and the model is linear, the popular, IV-based two stage least squares (2SLS) estimation method yields consistent estimates of the coefficients corresponding to the endogenous variables. However, if the models considered are non-linear, for example because the outcome variable is binary and the link function used for model estimation is the logit link, the 2SLS approach does not yield consistent coefficient estimates (Terza et al., 2008; Wooldridge, 2015). This is the case in our study, when the outcome variable of interest is MORT or ReAd, both binary variables. Therefore, we adopt an alternative IV-based estimation method, the two stage residual inclusion (2SRI), also called the control function method, which yields asymptotically unbiased and consistent estimates when the models are non-linear, such as the logit regression (Terza et al., 2008; Cai, 2010; Koladjo et al., 2018; Wooldridge, 2015). The 2SRI estimation has two stages. In the first stage, we fit the following models:

$$ABI_{ht} = \sigma_0 + \sigma_1 ABI_{ht-1} + \sigma_2^\top H_{ht} + \sigma_3^\top P_{iht} + \sigma_4 PE_{ipt} + T_t + \epsilon_{ipht}, \tag{2.2}$$

$$ABI_{ht}^2 = \gamma_0 + \gamma_1 ABI_{ht-1}^2 + \gamma_2^\top H_{ht} + \gamma_3^\top P_{iht} + \gamma_4 PE_{ipt} + T_t + \epsilon_{ipht}. \tag{2.3}$$

Then, in the second stage, we fit

$$\begin{aligned} f(y_{ipht}) = \alpha_0 + \alpha_1 ABI_{ht} + \alpha_2 ABI_{ht}^2 + \beta_1^\top H_{ht} + \beta_2^\top P_{iht} + \beta_3 ResABI_{ipht} + \beta_4 ResABI_{ipht}^2 \\ + \beta_5 PE_{ipt} + T_t + \epsilon_{ipht}, \end{aligned} \tag{2.4}$$

where $ResABI_{ipht}$ and $ResABI_{ipht}^2$ are the residuals obtained from models (2.2) and (2.3), respectively.

Finally, we discuss the appropriate statistical tests needed for our U-shaped relationships. The inclusion of both the linear and quadratic ABI_{ht} terms is necessary to test for the presence of a U-shaped relationship. However, though necessary, a significant α_2 coefficient alone is not sufficient to establish a U-shaped relationship. We rely on the three-step procedure outlined in Lind and Mehlum (2010) to formally test for the presence of a U-shaped relationship. First, α_2 needs to be significant and of the expected sign, i.e., positive. Second, the slope of the regression equation in (2.4) must be sufficiently steep at both ends of the ABI range. Suppose ABI_L is at the low end and ABI_H at the high end of the ABI range. Then, the slope at ABI_L must be negative and significant, and the slope at ABI_H must be positive and significant. Third, the *tipping point*, represented by $-\alpha_1/2\alpha_2$ and obtained by solving for the first order conditions in model (2.4), needs to be located well within the observed ABI range. We can confirm this by obtaining the 95% confidence interval for the tipping point and checking if the interval falls within the empirical ABI range. If all three conditions hold, then we can be reasonably certain that a U-shaped relationship exists.

2.5 Results

2.5.1 The U-shaped Relationship between ABI and Care Outcomes

The results of our 2SRI-based analysis of the effects of ABI on the three patient care outcome variables are reported in Tables 3 and 4. Table 3 presents the linear and quadratic integration components hierarchically, whereas Table 4 provides appropriate tests for a U-shaped relationship between ABI and care outcomes.

The results for mortality risk in Table 3 show that the estimated coefficients corresponding to the linear and quadratic terms of integration are both significant ($\widehat{\alpha}_1 = -4.616$, $p < 0.01$ and $\widehat{\alpha}_2 = 5.412$, $p < 0.05$), suggesting a U-shaped relationship between integration and risk of in-hospital mortality. Results in Table 4 also show that the slopes at the low and high ends of the ABI range are significant and the tipping point is $\frac{-\alpha_1}{2*\alpha_2} = 0.427$, with an estimated asymptotic 95% confidence interval of (0.283,0.570), which lies within the 0 to 1 empirical range observed for integration. These results indicate that when ABI is below the 0.427 tipping point, an increase in integration is associated with a steady decrease in the in-hospital mortality risk of CABG patients. However, when ABI is larger than the tipping point, an increase in integration is associated with a steady increase in the in-hospital mortality risk of CABG patients. The partial effect plot in the right panel of Figure 2 illustrates this U-shaped relationship. Taken together, these results offer support for hypothesis H1a.

Table 3 also reports the results for the 30-day all-cause readmission risk. We observe that the estimated coefficients corresponding to both the linear and the quadratic terms of ABI are not significant. Since significance of the coefficient corresponding to the quadratic term is a necessary condition for the presence of a U-shaped relationship, we do not find support for Hypothesis H1b. Moreover, the results show that there is also no evidence of a linear relationship between ABI and readmission risk. This finding is supported by the partial effect plot in the middle panel of Figure 2.

The results in Table 3 for log(LOS) show that the estimated coefficients corresponding to the linear and quadratic terms of ABI are both significant ($\widehat{\alpha}_1 = -0.5064$, $p < 0.01$ and $\widehat{\alpha}_2 = 0.5123$, $p < 0.01$), suggesting a U-shaped relationship between ABI and log(LOS). The slopes at the low and high ends of ABI are significant, as reported in Table 4. The tipping point, given by $\frac{-\alpha_1}{2*\alpha_2}$, is 0.494, with an estimated asymptotic 95% confidence interval of (0.346,0.642), which is within the 0 to 1 empirical range observed for ABI. Together, these results establish the existence of a U-shaped relationship between ABI and LOS, and show that an increase in integration is associated with a steady decrease in the LOS of CABG patients, when ABI is lower than the tipping point of 0.494. In contrast, an increase in ABI past the tipping point is associated with a steady increase in the LOS of CABG patients. This U-shaped relation is shown in the partial effect plot presented in the right panel of

Figure 2. Taken together, these results offer support for hypothesis H1c. In summary, we find support for Hypotheses H1a and H1c, but not H1b.

Next, we aim to provide more insights into the practical significance of our findings pertaining to H1a and H1c for a hospital that spans the spectrum of ABI. Thus, according to our analysis, a hospital that currently has an ABI of 10% and is seeking to increase integration up to the LOS tipping point (ABI = 49%) would benefit from a statistically significant reduction ($p < 0.01$) of 0.63 days (8%) in the expected risk-adjusted CABG LOS, from 8.17 to 7.54 days. Conversely, a hospital whose ABI increases from the LOS tipping point to 80% would experience a significant increase in expected LOS of 0.36 days (5%), from 7.54 to 7.91 days ($p < 0.01$). A similar analysis for mortality risk finds that an increase in ABI from 10% to the tipping point of 43% yields a drop in expected mortality risk of 0.5% (a 35% reduction), from 1.4% to 0.9% ($p < 0.01$). An increase in ABI from the mortality tipping point to 80% is associated with an increase in expected mortality risk of 0.8% (a 47% increase), from 0.9% to 1.7% ($p < 0.01$). Considering that CABG is among the most expensive cardiac procedures (e.g., Giacomino et al., 2016), these findings underscore the meaningful effect that ABI can have on both care quality and cost effectiveness.

2.5.2 The Moderation Effects of Teaching Status and Bed Utilization

The results for assessing the moderating roles of teaching status and bed utilization are reported in Table 5, and reveal that hospital teaching status and bed utilization do not have a significant moderating effect on the association between ABI and patient in-hospital mortality risk or 30-day readmission risk. Therefore, we do not find support for hypotheses H2a, H2b, H3a and H3b.

However, we find that both teaching status and bed utilization have significant moderating effects on the relationship between ABI and patient LOS. In more detail, the significant coefficient corresponding to $Teaching \times ABI$ (0.4107, $p < 0.05$) suggests a shift in the tipping point, and the significant negative coefficient corresponding to $Teaching \times ABI^2$ (-0.4966, $p < 0.05$) suggests a flattening of the curve for teaching hospitals (Haans et al., 2016). Thus, we find support for hypothesis H2c. Similarly, the significant coefficient corresponding to $Bed\ Utilization \times ABI$ (2.0069, $p < 0.01$) suggests a shift in the tipping point, and the significant negative coefficient corresponding to $Bed\ Utilization \times ABI^2$ (-2.1661, $p < 0.01$) suggests a flattening of the curve for higher bed utilization hospitals. Thus, we find support for hypothesis H3c.

The moderating roles of teaching status and bed utilization on the U-shaped relationship between ABI and LOS are illustrated graphically in Figure 3. The left panel plot corresponds to teaching status and shows that the U-shaped effect of integration on patient LOS is more pronounced in non-teaching hospitals and weaker, flatter in hospitals with a teaching mission. The right panel plot in Figure 3 shows the interaction plot of integration and bed utilization on patient LOS, at the 10th and 90th percentiles of bed utilization, corresponding to bed utilization values of 0.5 and 0.77, respectively. The U-shaped effect of integration on patient LOS is more pronounced when bed utilization is low, and weaker, flatter when bed utilization is high. Overall, this analysis provides new evidence on the moderating role of teaching status and bed utilization in a setting where the relationship between integration and patient LOS is non-linear.

2.6 Robustness Checks

Here we provide several tests to check the robustness of our results. (1) We firstly conduct pooled OLS model to shows the effects of endogeneity and then we tried different cluster level for standard error. (2) next, to test the robustness of U-shape effect in our model, we provide non-parametric GAM model and cubic regression model to test higher order effects. (3) We also provide the result for higher lagged variable as instrumental variables to reduce the potential sticky issues when one-year lagged variable is used as instrumental variable. (4)

Lastly, we provide two alternative measures of integration, one is based on hospital physician concentration activities based on the volume handled by physicians in each hospitals and the other one is based on physician multisiting activities across hospital systems.

2.6.1 Regular OLS Model

Here we provide several robustness checks for our main results. First, in the main results, we used the IV regressions due to the existence of endogeneity. In Tables 6 and 7 below present non-IV regression results for both our main and moderation effects. The results are similar, but all the linear effect models show insignificant effect of integration and the magnitude of the coefficients for ABI is slightly changed. All points out the effect from endogeneity issues.

2.6.2 Alternative Model Specifications

Here we report several additional analyses performed to assess the robustness of our results to alternative model specifications. First, we seek a data-driven confirmation that the hypothesized relationships are indeed non-linear. Our models specify linear and quadratic terms for ABI_{ht} to test for the existence of a U-shaped effect. As an alternative specification, we fit a generalized additive model (GAM) (Hastie and Tibshirani, 1990) in place of model (2.1). The GAM approach uses splines to approximate a functional form for each of the components specified in the model. Specifically, we fit

$$f(y_{ipht}) = \beta_0 + g(ABI_{ht}) + \beta_1^\top H_{ht} + \beta_2^\top P_{iht} + \beta_3 PE_{ipt} + T_t + \epsilon_{ipht}, \tag{2.5}$$

where $f(.)$ is a known link function, specified to be the log-link for LOS and the logit-link for both mortality and readmission, and $g(.)$ is an unspecified smooth function that is approximated using cubic splines. Figure 4, which shows the partial effect plots corresponding to ABI_{ht}, confirms the presence of a non-linear relationship between integration and care outcomes. For integration levels between 0.2 and 0.8, we note a U-shaped effect for all three outcomes, whereas the partial effect plots for LOS (left panel) and readmission risk (right panel) exhibit some unexpected tail behaviour. We attribute this behavior to the presence of relatively few, sparse observations (hospital-year combinations) in the tails, which makes the cubic spline estimation behave unexpectedly in those regions. Overall, this analysis offers further support to the findings obtained from the main analysis.

2.6.3 Different Cluster Level

Second, we examine the robustness of our results to different levels of standard error clustering. Our main results in Table 3 are based on robust standard errors clustered at the hospital level. However, patient characteristics, patient care, and patient outcomes may be correlated within a DRG group. Therefore, we investigate alternative clustering approaches by DRG code and by hospital-DRG combinations. We find that the standard errors re-estimated according to these two clustering approaches are smaller than in the original analysis, rendering the coefficients corresponding to the linear and quadratic terms of integration significant at the 1% level, for both LOS and mortality. Similarly, a clustering approach based on physician and hospital-physician combinations yielded integration effect estimates that are significant at the 1% level, for both LOS and mortality risk. Taken together, these results suggest that our earlier findings are robust to different standard error clustering approaches.

2.6.4 Different Lagged of Independent Variable

We examine the robustness of our results to the choice of our IV. In the main analysis, we use one-year lags of the endogenous ABI_i variable as the IV. One potential limitation of employing lagged endogenous variables as instruments is that they can be subject to serial correlation in the event of omitted variables (that are related with integration and patient care outcomes) that are correlated over time. Whereas these serial correlation effects are controlled for in our models via the use of year fixed effects (e.g., Tan and Netessine, 2014; Kesavan et al., 2014), to further alleviate such potential concerns, we fit our models using two-year lagged ABI as the instrumental variable. , i.e., we use ABI_{ht-2} instead of ABI_{ht-1} as the IV. The results are reported in Tables 8 and 9. While we note a significant sample size reduction caused by the two-year lag, the new IV yields results that are consistent with the findings from our main analysis, with the exception of the moderating role of bed utilization which is no longer significant.

Here, we fit our models using two-year lagged ABI as the instrumental variable, i.e., we use ABI_{ht-2} instead of ABI_{ht-1} as the IV.

2.6.5 Alternative Measures for ABI

In this section we perform two additional analyses to test the robustness of our findings.

Measure ABI based on physician multisiting volume First, we adopt an alternative definition of integration, as the ratio of the cases of single-site CABG surgeons handled in a hospital to the total surgeries volume performed by CABG surgeons. In contrast to our original definition of integration, which scaled the number of single-site CABG surgeons in a hospital by the number of CABG surgeons in that hospital, this alternative definition aims to better normalize for CABG volume differences among hospitals. To assess robustness of our results to this definition, we define it as the ratio using the fraction of the volume of single-siting CABG surgeons who work full-time to the annual volume CABG surgeons handled in that hospital.The results are reported in Table 10 reports integration as as the ratio of the surgery volume handled of single-site CABG surgeons in a hospital to the total surgeries volume performed by CABG surgeons in that hospital. Different to the original analysis, we do not find a significant relationship between integration and the risk of mortality and readmission. But we still have that the U-shaped associations between integration and patient LOS. Overall, these results with an alternative definition of Int_{ht} confirm our earlier findings, and offer support to hypothesized U-shaped relationship between hospital-physician integration and patient care outcome measures, namely LOS.

Measure ABI based on physician multisiting across hospital systemn We investigated further the idea of measuring hospital-physician integration at the level of a hospital system and, interestingly, found that the proportion of cases where splitting physicians treat patients outside of a focal healthcare system is small, around 10%. This small proportion of cases observed in our data is consistent with similar findings reported in KC and Tushe (2021). As such, our data suggests that when physicians split their activity across multiple hospitals, they tend to do so in hospitals within the same system. As a result, a measure of integration at the hospital system level would label the vast majority of physicians as "integrated" and would not have sufficient statistical power to discriminate between the performance of "integrated" and "non-integrated" hospital systems. Table 3 below provides results for an analysis based on a system-level measure of integration. Consistent with our comments above, the coefficient estimates for the focal ABI_System and ABI_System2 variables for LOS and mortality risk are statistically insignificant, respectively.The significant effect of ABI measured at hospital level and insignificant effect of ABI measured at system level support our understanding that hospitals, even members of the same hospital system, are likely to have different working environments, which affect the physician behaviors.

2.7 Discussion and Conclusions

Hospital-physician integration has emerged as a salient business strategy that hospital managers increasingly turn to in order to increase hospital revenue and improve patient care outcomes. Integration affords hospitals higher leverage in aligning physicians' incentives with organizational objectives, and promoting standardized care pathways that increase hospital adherence to evidence-based practices and improve patient care outcomes. Integrated physicians who concentrate all their activity in a single, focal hospital benefit by avoiding the non-trivial setup costs of travelling between different hospitals and adapting to different operating environments, technologies, and group members, which prior research has established as factors that reduce physician performance and productivity (e.g., KC and Tushe, 2021). However, hospitals with high levels of integration can face saturated physician workloads and high admission volumes that can hamper physician productivity and patient outcomes. Moreover, high levels of integration may hinder exposure to innovative ideas, treatment strategies, and technology, thus slowing the dissemination of best practices, which can gradually erode a hospital's competitive positioning. As such, a change in the level of hospital-physician integration may have mixed effects on patient outcomes, either positive or negative, depending on the current, base level of integration.

In this paper, we evaluate the relationship between activity-based integration and patient care outcomes, namely in-hospital mortality risk, 30-day readmission risk, and LOS. Our study adopts a granular perspective by focusing on patients treated for CABG and measuring ABI appropriately at the level of a cardiac surgery procedure, i.e., CABG. Using an instrumental variable modelling approach, and controlling for appropriate hospital- and patient-level characteristics, we find that ABI has a significant, U-shaped association with patient in-hospital mortality risk and LOS, whereas no significant association is identified between ABI and readmission risk. More specifically, as ABI increases from an initial low level, performance improves with integration (i.e., patient mortality risk and LOS decrease). However, as ABI increases past tipping points of 43% for mortality risk and 49% for LOS, performance decreases with integration (i.e., mortality risk and LOS increase). We further find that hospital contextual factors, namely teaching status and level of bed utilization, moderate the relationship between ABI and patient LOS. Our results indicate that non-teaching hospitals and hospitals with low levels of bed utilization are most sensitive to variations in ABI, as these hospitals exhibit a more pronounced U-shaped relationship between ABI and patient LOS.

2.7.1 Contributions to Theory

Our study makes several contributions to literature and theory. First, we operationalize integration based on actual physician activity, in contrast to some of the extant literature which relies on employment or contractual agreements between hospitals and physicians (e.g., Mishra et al., 2020; Zepeda et al., 2020). Considering that, in practice, employment can take a variety of contractual forms (e.g., Short and Ho, 2019; Mishra et al., 2020) that may influence a physician's incentives to operate at a single facility, we believe that tracking actual physician activity provides an alternative, more specific proxy for integration than potentially relying on blanket, facility-wide contracts. This activity-based approach also affords us the flexibility to measure integration and its implications on care outcomes at the granular level of a specific surgery procedure, as opposed to the level of a clinical service area (e.g., Zepeda et al., 2020) or the level of a hospital (e.g., Scott et al., 2017; Abdulsalam et al., 2018; Mishra et al., 2020). We also note that, while some prior studies have examined the concentration of physician activity as a potential determinant of physician-level performance (e.g., Huckman and Pisano, 2006; KC and Tushe, 2021), to the best of our knowledge, the role of activity concentration as a driver of organizational-level (i.e., hospital, departmental, etc.) performance has not previously received much attention. Our work can help bridge the two literature streams. Thus, our study contributes to the literature by demonstrating the implications of integration at the level of a specific procedure and establishing an alternative, de facto approach to measuring integration.

Second, we theorize and find evidence for a U-shaped relationship between ABI and measures of care quality such as mortality risk and LOS. To our knowledge, this non-linear relationship has not been previously reported in the integration literature. As such, our study extends this literature and, to the extent to which physician employment and physician concentration of activity overlap, may offer a potential explanation for the inconclusive findings reported previously on the association between employment-based integration and performance. For example, our study does not support the lack of a linear association between integration and LOS reported in Scott et al. (2017), but confirms the negative linear association found in Mishra et al. (2020)[2], while also extending these results with evidence of a significant U-shaped relationship. We also confirm prior findings in Scott et al. (2017), Mishra et al. (2020), and Short and Ho (2019) that no linear association exists between integration and readmission risk, while also offering evidence that this result extends to the nonlinear case. Prior studies underscore the important role that clear, well-articulated discharge instructions play in reducing readmission risk (Regalbuto et al., 2014; Senot et al., 2016). Providing discharge instructions and education to patients is a responsibility that physicians share with nurses and other care providers, with nurses taking a leading role in this process. Therefore, it is plausible that physician integration may play a smaller, less influential role on readmission risk. Additionally, while we do not support the negative linear association between integration and mortality risk identified in Mishra et al. (2020), we confirm prior results which find no linear association between integration and mortality risk (Madison, 2004; Carlin et al., 2015; Scott et al., 2017). However, in contrast with these prior studies, we do find evidence that the relationship between integration and mortality risk is in fact U-shaped, suggesting that a linear model would be misspecified and unable to capture the true association between ABI and mortality risk. Our results may also help reconcile the above findings with the surprising positive association between integration and mortality risk uncovered in Chukmaitov et al. (2015), considering that, according to our study, the nature of this association is dependent on a the range of integration values considered.

Third, our study identifies teaching status and bed utilization as contextual factors that moderate the U-shaped relationship between ABI and LOS. The significance of these moderators is also documented in Mishra et al. (2020) for the case of a linear association between EBI and LOS. We find that a teaching mission and high levels of bed utilization act

[2] Mishra et al. (2020) investigate physician contracting emphasis (PCE), which is the inverse of employment-based physician integration. In an effort to compare the implications in Mishra et al. (2020) with ours, we assume their PCE results extend to physician integration with an appropriate sign change.

as substitutes to ABI, which suggests that the LOS performance of non-teaching hospitals and hospitals with below-median levels of bed utilization is more sensitive to variations in ABI. Thus, these hospitals stand to derive larger LOS benefits from increases in integration when integration levels are low. Our results also show that teaching status and bed utilization do no influence in a significant way the U-shaped relationship between ABI and mortality risk. Based on our analyses, we find no significant differences between the mortality rate performance of teaching and non-teaching hospitals, as well as between hospitals with high or low levels of bed utilization. This finding regarding the non-influential role of teaching activity for the mortality risk of CABG patients is consistent with prior observations that the literature commonly hypothesizes that teaching hospitals perform differently, yet fails to find support for such hypotheses (Dobrzykowski and Tarafdar, 2015). The finding that teaching status and bed utilization play different contingency roles vis-à-vis ABI and different care outcomes holds theoretical implications, as it establishes teaching status and bed utilization as more influential structural elements for better efficiency of care (as measured by LOS) relative to better quality of care (as measured by mortality risk).

Fourth, we conceptualize the relationship between ABI and hospital performance by utilizing individual and organizational learning as theoretical lenses. We note that, while ABI fosters a work environment that nurtures learning, with positive ramifications for care outcomes, the benefits resulting from ABI can be eventually suppressed and counterbalanced by increased physician workloads and diminished, potentially transformative, informational exchanges with outside clinicians. Thus, our empirically validated approach of balancing the benefits of ABI with its potential drawbacks adds to the growing discussion on the implications of integration.

2.7.2 Contributions to Practice

Our study offers several pertinent implications for administrators evaluating their hospital's physician integration initiatives. First, our analysis suggests that, in general, patient care outcomes are maximized when a hospital maintains an about equal mix of physicians who work exclusively in that hospital and physicians who split their activity across multiple hospitals. More specifically, we find that ABI levels of 49% and 43% are best for LOS and in-hospital mortality, respectively. We also do not find a significant association between ABI and readmission risk. Contrasting the linear association between ABI and physician workload, as suggested in Table 2, with the U-shaped association between ABI and care outcomes, such as LOS and mortality risk, points to a trade-off between revenues and care outcomes once ABI exceeds the aforementioned tipping points. Thus, while a hospital at low levels of integration can potentially improve both financial and clinical performance by increasing integration, this dual improvement benefit becomes more challenging once integration exceeds the tipping point.

Second, our analysis suggests that the implications of ABI for LOS performance are contingent on hospital teaching status and bed utilization. ABI is less influential on the LOS of teaching and high utilization hospitals, suggesting that the trade-off between revenue growth and LOS improvement is less pronounced in these environments. In general, considering that our results provide evidence that the implications of integration are a function of a hospital's current level of integration, past performance improvements resulting from higher integration should not be taken for granted in the future, as integration continues to increase. Hospital administrators are advised to closely and carefully assess how care outcomes change in response to higher integration levels, and look for signs of performance plateau or decline that may indicate that the turning point is near or has been reached. In a broader sense, our findings may temper expectations, for hospital administrators and physicians practices alike, on the benefits of activity-based integration. Considering the investments needed to attract and retain physician specialists who work exclusively in one hospital, we caution healthcare decision makers to avoid adopting a myopic perspective when evaluating the benefits of integration, since our study suggests that less can be more when it comes to integration.

2.7.3 Limitations and Conclusions

This study is not without limitations, which may offer opportunities for future research. Our data does not offer information on the specific type of physician employment agreements or contracts in use at the hospitals analyzed. Physicians operating in a single hospital may be subject to different employment contracts, performance expectations and incentives (Darves, 2014). Therefore, future research could investigate whether contract variety impacts care outcomes and the potential interplay between the activity-based and employment-based forms of integration. Given that our study has focused on a particular cardiac surgery procedure, CABG, care should be taken when generalizing our results to other procedures, particularly outside of cardiovascular services. Future research can investigate the generalizability of our results to broader sets of medical procedures, both surgical and otherwise.

In closing, we believe this study extends existing knowledge by providing one of the first examinations of the non-linear association between activity-based hospital-physician integration and care outcomes. We hope our findings are relevant to academics and practitioners alike and offer further specificity to the ongoing debate on the benefits of integration.

Chapter 3

Physician Collaboration and Care Efficiency in the Emergency Department

3.1 Abstract

Enhanced physician collaboration promotes improved information sharing and reduces the likelihood of duplicated actions that potentially reduce the efficiency of care delivery. Collaboration, operationalized based on physician shared experience and diversity of collaborators, has been considered as a determinant of service quality. Increasing shared experience with a specific collaborator(s) helps to elevate familiarity, and increasing the number of ones' unique collaborators helps to obtain higher levels of flexibility. In an emergency department (ED) setting, physicians often need to collaborate with each other to decide on the care services needed by a patient. In this study, we evaluate the impact of peer collaboration in a hospital ED setting and study the relationship between physician familiarity and level of partner exposure and measures of care efficiency such as ED visit duration and the number of procedures received. Our findings indicate that both physician familiarity and partner exposure help improve care efficiency, with the benefits being stronger for more severe patients. In post hoc analyses, we find that physician multi-siting (i.e., a physician who works at multiple ED locations) *suppresses* the benefits of familiarity and partner exposure on care efficiency. We also find that physicians' levels of partner exposure act as complements. This suggests that, while the best care efficiency is achieved by physician teams with high levels of partner exposure, physicians with limited partner exposure are better off being paired with physicians that have been exposed to a larger number of partners.
Keywords: collaboration, familiarity, partner exposure, care efficiency, emergency department

3.2 Introduction

The emergency department (ED) has always been a key area of focus for hospital management. In United States, the Centers for Disease Control and Prevention (CDC) reports that there are about 130 million visits to the ED annually (Cairns et al., 2021).

In this high-intensity, high-velocity, and high-volume working environment, ED physicians must develop astute clinical and diagnosis capabilities, as well as effective collaboration with healthcare providers to make appropriate patient treatment decisions. Inappropriate decisions may result in wasted resources, and severe consequences for the patients and the hospital (Rodziewicz et al., 2021). Although healthcare professionals make every effort to provide appropriate and suitable service to patients, ED professionals with the need to provide non-terminating service for many unpredictable and complex tasks inevitably face many challenges when they cooperate.

A professional's collaboration can refer to temporary but multidisciplinary teamwork aimed at the common goal of achieving positive health outcomes for patients (Babiker et al., 2014; Bekkink et al., 2018). It could involve professionals with different roles across a variety of work environments and clinical specialties. For instance, ED general physicians would collaborate with triage nurses, residents and trainees when admitting and providing service to patients (Kim et al., 2022), communicate with inpatient physicians when preparing patients for admission into the inpatient department, interact with paramedics when receiving patients delivered through ambulance (Lu and Lu, 2018; Smith et al., 2015; Akşin et al., 2021), and cooperate with other ED physicians for inter-shift patient hand over (Ye et al., 2007). An effective professional collaboration is a foundational component for effective and efficient service delivery (Huckman and Staats, 2011; Huckman et al., 2009; Kossaify et al., 2017). However, it is hard to pursue and achieve. Professional collaboration focuses not only on delivering services but also synchronizing various critical streams of information and data along the care delivery process (Horsky et al., 2015; Avgerinos et al., 2020). Although hospitals and healthcare organizations have recently made significant investments in providing auxiliary systems to improve collaboration efficiency, either by providing electronic information sharing systems (Li et al., 2022; Horsky et al., 2015), or by providing more standardized procedure codes for physicians to follow during collaborations (Dahlquist et al., 2018), poor communication and collaboration between care providers continue to be main driver of medical errors in EDs (Källberg et al., 2015; Pham et al., 2011).

While auxiliary support systems guarantee accuracy in information delivery, knowing who you are working with plays a significant role in collaboration. Especially with unstable working hours to keep ED operations around the clock (Batt et al., 2019), physicians have less opportunity to maintain a stable collaboration with specific peers. Meanwhile, partner familiarity and partner exposure have been highlighted in the healthcare OM literature as primary factors that affect collaboration efficiency (Kim et al., 2022; Avgerinos and Gokpinar, 2017b; Lu and Lu, 2018; Avgerinos et al., 2020; Akşin et al., 2021). It is important to note that partner familiarity and partner exposure have related but different effects in professional collaboration. When considering collaboration as a form of information exchange, partner familiarity can be considered as bandwidth for information sharing, that expands the bandwidth and speeds up information transmission, whereas partner exposure could be considered as the number of information interfaces, that provides access to more information.

When looking at related literature in healthcare, we find that collaboration focus on inter-professional, inter-disciplinary and inter-organizational are the main streams, but there is less focus on collaboration between peers (Kim et al., 2022; Avgerinos and Gokpinar, 2017b; Karam et al., 2018; Fewster-Thuente and Velsor-Friedrich, 2008). Furthermore, most researchers examine partner familiarity in collaboration between professionals of different specializations or roles such as nurses and physicians (Kim et al., 2022; Avgerinos and Gokpinar, 2017b; Avgerinos et al., 2020), new recruits and senior paramedics (Akşin et al., 2021) while paying less attention to collaboration between peer professionals, such as general physicians, in the ED. In general, there is little work that relates to peer collaboration in the healthcare operations management literature. Moreover, prior literature have mainly studied partner exposure in collaboration for each member and but have not accounted for the difference in partner exposure among collaborators. We wonder whether collaboration performance is not only affected by the roles played by the collaborators, but also by differences in partner exposure.

This study aims to answer several research questions pertaining to the relationship between ED physician collaboration and patient care efficiency as follows: (1) does familiarity between collaborating ED physicians affect collaboration performance? (2) does the level of partner exposure of collaborating ED physicians affect collaboration performance? (3) does task complexity moderate the effects of familiarity on collaboration performance?

To address the aforementioned questions, we use ED visit-level data spanning 2011 - 2014 from the State Emergency Department Database (SEDD) for the U.S. state of Florida. This database tracks each unique ED visit that did not result in an inpatient admission, such that ED physicians provide all needed services to diagnose and treat the patients. For each visit, the IDs of all physicians involved in treating the patient are recorded. According to our data, most ED visits involve up to two ED physicians, with one physician assigned as the attending physician and the other assigned as the operating physician. The attending physician is responsible for the care and treatment given to a patient, whereas the operating physician represents a physician who rendered additional, distinct care services to the patient. Our study focuses on ED visits having unspecific chest pain (UCP) as the primary concern and the services of two different physicians. We focus on unspecific chest pain (UCP) as the primary reason for visit, as it is one of common public health concerns and also is one of top three reasons for treat-and-release ED visiting but with various causes ranging from potentially fatal cardiac causes to psychological issues. Any mishaps in diagnosing UCP could result in potentially fatal consequences to the patient. For this reason, physicians involved in caring for UCP patients benefit from ample and varying experiences to causes and symptoms of UCP.

Based on our empirical analysis, we find that UCP patients receiving service from a pair of physicians with higher familiarity experience higher care efficiency, as measured by the total ED duration and the number of procedures received. A 1% increase in familiarity between the pair of physicians is associated with a 3% reduction in total ED duration for the patients. For a patient whose ED duration is equal to the average (29.8-hour), that effect translates to a duration reduction by about 0.09 hour, around 5 minutes. Similar results are found related to reducing the number of procedures. A 1% increase in familiarity between the pair of physicians is associated with a 2.2% reduction in the total number of procedures. We also find that UCP patients receiving service from physicians with higher levels of partner exposure experience higher care efficiency, as measured by the total ED duration and the number of procedures received. A 0.01 unit increase in partner exposure of the attending physician is associated with 0.55% reduction in total patient ED visit duration and 0.005 reduction in the number of procedures. Similar results are found related to partner exposure of operating physician . A 0.01 unit increase in partner exposure for the attending physician is associated with a 0.64% reduction in the number of procedures and 0.003 reduction in the number of procedure. Finally, we find that the effects of familiarity on care efficiency is enhanced for more severe patients. With a high severity condition (in 90% quantile of total chronic diseases), a patient expect 0.36% reduction in LOS with 1% increasing in familiarity, comparing to 0.28% reduction for low severity condition (in 10% quantile of total chronic diseases). Our findings are consistent under several robustness checks. Next, in our post hoc analyses, we test the moderating effects of several physician characteristics that have not been previously investigated in the literature. Specifically, we examine whether the attending (operating) physician's level of partner exposure moderates the effect of the operating (attending) physician's level of partner exposure on care efficiency. We find that the two physicians' levels of partner exposure are substitutes with respect to their effect on care efficiency.

Our study makes several contributions to the healthcare OM literature. First, we consider the collaboration among peer physicians in an ED setting. Our results underscore the importance of a physician pairing strategy that considers the physicians' levels of familiarity and individual partner exposure. Physician scheduling plays a critical role in ED planning, and has to account for fairness, limited labor resources, and complementary skills. Our study adds to the ED physician scheduling literature by suggesting that familiarity and partner exposure levels should be considered during the scheduling and assignment of ED physicians to specific shifts. Second, we also contribute to the growing literature that investigates the role of patient severity and complexity by proffering partner familiarity and partner exposure as operational variables that are more influential for the care of patients with higher severity.

3.3 Literature Review and Hypothesis Development

3.3.1 Collaboration: Familiarity and Partner Exposure

The contemporary workplace is becoming more distributed, pervasive and more flexible compared with the traditional workplace, to handle the uncertainty and complexity of the contemporary tasks and cope with a rapidly changing external environment (Bennis, 2017). Motivated by this strategic change, more temporary organizations or temporary teams are introduced and more and more heavily relied upon in different industries, such as sports teams (Dalal et al., 2017), film projects (Bechky, 2006), healthcare (Kim et al., 2022), software R&D (Huckman et al., 2009), etc. Temporary teams bring together individuals from different groups with a variety of professional skills to accomplish a complex and important task in a given time period. Usually, the team is disbanded when the respective task is completed (Akşin et al., 2021; Dalal et al., 2017; Bechky, 2006). Based on the scope and goal of the task, members of the team collaborate, contribute their knowledge and opinions, while at the same time working together simultaneously to accomplish the task, such as performing surgery (Akşin et al., 2021; Avgerinos et al., 2020), competing in sports events (Berman et al., 2002; Dalal et al., 2017), and flying commercial aircraft (Hackman, 1993). Additionally, team members can provide a work pipeline where each member fulfills a specific part sequentially, and the task is handed over to other members till the completion of the task. For instance, patient referral (Senot, 2019) and inter-hospital patient transfer decisions (Lu and Lu, 2018) are examples of collaboration across organizations.

Those temporary teams are often built for a limited time and based on the requirement of specific skill sets. It is also common for those teams to choose members from a "pool" of professionals yielding random combinations of professionals (Akşin et al., 2021; Kim et al., 2022). As a result, members in the temporary team often have not collaborated before and the challenge is to swiftly build up trust among the team members. Exposing those challenges, many empirical studies have demonstrated the value of familiarity in collaboration, particularly among temporary team members (Huckman et al., 2009; Huckman and Staats, 2011; Kim et al., 2022). Huckman and Staats (2011) define familiarity as the individuals' previous experience working with other members of their current team and highlight the positive impact of familiarity on productivity. There is a stream of healthcare operations management literature that discusses the positive effects of familiarity on efficiency, with benefits including lower ED visit duration (Niewoehner et al., 2022; Kim et al., 2022), lower surgery time (Avgerinos and Gokpinar, 2017b; Reagans et al., 2005), an accelerating patient pick-up rate (Niewoehner et al., 2022), and higher care effectiveness such as reduced readmissions and ED visits (Senot, 2019; Xiao et al., 2015). Meanwhile, there are a few studies that investigate the side effects of familiarity in team work.

Focusing on group longevity, which is defined as the average time that team members have been working together, Katz (1982) finds that project groups faced increasing ossification of key information and knowledge, both within and outside their organizations, as group longevity increases, which adversely impacted performance. Berman et al. (2002) found a non-monotonic relationship between levels of shared team experience and team performance, which demonstrate that the value of shared experience, a measure for firm-level tacit knowledge, is positive but subject to diminishing returns. At the extreme situation, the positive effects of shared experience may become negative as the effects of knowledge ossification begin to outweigh any benefits of collective knowledge accumulation. These studies indicate the importance of knowledge generation and dissemination, in terms of exploration and exploitation in learning. Theoretical arguments and empirical findings suggest that partner exposure can enhance creativity and problem solving (Kane et al., 2005; Fang et al., 2010; Choi and Thompson, 2005) by bringing advanced knowledge from outside groups while keeping a certain level of familiarity.

Partner exposure is introduced as the individuals' previous experience working with other members excluding their current team members. In the context of ambulance services, Akşin et al. (2021) measures the new recruits' prior partner exposure using the distribution of cumulative experience over prior partners. Their analysis focuses on ambulance transports involving patient pick up at the scene and hand-over at the ED and investigates the impact of prior partner exposure on time spent at different parts of the transport process. They find a positive effect from partner exposure that depends on the level of process standardization, and also suggest that the benefits from partner exposure can exceed that from team familiarity for green hands. Avgerinos et al. (2020) found that the benefits on team productivity generated from hierarchical familiarity (e.g., surgeon to nurse) is not as pronounced as the benefits derived from horizontal familiarity (e.g., surgeon to surgeon). Kim et al. (2022) operationalizes partner exposure as the number of partners with different roles that a team member has worked with prior to the current task. This study evaluates the role of partner exposure for team members who occupy specialized roles that are differentiated by authority and skill, and argues that partner exposure has a higher positive performance effect for members in a decision-initiating role, such as attending physician, than those in decision-executing role, such as residents and nurses. The aforementioned studies examine the implications of an individual providers' level of partner exposure independently of other team members' levels of partner exposure. This approach assumes that there no interaction exists between the team members' levels of partner exposure with respect to their implications for care outcomes. Nevertheless, we argue that individual team members are learning from their co-workers in an effort to achieve better performance, with different learning rates and outcomes that depend on the interrelationship among members (Argote and Fahrenkopf, 2016; Thomas-Hunt et al., 2003; Nembhard and Edmondson, 2006). As mentioned by Gurvich and Van Mieghem (2015), there are unavoidable bottlenecks in teamwork, especially in teams that require both collaboration and multitasking, and Avgerinos and Gokpinar (2017b) indicates bottlenecks could be associated with uneven familiarity levels among team members. Building upon and extending these prior findings, we suggest that differing levels of partner exposure between team members may influence team dynamics and care outcomes. To this end, we investigate these relationships in this study, since they have not previously received attention in the literature.

3.3.2 Emergency Department Performance

Healthcare is a complex, knowledge intensive service industry in which both individuals and organizations rely on repetitive practice and learning to deliver better performance and reach higher productivity (Froehle and White, 2014). Meanwhile, hospitals, with the need to provide service 24 hours, 7 days a week, inevitably involve many temporary teamwork due to discrete scheduling and task complexity (Batt et al., 2019). Effective communication and efficient handover among healthcare providers in temporary teams are critical for patient safety. Effect of familiarity on healthcare performance among temporary team members have been repeatedly discussed both for simultaneous teamwork and sequential teamwork, while partner exposure has been recently discussed for simultaneous teamwork. Table 12 provides summary of the literature related to familiarity and partner exposure in healthcare setting.

The ED provides a great setting for us to explore aspects related to familiarity and partner exposure in healthcare, as it provides a working environment that involves both simultaneous and sequential collaboration. In the setting of the ED, physician collaboration occurs mostly in two specific contexts: (1) the admitting physician collaborates with another physician for extra support or assistance; (2) the admitting physician collaborates with another physician in the next shift when handing over a patient at the end of the shift (Ye et al., 2007; Dahlquist et al., 2018). These forms of collaboration are generally observed in contexts where by condition of the patient is severe enough to require the services of multiple physicians or extra care time. But limited studies focus on familiarity either at the setting of simultaneous teamwork (Niewoehner et al., 2022) and sequential teamwork (such as handoff) (Batt et al., 2019; Ye et al., 2007), even less on evaluating the effect of partner exposure in the ED setting (Kim et al., 2022).

3.3.3 Familiarity and ED Team Performance

The significant level of physician discretion over patient care has a large influence on service quality. Familiarity, leadership, and social ties in working teams have been considered as key factors in influencing team dynamics and performance (Edmondson, 1999; Nembhard and Edmondson, 2006). The quality of the working relationships between the members of the care team is critical to delivering timely and effective patient care. Since teams differ in terms of members, skills, experience level, and social connection, a physician working with the same group can focus his/her efforts and tailor his/her work routines to fit the peculiarities of that team, in the process developing a deep level of understanding of who knows what and knowing how to work together (Reagans et al., 2005).

As team members acquire experience working together, they develop a shared language or a common set of terms (Weber and Camerer, 2003; Argote and Fahrenkopf, 2016), an important aspect of the recognition and connection that enables members to perform tasks faster and more reliably (Thomas-Hunt et al., 2003). The importance of team familiarity, the degree to which team members have worked with one another in the past, has been observed in several settings. Comparing to patients with elective admission to the inpatient department, whose medical records have been collected and reviewed by professionals in advance, ED patient visits are unpredictable and under emergency circumstances. Hence, it's critical to collect information and disseminate to colleagues in a fast and accurate way. On the other hand, the ED is a high-volume and high-velocity working environment, where ED physicians require not only collaboration but also multitasking. For instance, a physician may admit a new patient, while writing the discharge document for another patient and ordering tests for yet another patient. Though multitasking increases the rate of service, it also induces issues of interruption and discretionary switching to collaborative tasks. Those interruptions generally require re-configuring and refreshing information during each task switching (Gurvich et al., 2020; Laxmisan et al., 2007; Froehle and White, 2014). A team with higher familiarity possesses more tacit information that enhances communication efficiency, which could help integrate different treatment options and clinical decisions more efficiently (Berman et al., 2002), and encourages physician multitasking without impairing performance, as reflected by the lack of a significant increase in the ED visit duration (Niewoehner et al., 2022).

In summary, there is strong evidence in the literature that suggests that peer familiarity fosters better communication, and higher levels of trust, which in turn are associated with improved team performance. Taken together, even though a team could be temporary, partner familiarity would provide a wider bandwidth for more efficient knowledge transfer and quicker learning rate to deliver better performance through learning together from past successes and failures (Avgerinos et al., 2020; KC et al., 2013). Therefore, we hypothesize the following.

H1. *Higher partner familiarity between ED physicians is associated with better operational efficiency, as measured by (a) lower ED visit duration and (b) lower number of procedures.*

3.3.4 Partner Exposure and ED Team Performance

We consider familiarity between two specific ED physicians as the focal learning experience, since familiarity measures prior shared working experience between the pair of ED physicians involved in the current task (i.e., patient visit). In contrast, partner exposure is treated as a related but non-focal learning experience with physicians outside of the current collaboration.

Adopting a learning theoretical lens, familiarity can be construed as an exploitation-type learning activity, whereas partner exposure is an exploration-type activity in learning for the current collaboration.

Similar to other studies that adopted a task-focused or organizational/group-focused approach, here we adopt an individual-focused approach, where for a given ED visit, the relationship with the other ED physician involved in treating the patient is considered focal, whereas relationships with other ED physicians would be considered related, but non-focal. Researchers who focus on experience and learning emphasize the importance of both focal and related experiences (KC and Staats, 2012; Huckman and Pisano, 2006). Though accumulating a focal experience could improve performance from different aspects, such as by reducing distractions from switching between tasks (Staats and Gino, 2012; Froehle and White, 2014) and accumulating group-specific experience (Huckman and Pisano, 2006), the variety of related experiences would also enhance the rate of learning, with potential knowledge transfer from outside experts (Narayanan et al., 2014; Marco et al., 2019; Kane et al., 2005). Hence, physicians who accumulate various working experiences through exposure to different partners have thus an opportunity to keep learning.

Meanwhile, considering patients who go to the ED may suffer from more severe symptoms without a clearer awareness of their condition, ED physicians require a breadth of knowledge to diagnose and treat a wide variety of patient conditions. Partner exposure can help enrich a physician's breadth of knowledge, fostering better physician performance (Huckman and Staats, 2011).

Finally, working consistently with the same group runs the risk of knowledge ossification as people are less excited in communication and sharing thoughts (Katz, 1982). This negative effect as a result of less exploration to external information and can be mitigated by introducing partner exchange and rotation (Kane et al., 2005). Hence, partner exposure is necessary to keep knowledge sharing and motivate learning for other professionals. Based on these three explanations for why partner exposure improves physician's performance in a team, we propose our second hypothesis:

H2. *Higher partner exposure of ED physicians is associated with better operational efficiency, as measured by (a) lower ED visit duration and (b) lower number of procedures.*

3.3.5 Moderating Role of Patient Severity

Patient severity is a critical input in the ED triage process. For example, the Emergency Severity Index (ESI) is used to identify patients' level of urgency and resources needed, based on patient's symptoms and historical clinical records (Farrohknia et al., 2011). This is because patients with severe conditions require immediate attention and need to be treated as soon as possible and with prudent clinical decisions among options of treatment plans. A severe case may also manifest as a simple symptom but with complex causes that could lead to fatal consequences. For instance, patients with chest pain, coming with other severe symptoms such as acute respiratory distress, are evaluated within the context of ESI Level-1 (highest priority) to receive a diagnostic test such as electrocardiogram (ECG) within 10 minutes of arriving at the ED, to determine whether the patient requires an immediate life-saving intervention (Gilboy et al., 2005). This level of urgency is required since the cause of the chest pain can be severe cardiac disease, such as AMI or aortic dissection. However, the causes of chest pain can vary considerably and include non-cardiac related but potentially fatal conditions such as pulmonary embolism (PE). As a consequence, ED physicians need to follow a clear routine of checking for these severe causes.

Given the need for urgent care for more severe patients, we argue that partner familiarity between the attending and operating physician is more valuable when patient needs are more complex. Patient severity raises several challenges for an effective collaboration between the ED physicians involved in treating a patient. First, more complex patient cases require a larger volume of information to be transferred between the physicians. This information may relate to patient's health history including comorbidities, potential allergies and medication adverse interactions, etc., and is essential for an accurate diagnosis and course of treatment. A lack of understanding of the potential interactions between the patient's condition, medication, and treatment options, which is further amplified when two physicians are involved, raises the risk of complications. Therefore, this transfer of knowledge between physicians is harder for more complex situations (Singh et al., 2010) and, thus, riskier if not handled properly. Research on learning also suggests that repeated interactions are more important when tasks are complex (Argote, 1993; Edmondson et al., 2001), suggesting that more frequent interactions between providers, who are thus becoming increasingly familiar with each other, should be more beneficial to complex, severe patients.

Treating more severe patients also requires sharing and assimilating knowledge between the two physicians, and searching and adopting the optimal treatment, which is enhanced by familiarity between the physicians, as familiarity helps individuals know what to expect from each other and know who can do what, which contribute to searching and adopting the optimal treatment for patients (Reagans et al., 2005). Partner familiarity also enhances the communication efficiency which facilitates integration of the treatment plan, faster thinking, reducing the potential for negative impacts caused prolonged delay of treatment (Niewoehner et al., 2022; Avgerinos and Gokpinar, 2017b). More importantly, partner familiarity breeds mutual trust, which fosters collaborator's willingness and confidence to rely on other's expertise (Dobrzykowski and McFadden, 2020). Though it is difficult to achieve joint decision making between physicians, given that complex tasks are ambiguous and unpredictable and the cost of making mistakes is too high, we argue that mutual trust and confidence generated from collaboration would help physicians in complex decision making working environment (Edelenbos and Klijn, 2007).

Finally, if building more familiarity is likely to enhance transfer of knowledge and information, trust, and search for optimal treatment plan, as noted earlier, and complex patients present more information to be shared and higher treatment course challenges, then we might expect familiarity between the two physicians to offer more value to more severe patients. Thus, we hypothesize the following.

H3. *Higher partner familiarity between ED physicians is related to more efficient care for more severe patients compared with less severe patients, as measured by (a) ED visit duration and (b) number of procedures.*

3.4 Data Description and Variable Definitions

3.4.1 Physician Collaboration

In this paper, we consider patients who received services from more than one physician during their ED visits, and conduct econometric analysis to understand the effect of the prior collaboration levels of the physicians on care efficiency. The first physician, i.e. the "attending" physicians, is responsible for attending and providing primary check for patients in ED. The second physician, the "operating" or "performing" physician, is a physician who renders additional services to the patients. In our data, we observe that majority of the physicians wear both the "attending" and "operating" hat, indicating that the operating physicians are unlikely to be trainees. For this reason, we make the reasonable assumption that the physician pair involved in caring for the patients in our data are two physicians instead of an attending physician and a resident pair.

To assess this assumption, we further evaluate the difference in total visit duration between the patient visits cared for by a single physician who acts as the attending and operating physician and two distinct physicians. The results presented as side-by-side boxplots in 5 show that the average (median) duration in ED for visits involving a single physician is 5 (15) hours, while the average (median) duration in ED for visits involving two distinct physicians is 28 (29.77) hours. The general ED shift runs from 8 to 12 hours, it could be up to 24 hours, but this is rare.

Our analysis focuses on patients whose primary reason for ED visit is unspecific chest pain (UCP), as it is one of the common public health concerns and is one of top three reasons for treat-and-release ED visits, according to the HCUP Statistical Brief #286. The underlying reasons for chest pain vary, ranging from serious cardiac causes to mental disorders such as panic attack (Foldes-Busque et al., 2011). Between 52% and 77% of patients who visit the ED with complaints of chest pain leave ED without a clear diagnosis (Foldes-Busque et al., 2011; Cullen et al., 2015). However, patients would naturally be worried when their symptoms go unexplained and could doubt the diagnoses and treatments received (Stone et al., 2002). Given the divergent and complex nature of the causes of chest pain and potential adverse outcomes to patients, physicians are compelled to develop a comprehensive understanding of all possible mechanisms for chest pain to provide an efficient diagnostic evaluation, learning from their own experiences and/or from others.

We use data from Florida state ED database, spanning 2011-2014. The number of unique ED physicians in our data is 10,449, 11,333, 12,165, and 12,273 for 2011 to 2014, respectively. We identify 561,113 patients with chest pain as the reason for ED visit, who received care service from both an attending physician and an operating physician. Among those, 43,273 (8%) patients received care services where the attending and operating physicians are different, with 12,306 unique pairs of physicians who collaborated, in 196 different ED facilities. We consider the time unit to be a quarter, which means our key independent variables, partner familiarity and partner exposure, are computed as aggregates at the quarter level (more on this in the next section).

3.4.2 Independent Variables

Following the stream of literature on familiarity (Huckman et al., 2009; Niewoehner et al., 2022; Avgerinos et al., 2020; Akşin et al., 2021), we measure familiarity of a pair of physicians as the total number of patient visits they collaborated on in the quarter prior to the quarter when the focal visit occurs. Their shared experience counts even when their roles switch. For instance, suppose physician A (the attending physician) collaborated on 4 patient visits with physician B (the operating physician) in quarter 1 of 2012. Suppose further that physician B (the attending physician) collaborated on 3 patient visits with physician A (the operating physician) in quarter 1 of 2012. Then, the familiarity between physician A and B, $Familiarity_{AB}$, takes the value 7 for any patient visit that they collaborate on during quarter 2 of 2012. Formally, we define familiarity between physician x and physician y as follows during quarter t:

$$Familiarity_{xyt} = SharedExp^{y}_{xt}$$

where $SharedExp^{y}_{xt}$ represents the shared experience between physician x, either working as attending or operating physician, and physician y during quarter t. We log-transform familiarity before fitting our model as is common in the literature (e.g. Avgerinos and Gokpinar, 2017b).

Following Akşin et al. (2021), we operationalize the partner exposure variable using Herfindahl–Hirschman Index (HHI) to measure the dispersion of collaboration experience a physician generated through working with other ED physicians. A larger value of the partner exposure variable means that most of the collaboration experience of a physician were generated with fewer partners. A lower value means the collaboration experiences were more balanced out with higher number of partners. More formally, we operationalize the partner exposure for physician x during quarter t as

$$PartnerExposure_{xt} = \sum_{y \in P, y \neq p}^{P} \left(\frac{SharedExp^{y}_{xt}}{SharedExp_{xt}} \right)^2,$$

where $SharedExp^{y}_{xt}$ is as defined above, and $SharedExp_{xt}$ represents the total number of visits that physician x handles with any physician in the ED during quarter t, and P represents the set all physicians in our data.

3.4.3 Dependent Variable

We test the effect of familiarity and partner exposure on ED total visit duration and number of procedures received during an ED visit, two important measures of ED care efficiency (Varon et al., 1994; Svenson et al., 1997). The visit duration measures the total number of hours a patient spends in the ED, between being admitted by the admitting physician or triage nurse and discharge. The average visit duration for visits in our data is 29.77 hours. Summary statistics for patient level variables are given in Table 13.

3.4.4 Control Variables

We include control variables at the patient, physician and hospital levels. At the patient level, we include age, gender, severity level (measured using the number of chronic conditions reported at admission), insurance type, patient arrival time (Morning, 7:00am–3:00pm; Afternoon, 3:00pm–11:00pm; Night, 11:00pm–7:00am), indicator for whether the admission day is a weekend, admission quarter of year, year of admission.

At the physician level, in addition to the two main independent variables, i.e. familiarity and partner exposure, we control for physician multi-siting status (`multisiting`). In our setting, a multi-siting physician is a physician who works at multiple ED facilities during the quarter of the focal visit. A multi-siting physicians' splitting activities reduce the accumulated working experience and familiarity with colleagues in a focal hospital, which could impact the variables of interest, i.e. familiarity and partner exposure, and patient care outcomes (Huckman and Pisano, 2006; KC and Tushe, 2021). We include multi-siting status indicator variables for both the attending and operating physicians handling the focal visit. To control for the effect of working and learning from self, in addition to learning from other team members, we also include the fraction of cooperation variable (`fraction_coop`), which is the ratio of the number of visits that a physician had worked with other physicians to the number of visits that a physician worked alone covering both attending and operating physician roles. Finally, we control for cumulative case volume for each physician (`total_experience`), a proxy for physician experience, a common control variable in studies that examine effect of familiarity (Akşin et al., 2021; Niewoehner et al., 2022). Summary statistics pertaining to physician level variables are given in Table 14.

At the ED level, we control for ED total visits, and ED utilization (Akşin et al., 2021), which is defined as the ratio of total ED visits to the total available ED physicians during the focal quarter. We also control for the fraction of chest pain visits, i.e. the ratio of the number of chest pain visits to the number of total visits. In addition, we control for teaching status, location (urban vs rural), and ownership status (For profit, Not for profit, Government, etc), which are all common control variables in healthcare operations management literature. Summary statistics for ED level variables appear in Table 15.

3.5 Econometric Model and Results

3.5.1 Econometric Model

As stated earlier, the unit of our analysis is a patient visit. Let Y_{ihtxy} represent the outcome variable, i.e. ED visit duration or number of procedures, for patient-visit i, at hospital ED h, during quarter t, receiving care service from attending physician x and operating physician y. To test our hypotheses, we estimate the following model

$$\begin{aligned} f(Y_{ihtxy}) \quad = \quad & \alpha_0 + \alpha_1 Familiarity_{xyt-1} + \alpha_2 PartnerExposure_{xt-1} + \alpha_3 PartnerExposure_{yt-1} + \\ & \alpha_4 Familiarity_{xyt-1} \times Severity_{ihtxy} + \alpha_5 Multisiting_{xt} + \alpha_5 Multisiting_{yt} + \\ & \alpha_6 PControl_{iht} + \alpha_7 APControl_{tx} + \alpha_8 OPControl_{ty} + \alpha_9 EDControl_{ht} + \\ & T_t + \epsilon_{ihtxy} \end{aligned} \tag{3.1}$$

where, $Familiarity_{xyt-1}$ represents the familiarity of attending physician x and operating physician y during quarter $t-1$, $PartnerExposure_{xt-1}$ represents the partner exposure level of attending physician x during quarter $t-1$, $PartnerExposure_{yt-1}$ represents the partner exposure level of operating physician y during quarter $t-1$, $PControl_{ihtxy}$ represents a vector of the patient level control variables, $APControl_{tx}$ represents a of vector of control variables for attending physician x, $OPControl_{ty}$ represents a of vector of control variables for operating physician y, $EDControl_{ht}$ represents a of vector of control variables for the ED, T_t represents year-quarter fixed effects, and ϵ_{ihtxy} represents visit level random error term. Finally, f is a link function, which is the natural logarithm function for ED duration and the identity function for the number of procedures.

We lag familiarity and partner exposure variables by one quarter to reduce concerns about endogeneity induced by reverse causality in the relationship between these variables and ED visit duration and number of procedures. We do this because it is possible that physicians with lower levels of care efficiency in a quarter may also experience a systematic change in their levels of collaboration, in terms of familiarity and partner exposure. Furthermore, in many hospital EDs, temporary teams of attendings, nurses, and residents are formed ad hoc every shift, with no particular staffing policy (Kim et al., 2022), which further mitigates any concerns of endogeneity and allows for an unbiased estimation of the effects of ED physicians' familiarity and partner exposure levels on care efficiency.

3.5.2 Results

The results pertaining to our hypotheses are reported hierarchically in Table 17, which presents results from the different versions of our models. We first test the effect of familiarity between the pair of physicians on care efficiency, and then include the effect of partner exposure separated by physician role. Lastly, we report results pertaining to the moderating role of patient severity on the effect of physician familiarity on care efficiency. All reported standard errors are cluster robust standard errors at the ED physician pair level, unless stated otherwise. The results provided in column (1) of Table 17 show the relationship between familiarity and ED duration is negative and statistically significant ($\alpha_1 = -0.2977, p < 0.01$), suggesting that that an increase in physician familiarity is associated with a lower ED duration. Thus, we find strong support for hypothesis H1a.

According to results in column (2), there is a significant association between the level of partner exposure of both the attending ($\alpha_2 = 0.4416, p < 0.01$) and the operating ($\alpha_3 =$

$0.43376, p < 0.01$) physicians and ED duration. These results suggest that higher levels of partner exposure are beneficial for ED duration, thus offering support to hypothesis H2a. When interpreting these results, it should be noted that due to our operationalization of the partner exposure variable as HHI, a higher value is indicative of exposure to fewer partners. The results in column (3) show that the interaction coefficient between familiarity and patient severity is negative and statistically significant ($\alpha_4 = -0.0136, p < 0.01$). This suggests that the effect of familiarity on ED duration is stronger and more beneficial for severe patients, offering support for hypothesis H3a.

The results presented in columns (4) – (6) for the number of procedures mirror the findings reported above for ED duration. Thus, we find support for H1b, which posits that familiarity is negatively associated with a the number of procedures ($\beta_1 = -0.2285, p < 0.01$); H2b, which posits that increases in the levels of partner exposure for the attending ($\beta_2 = 0.5284, p < 0.01$) and operating ($\beta_3 = 0.2991, p < 0.01$) physicians are associated with a decrease in the number of procedures; and H3b, which posits that patient severity moderates the effect of familiarity on the number of procedures, such that the effect of familiarity on the number of procedures is stronger for more severe patients ($\beta_4 = -0.0263, p < 0.01$). In sum, we find support for all our hypotheses.

3.6 Robustness Checks

In this section, we are testing the robustness of our results to alternative operationalizations of familiarity and partner exposure.

3.6.1 Cumulative Familiarity and Partner Exposure

In our main results, we operationalize familiarity and partner exposure based on the last quarter collaboration experience. In this section, we consider an alternative operationalization based on cumulative collaboration experience that is measured from the beginning of our data to the prior quarter corresponding to the focal visit. This approach assumes that all past collaboration experience should impact on individual behavior and is widely used in the literature when evaluating the effects of learning by doing at individual and group levels (Reagans et al., 2005; Huckman and Staats, 2011; Akşin et al., 2021). The results corresponding to the alternative operationalizations are reported in Table 18. Overall, the results are largely consistent with our main analysis results, however, we observe a weaker relationship between the operating physician's level of partner exposure and the number of procedures.

3.6.2 Partner Exposure as a Function of the Number of Coworkers

In our main analysis, we use the HHI to measure partner exposure. This approach captures the workload distribution across different partners for a given physician. Here, we explore an alternative operationalization of partner exposure based on the total number of distinct partners that the focal physician has worked with in the previous quarter (of the focal visit). Results with this alternative operationalization are reported in Table 19, and are consistent with the main results reported in Table 17.

3.7 Post Hoc Analysis

3.7.1 Interaction Between Physicians' Levels of Partner Exposure

Our main results report the effect of partner exposure for each individual physician, which is also consistent with current literature (Akşin et al., 2021; Kim et al., 2022). Building on our main results, we are also interested in testing for the presence of an interaction between the physician's levels of partner exposure. Individuals working in groups or organizations are typically influenced by their peers. As such, we next explore whether the two ED physicians' levels of partner exposure are potentially complementary and synergistic or, rather, substitutes. Results for this analysis are presented in Table 20. We observe that the estimated coefficients of interaction terms of partner exposure are both significant and negative for the two measures of care efficiency investigated. Specifically, the coefficient is -0.6184 ($p < 0.01$) for ED duration and -0.9469 ($p < 0.01$) for the number of procedures. Interestingly, as the sign of the interaction term is different from the signs of partner exposure main effects, we conclude that the two physicians' levels of partner exposure are substitutes. This effect is illustrated in the interaction plots included in Figures 7 and 8, where the low and high levels of partner exposure correspond to the 10th and 90th percentiles of partner exposure, respectively. These results yield several implications. First, the negative interaction term suggests that a physician's potentially low level of partner exposure can be compensated for by the other physician's potentially high level of partner exposure. As such, while the best care efficiency is achieved by physician teams with high levels of partner exposure, our results suggest that physicians with limited partner exposure are better off when paired with physicians that have been exposed to a larger number of partners. These results thus offer insights to hospital managers seeking to maximize the benefits of physician collaboration. Although, partner exposure helps improve care efficiency, especially for complex tasks, the benefits are less significant when the other physician has less partner exposure. Prior literature on individual learning has shown that individuals are more committed to organizational objectives when they have the opportunity to participate and contribute to the decisions made in the organization (Mathieu and Zajac, 1990) and are slower to adapt when they are less exposed to and involved in team-based decisions.

3.7.2 Moderating Role of Physician Multi-siting Status

Working consistently in a familiar environment is beneficial for physicians, as it provides them with the opportunity to master established routines and practices, and learn how to work together and generate tacit as well as explicit knowledge inside the organization (Reagans et al., 2005; KC et al., 2013; Huckman and Pisano, 2006). Therefore, if physicians work at a single site, this should mitigate the negative consequences of switching between different environments and teams, as physicians don't need to spend extra effort to get familiar to the environment but only the professionals with whom they collaborate. In other words, the multi-siting status, or equivalently single-siting status, of a physician can be a moderator for the effects of physician partner exposure on care efficiency. To test the moderating effect of multi-siting status of the physician pair offering care service for a given patient visit, we create a three-level factor variable, `Paired_multisiting`, which represents whether the two physicians are multi-siting, single-siting, or not. A physician is considered multi-siting if s/he works in multiple ED facilities during a given quarter. `Paired_multisiting` takes the level "Single" if the pair of physicians are both single-site physicians, it takes the level "Mixed" if one of the physicians is single-site physician and the other is a multi-site physician, and it takes "Multi" if both are multi-site physicians.

Table 21 reports the results for the moderating role of `Paired_multisiting` on the effects of both familiarity and partner exposure on care efficiency. The reference level is `Paired_multisiting` = Single. The coefficients corresponding to the interaction terms of `Paired_multisiting_Multi` with familiarity and partner exposure are positive and statistically significant, indicating that multi-siting behavior moderates the effects of familiarity and partner exposure on care efficiency, respectively. The plots for the partial effect of physician multi-siting behavior on the relationship between familiarity and ED visit duration and number of procedures, respectively, are reported in Figure 9. Both panels of Figure 9 show that the benefits of familiarity on care efficiency are weakened when both physicians are multi-siting, with the effect being stronger for the number of procedures. The plots for the partial effect of attending physician's multi-siting behavior on the relationship between the attending physician's level of partner exposure and ED visit duration and number of procedures, respectively, are reported in Figure 10. Both panels of Figure 10 show that the benefits of attending physician's level of partner exposure for care efficiency are weakened when both physicians are multi-siting, with the effect being stronger for the number of procedures. Similar effects are observed for the partial effect of operating physician's multi-siting behavior on the relationship between the operating physician's level of partner exposure and ED visit duration and number of procedures, respectively, as reported in Figure 11.

3.8 Discussions and Conclusions

3.8.1 Implications and Contributions

The impact of partner familiarity and partner exposure for collaboration during teamwork has been discussed to a varying extent for different industries (Huckman et al., 2009; Dahlquist et al., 2018; Bechky, 2006; Kim et al., 2022). In this paper, we develop hypotheses evaluating how peer collaboration can affect the operational performance in a ED healthcare setting. We study the collaboration among ED physicians who fill the roles of attending and operating physicians in a care team and contribute several novel results to theory and practice.

First, our empirical analysis reveals that chest pain ED patients who are cared for by a pair of physicians with higher familiarity receive more efficient care, as measured by the ED duration and the number of procedures received. This result underscores the important role that physician familiarity plays in enhancing communication between physicians engaged in caring for ED patients. The information transfer between pairs of physicians enjoying high levels of familiarity benefit from added clarity, lower ambiguity, and less confusion about the specific care procedures and diagnostics performed initially by the attending physician and added upon later by the operating physician. The clarity of this exchange promotes trust and enables the physician team to care for patients by avoiding time-consuming and costly repetitions and redundancies, which ultimately translates into more efficient care.

Second, we find that patients who are cared for by physicians with higher levels of partner exposure receive more efficient care, as measured again by the ED duration and the number of procedures received. Physicians having a significant number of professional collaborations have more opportunities to acquire a breadth of knowledge by learning from many, observe and internalize best practices, sharpen diagnostic and treatment abilities, improve communication and collaboration skills. As a result, physicians benefiting from these experiences are able to deliver more efficient care even in an environment where patients have heterogeneous needs.

Third, we find that the effect of familiarity on care efficiency increases with patient severity, with the most complex and sick patients benefiting the most. Taken together, our findings have implications for providers and suggest that physician familiarity should be a consideration in the scheduling of physicians. We concur with Niewoehner et al. (2022) in suggesting that schedulers and managers responsible with task assignment should consider staffing familiar physicians together, especially when the proportion of severe patients is highest. At the same time, our findings vis-à-vis the role of partner exposure suggest that schedulers carefully balance the staffing of familiar and unfamiliar physicians, such that knowledge dissemination through increased partner exposure and familiarity building are simultaneously nurtured during ED shifts.

Our post-hoc analyses yield several notable findings and implications as well. We first examine whether the attending (operating) physician's level of partner exposure moderates the effect of the operating (attending) physician's level of partner exposure on operational performances. We find that the two physicians' levels of partner exposure are substitutes with respect to their effect on reducing the patient time and procedure. This finding is particularly interesting as previous studies have predominantly focused on partner exposure from the perspective of an individual working independently, with less attention given to the level of partner exposure for members of a team. The substitution effect we observe between the levels of partner exposure of the attending and operation ED physicians suggests that, while the best care efficiency is achieved by physician teams with high levels of partner exposure, physicians with limited partner exposure are better off when paired with physicians that have been exposed to a larger number of partners.

Second, we also examined the impact of physicians' level of organizational familiarity (defined as a function of whether a given physician works for a single ED or multiple ED locations) on the relationship between partner familiarity and exposure and operational performance. We observe that organizational familiarity complements the relationship between partner familiarity and care efficiency, but substitutes the relationship between partner exposure and care efficiency. Much of the literature focusing on organizational familiarity positions individual familiarity as an extra benefit, however, without providing an analysis of the relationship between the two forms of familiarity. In addition, the literature focusing on individual familiarity has generally not considered the added impact of organizational familiarity, specifically on the impact of alternating working environments. Our findings thus extend the study of familiarity by juxtaposing the roles of individual and organizational familiarity on care efficiency in an ED setting.

3.8.2 Limitations and Conclusions

Our work on the care efficiency implications of physician collaboration in an ED setting is not without limitations. However, we believe that these limitations represent viable opportunities for future research. First, our data does not allow us to distinguish between sequential and simultaneous forms of collaboration between the pair of physicians. Future research could examine and contrast these alternative forms of physician collaboration in the ED. Simultaneous collaboration assumes that physicians work together at the same time to provide patient care, while sequential collaboration assumes that the operating physician builds upon the diagnostics, tests, and care procedures first performed by the attending physician. These different forms of collaboration require the two ED physicians to be involved in both direct (e.g., oral) and indirect (e.g., written) communication. A different form of sequential collaboration that future research could investigate involves patient hand off at the end of ED shifts. As also explained earlier in our study, sequential forms of collaboration rely primarily on indirect communication and information sharing. For instance, at the end of the shift, the first attending physician would prepare notes about the patient's condition, lab tests and results, and provide instructions on the care decisions that need to be made by the next ED attending physician in the ensuing shift.

Second, our investigation is limited to patients with unspecific chest pain. Though patients with chest pain represent a suitable study cohort, due to their high triage level and complex causes, future research could test whether our findings extend to other ED patient conditions as well. In this research, we operationalized familiarity and partner exposure at the level of an individual physician. However, such measures can also be defined and investigated at the hospital level. We leave such investigations for future studies, which can also examine the interplay between physician-level and hospital-level measures of familiarity and partner exposure. Finally, while we focus on care efficiency, as measured by total ED duration and number of procedures, future research could explore other operational performance metrics, such as waiting time in the ED, the potential for redundant, duplicated procedures, and three- or seven-day ED revisit rates.

Despite the aforementioned limitations, our study provides several useful contributions and insights pertaining to the benefits of peer collaboration between ED physicians. We demonstrate that both familiarity and partner exposure contribute to better care efficiency during collaboration. Moreover, we introduce several moderating factors at patient and physician levels that enhance (e.g., patient severity) or weaken (e.g., physician multi-siting) the benefits of familiarity and partner exposure for care efficiency. In summary, we believe this study extends existing knowledge of familiarity and partner exposure as forms of physician collaboration and provides practical implications for ED operations management.

Chapter 4

Conclusions

This dissertation is inspired by prevailing managerial problems in healthcare operations management, specifically as they relate to the understanding of how different relationships between care providers, namely between physicians and hospitals and between peer physicians, correlate to care outcomes and care efficiency. Leveraging visit-level secondary data spanning multiple years from hospitals in Florida and econometric modeling, this dissertation makes several contributions to the theory and practice of healthcare operations management.

The first essay describes the impact of hospital-physician integration on care outcomes that are critically important in the U.S. value-based healthcare system. I observe that activity-based hospital-physician integration has a U-shaped relationship with length of stay and in-hospital mortality risk. While activity-based hospital-physician integration fosters a work environment that nurtures learning, the benefits of integration can eventually be suppressed and counterbalanced by increased physician workload and diminished informational exchange with outside clinicians. I theorize and find evidence for a U-shaped relationship, which adds to the growing discussion on the implications of integration. Second, I observe that teaching status and elevated levels of bed utilization can suppress the effect of the activity-based hospital-physician integration on length of stay.

Hospital-physician integration has emerged as a salient business strategy that hospital managers increasingly turn to in order to increase hospital revenue and improve patient care outcomes. In contrast to some of the extant literature that relies on employment or contractual agreements between hospitals and physicians, I operationalize integration based on actual physician activity. Our demonstration of the U-shaped effects has important implications for the healthcare system, given the increasing trend of hospital employment of physicians over the last decade, especially for younger physicians. As a result, hospitals have been making significant investments to acquire and retain physician specialists as full-time employees. In spite of these trends, there has been mixed evidence on the benefits of integration for care outcomes. Therefore, this study cautions healthcare decision makers to avoid adopting a myopic perspective when evaluating the benefits of integration. Especially, I argued the negative effects of high integration are from reduced information sharing with external sources. Hence, the results suggest hospital decision makers to put effort to ensure that their physicians get access to advanced knowledge while keeping a highly integrated working environment, which should benefit in delivering effective care.

The second essay investigates the effects of physician collaboration on care efficiency in an emergency department setting. I use physician familiarity and level of partner exposure as distinct dimensions of a physician's professional relationships and collaboration. I find that physician familiarity benefits care efficiency, especially for patients with severe conditions. These findings have implications for providers, suggesting that schedulers and managers responsible with task assignment should consider staffing familiar physicians during the same shifts. This approach would benefit especially the shifts with high proportions of severe patients. I also observe that physicians' levels of partner exposure benefit care efficiency. These benefits are observed regardless of the team role played by individual physicians, namely as attending or operating physician. This finding is particularly interesting, as previous studies have predominantly focused on partner exposure from the perspective of an individual working independently, with less attention given to the level of partner exposure for members of a team. Similar to the first essay, the second essay also underscores the important role of physician multisiting for care efficiency. To this end, I observe that physician multisiting behavior suppresses the benefits of physician familiarity and partner exposure on care efficiency. These findings extend the extant literature that investigates the implications of familiarity and partner exposure as forms of team collaboration in a healthcare setting.

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Appendices

A Appendix: Figures and tables in chapter 2

A.1 Figures

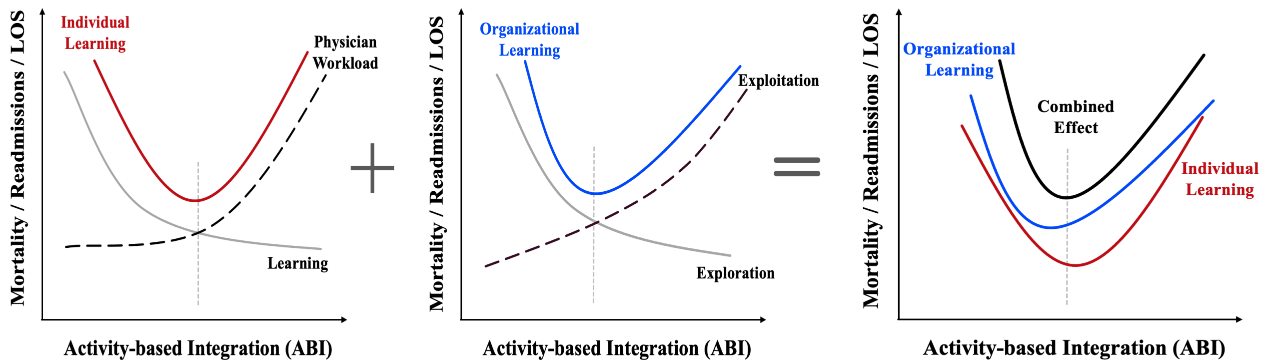

Figure 1: Theoretical mechanisms shaping the relationship between ABI and care outcomes.

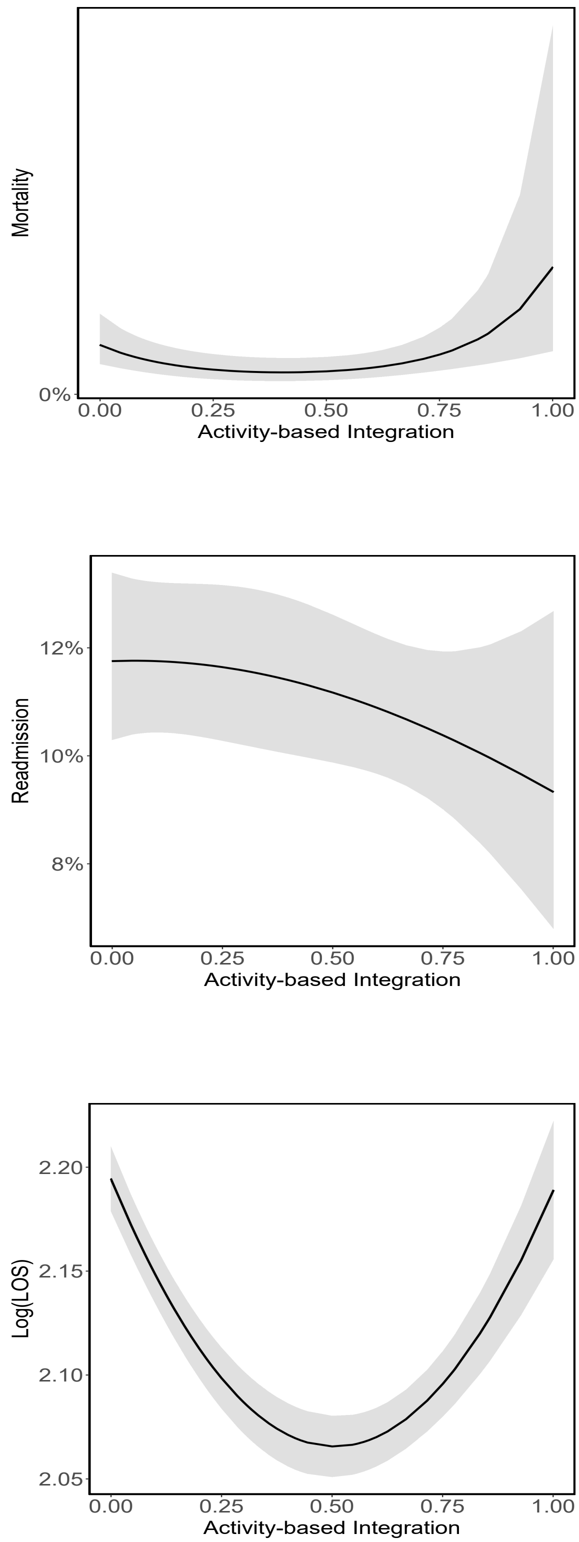

Figure 2: Partial effect plots of mortality risk (upper panel), readmission risk (middle panel) and integration on LOS (lower panel), obtained from the 2SRI model results.

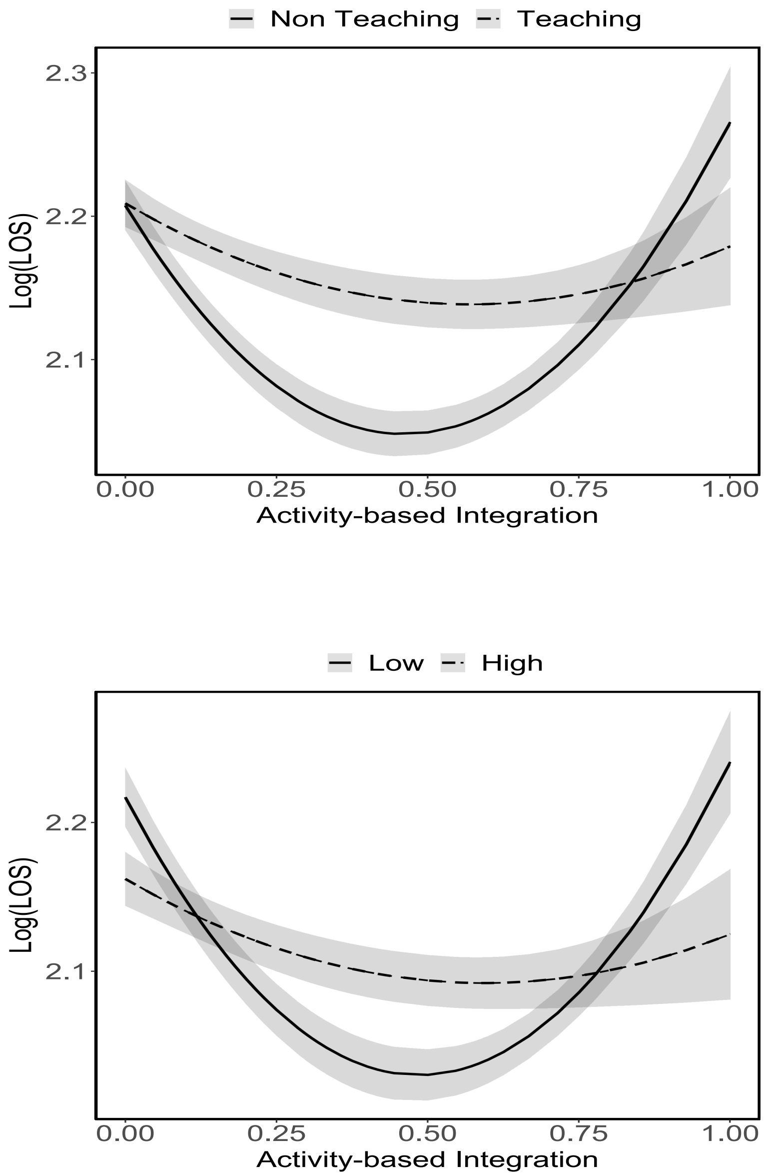

Figure 3: Partial effect plots of hospital-physician integration on patient LOS moderated by hospital teaching status (upper panel) and bed utilization (lower panel).

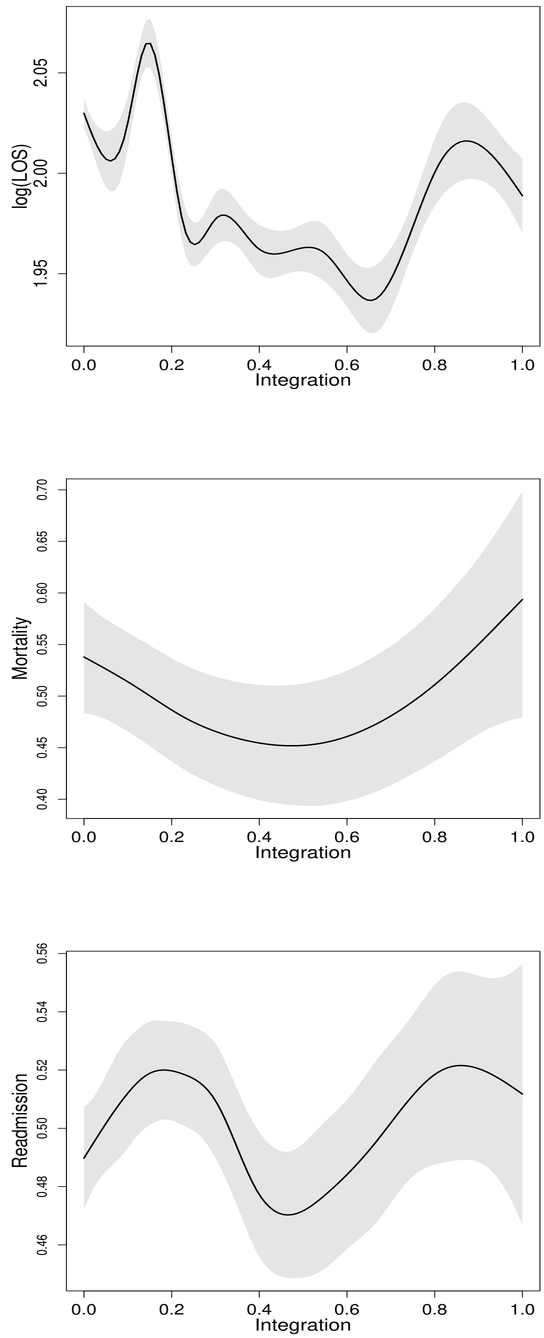

Figure 4: Partial effect plots of integration on LOS (upper panel), mortality risk (middle panel), and readmission risk (lower panel). The plots are obtained from a generalized additive model (2.5).

A.2 Tables

Table 1: Summary statistics for the patient-level variables. The mean, median and standard deviation (SD) are reported for numerical variables, and the percentage in each category for categorical variables. N = 33,505 observations.

		Mean	SD	Median
Numerical variables				
Age		66.0	10.5	67.0
Length of Stay (days)		9.1	5.0	8.0
Number of Diagnoses		13.7	5.9	13.0
Number of Procedures		7.3	3.2	7.0
Categorical variables (%)				
In-hospital Mortality		1.3		
Readmission		12.3		
Admission Type	Emergency/Urgent	57.5		
Primary Payer	Medicare	65.1		
	Private insurance	24.9		
	Other	10.0		
Sex	Male	75.6		
Race	White	78.0		
	Black	6.8		
	Hispanic	11.7		
	Asian or Pacific Islander	1.0		
	Native American	0.1		
	Other	2.3		
Comorbidities (%)				
	Alcohol abuse	4		
	Chronic pulmonary disease	24		
	Renal failure	14.7		
	Hypertension	82.5		

Table 2: Mean and Standard deviations (SD) for, and pair-wise correlations among, hospital-level variables.

	Mean	SD	1	2	3	4	5
1. Bed Size	462	326					
2. Bed Utilization	65	24	-0.008				
3. ABI	0.27	0.28	0.042	-0.110*			
4. Physician Workload	113.45	43.60	0.067	0.087	0.213***		
5. For Profit	43.84%		0.425***	0.066	-0.297***	-0.168***	
6. Teaching	47.46%		0.279***	0.180***	-0.168***	-0.043	-0.123**

Notes: For Profit ("Yes", "No") and Teaching ("Yes","No") are indicator variables, and correlations for these are point biserial correlations. ***: $p \leq 0.001$; **: $p \leq 0.01$; *: $p \leq 0.05$.

Table 3: Effect of ABI on log(LOS), Mortality and Readmission.

	log(LOS)		Mortality		Readmission	
ABI	−0.1260**	−0.5064***	−0.7777	−4.6161***	−0.1683	−0.0001
	(0.0592)	(0.1420)	(0.8205)	(1.6476)	(0.1948)	(0.4471)
ABI^2		0.5123***		5.4120 **		−0.2641
		(0.1889)		(2.1988)		(0.6367)
Control Variables						
Teaching_Yes	0.0407*	0.0487**	0.1968	0.2728	−0.0500	−0.0571
	(0.0226)	(0.0218)	(0.2450)	(0.2515)	(0.0774)	(0.0770)
Size_Medium	0.0081	0.0105	−0.5607*	−0.4634	−0.1075	−0.1078
	(0.0297)	(0.0276)	(0.3384)	(0.3361)	(0.0725)	(0.0720)
Size_Small	−0.0018	−0.0719	−0.9860	−1.6835**	−0.3291***	−0.2906**
	(0.0445)	(0.0591)	(0.7415)	(0.6700)	(0.0863)	(0.1213)
For-Profit_Yes	−0.0172	−0.0045	0.2685	0.3455	0.1973***	0.1874***
	(0.0227)	(0.0232)	(0.2655)	(0.2706)	(0.0664)	(0.0721)
Bed Utilization	−0.0138	0.0278	0.5691	0.9940	0.9666***	0.9335***
	(0.1067)	(0.0986)	(1.3609)	(1.4413)	(0.3348)	(0.3394)
Ave Physician Workload	−0.0195	−0.0264**	−0.2547**	−0.3135**	−0.0695*	−0.0658
	(0.0125)	(0.0122)	(0.1030)	(0.1024)	(0.0410)	(0.0437)
Physician Experience	−0.0175***	−0.0173***	0.1221	0.1214	0.0184	0.0174
	(0.0063)	(0.0061)	(0.0902)	(0.0897)	(0.0302)	(0.0302)
P_{iht}	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs	24,105	24,105	24,679	24,679	24,105	24,105
R^2	0.414	0.418				
AIC			2,227	2,217	17,266	17,335

Notes: Cluster robust standard errors in parentheses. ***: $p \leq 0.01$; **: $p \leq 0.05$; *: $p \leq 0.1$. P_{iht} is a vector of the patient level characteristics included in the model: age, age^2, race, gender, admission type, payment type, number of diagnosis, length of stay (for MORT and ReAd), number of procedures, common comorbidities (see Table 1).

Table 4: Tests for U-shaped relationships. We report estimates and tests of the slopes at the low and high ends of ABI, as well as the estimate and 95% confidence interval of the tipping point.

	coef	log(LOS)	Mortality
ABI	$\widehat{\alpha}_1 =$	-0.5064^{***}	-4.6162^{***}
		(0.1420)	(1.6476)
ABI^2	$\widehat{\alpha}_2 =$	0.5123^{***}	5.4120^{**}
		(0.1889)	(2.1988)
Slope at ABI_L	$\widehat{\alpha}_1 + 2\widehat{\alpha}_2 ABI_L =$	-0.4551^{***}	-4.0748^{***}
		(0.1248)	(1.4512)
Slope at ABI_H	$\widehat{\alpha}_1 + 2\widehat{\alpha}_2 ABI_H =$	0.5183^{**}	6.2080^{**}
		(0.2523)	(2.9857)
Tipping point	$-\widehat{\alpha}_1/(2\widehat{\alpha}_2) =$	0.4941	0.4265
95% confidence interval, Delta method		(0.3461,0.6422)	(0.2829,0.5700)

Notes: Cluster robust standard errors in parentheses. ***: $p \leq 0.01$; **: $p \leq 0.05$; *: $p \leq 0.1$.

Table 5: Moderating effects of teaching status and bed utilization.

	Teaching Status			Bed utilization		
	Mortality	Readmission	log(LOS)	Mortality	Readmission	log(LOS)
ABI	-3.5584^{*}	0.5094	-0.6758^{***}	-7.1517	0.6516	-1.7906^{***}
	(2.0644)	(0.4801)	(0.1653)	(8.4898)	(1.8530)	(0.4547)
ABI^2	4.5824^{*}	-0.5115	0.7301^{***}	7.7477	-0.9174	1.8936^{***}
	(2.5563)	(0.7071)	(0.2085)	(8.4620)	(1.8099)	(0.3935)
Control Variables						
Teaching_Yes	0.6386	0.1617	0.0069	0.2574	-0.0557	0.0476^{**}
	(0.4666)	(0.1261)	(0.0354)	(0.2631)	(0.0778)	(0.0219)
Size_Small	-1.8220^{***}	-0.3421^{***}	-0.0404	-1.6770^{**}	-0.2926	-0.0635
	(0.7006)	(0.1252)	(0.0543)	(0.6745))	(0.1279)	(0.0630)
Size_Medium	-0.4854	-0.1222	0.0129	-0.4586	-0.1088	0.0109
	(0.3327)	(0.0766)	(0.0273)	(0.3393))	(0.0729)	(0.0276)
For-Profit_Yes	0.3668	0.2045^{***}	-0.0042	0.3459	0.1882^{***}	-0.0056
	(0.2652)	(0.0732)	(0.0225)	(0.2752)	(0.0723)	(0.0218)
Bed Utilization	1.3487	1.1191^{***}	0.0426	0.4082	1.0676	-0.2156
	(1.5938)	(0.3334)	(0.1041)	(2.5697)	(0.6696)	(0.1658)
Ave Physician Workload	-0.3100^{***}	-0.0688^{*}	-0.0263^{**}	-0.3117^{***}	-0.0652	-0.0278^{**}
	(0.0997)	(0.0387)	(0.0119)	(0.1013)	(0.0433)	(0.0124)
Physician Experience	0.1047	0.0073	-0.0145^{**}	0.1308	-0.0652	-0.0145^{***}
	(0.0877)	(0.0300)	(0.0058)	(0.0825)	(0.0433)	(0.0053)
Interaction effects						
Teaching×ABI	-2.6877	-0.9929^{*}	0.4026^{*}			
	(2.3295)	(0.5942)	(0.2170)			
Teaching×ABI^2	2.1703	0.4691	-0.4867^{**}			
	(2.7508)	(0.72091)	(0.2396)			
Bed Utilization×ABI				6.1756	-0.9939	1.9652^{***}
				(12.1230)	(2.6332)	(0.6969)
Bed Utilization×ABI^2				-5.3922	0.9968	-2.1817^{***}
				(12.317)	(2.6877)	(0.6353)
P_{iht}	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Cluster robust standard errors are reported in parentheses. ***: $p \leq 0.01$; **: $p \leq 0.05$; *: $p \leq 0.1$. P_{iht} is a vector of the patient level characteristics included in the model: age, age^2, race, gender, admission type, payment type, number of diagnosis, length of stay (for MORT and ReAd), number of procedures, common comorbidities.

Table 6: Effects of ABI on log(LOS), Mortality and Readmissions. Results from non-IV model.

	log(LOS)		Mortality		Readmission	
ABI	−0.1425	−0.5008***	−0.1684	−1.8053**	0.0138	−0.0743
	(0.0914)	(0.2001)	(0.3781)	(0.7540)	(0.1244)	(0.2693)
ABI^2		0.4307**		2.0514***		0.1080
		(0.2195)		(0.7703)		(0.2930)
Control Variables						
Teaching_Yes	0.1034**	0.1009**	0.1216	0.1172	−0.0446	−0.0449
	(0.0523)	(0.0505)	(0.1986)	(0.1991)	(0.0699)	(0.0702)
Size_Medium	0.0093	0.0072	−0.5483**	−0.5445**	−0.1676**	−0.1679**
	(0.0618)	(0.0597)	(0.2677)	(0.2496)	(0.0773)	(0.0772)
Size_Small	−0.0293	−0.0790	−0.7714**	−0.9837***	−0.3508***	−0.3624***
	(0.1073)	(0.1181)	(0.3195)	(0.2932)	(0.0941)	(0.1005)
For-Profit_Yes	−0.0036	0.0027	0.3511	0.3751*	0.2476***	0.249***
	(0.0453)	(0.0440)	(0.2228)	(0.2164)	(0.0654)	(0.0662)
Bed Utilization	0.0616	0.0968	0.4259	0.5522	0.8535	0.8622
	(0.2221)	(0.2138)	(1.0300)	(0.9893)	(0.3031)***	(0.3066)***
Ave Physician workload	−0.0394	−0.0444*	−0.2027***	−0.2240***	−0.0743	−0.0754
	(0.0259)	(0.0253)	(0.0737)	(0.0727)	(0.0305)	(0.0308)
Physician experience	−0.0175***	−0.0173***	0.1221	0.1214	0.0184	0.0174
	(0.0063)	(0.0061)	(0.0902)	(0.0897)	(0.0302)	(0.0302)
P_{iht}	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs	32,687	32,687	33,505	33,505	32,687	32,687
R^2	0.395	0.396				
AIC			3,803	3,795	23,484	23,486

Notes: Cluster robust standard errors in parentheses. ***: $p \leq 0.01$; **: $p \leq 0.05$; *: $p \leq 0.1$. P_{iht} is a vector of the patient level characteristics included in the model: age, age^2, race, gender, admission type, payment type, number of diagnosis, length of stay (for MORT and ReAd), number of procedures, common comorbidities (see Table 1 in the manuscript).

Table 7: Moderating effects of teaching status and bed utilization. Results from the non-IV model.

	Teaching Status			Bed utilization		
	Mortality	Readmission	log(LOS)	Mortality	Readmission	log(LOS)
ABI	−1.1695	0.2321	−0.7353***	−6.8266	−1.6951	−2.9797***
	(1.1288)	(0.3154)	(0.2953)	(6.5692)	(1.5405)	(0.9839)
ABI^2	1.6688	0.0349	0.6840***	7.6008	1.9055	2.8392***
	(1.0561)	(0.3236)	(0.2780)	(5.4646)	(1.3739)	(0.8487)
	(2.5563)	(0.7071)	(0.2085)	(8.4620)	(1.8099)	(0.3935)
Control Variables						
Teaching_Yes	0.5311	0.0858	0.0226	0.2131	−0.0645	0.1045*
	(0.4026)	(0.1162)	(0.0848)	(0.2332)	(0.0709)	(0.0536)
Size_Small	−0.9220***	−0.3532***	−0.0176	−0.7557**	−0.3433***	−0.0743
	(0.3524)	(0.1163)	(0.1129)	(0.3029)	(0.1014)	(0.1221)
Size_Medium	−0.5813**	−0.1667**	0.0110	−0.5501*	−0.1604**	0.0100
	(0.2866)	(0.0796)	(0.0597)	(0.2918)	(0.0783)	(0.0624)
For-Profit_Yes	0.4370 *	0.2682***	0.0048	0.3961	0.2587***	0.0070
	(0.2428)	(0.0664)	(0.0433)	(0.2448)	(0.0662)	(0.0438)
Bed Utilization	0.8248	1.0121	0.0504	−0.2072	0.6164	−0.4975
	(1.2595)	(0.3006)	(0.2293)	(2.2458)	(0.5470)	(0.4034)
Ave Physician Workload	−0.2468***	−0.0814 ***	−0.0346***	−0.2574	−0.0880 ***	−0.0426
	(0.0804)	(0.0285)	(0.0256)	(0.0840)	(0.0324)	(0.0270)
Physician Experience	0.0841	0.0159	−0.0218	0.0981	0.0228	−0.0215*
	(0.0909)	(0.0293)	(0.0134)	(0.0844)	(0.0270)	(0.0125)
Interaction effects						
Teaching×ABI	−1.7205	−0.5015	0.7728*			
	(2.0406)	(0.5538)	(0.4475)			
Teaching×ABI^2	1.2008	−0.0960	−0.9049**			
	(2.1000)	(0.6071)	(0.4564)			
Bed Utilization×ABI				7.5769	2.5057	3.9513**
				(9.5268)	(2.2022)	(1.5396)
Bed Utilization×ABI^2				−8.5319	−2.7944	−3.8857***
				(8.1119)	(2.0570)	(1.4052)
P_{iht}	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Cluster robust standard errors are reported in parentheses. ***: $p \leq 0.01$; **: $p \leq 0.05$; *: $p \leq 0.1$. P_{iht} is a vector of the patient level characteristics included in the model: age, age^2, race, gender, admission type, payment type, number of diagnosis, length of stay (for MORT and ReAd), number of procedures, common comorbidities.

Table 8: Effect of ABI on log(LOS), Mortality and Readmission with two-year lagged ABI as IV.

	Mortality		Readmission		log(LOS)	
ABI	0.2612	-4.532^{*}	0.3663	0.0305	-0.1637^{**}	-0.6778^{***}
	(1.0584)	(2.7310)	(0.2349)	(0.6865)	(0.0755)	(0.2188)
ABI^2		6.1327^{*}		0.4206		0.7438^{**}
		(3.6049)		(0.9153)		(0.2993)
Control Variables						
Teaching_Yes	0.2631	0.3729	0.0137	0.0185	0.0452^{*}	0.0639^{**}
	(0.2769)	(0.2996)	(0.0803)	(0.0824)	(0.0248)	(0.0260)
Size_Medium	-0.8898^{*}	-0.76853^{*}	-0.1465	-0.1414	-0.0057	-0.0048
	(0.4604)	(0.4256)	(0.0913)	(0.0945)	0.0319	(0.0290)
Size_Small	-1.2075	-1.9183^{**}	-0.3792^{**}	-0.4240^{***}	-0.0249	-0.1273^{*}
	(0.8222)	(0.7754)	(0.1219)	(0.1595)	(0.0509)	(0.0686)
For-Profit_Yes	0.8369^{***}	0.8814^{***}	0.4066^{***}	0.4106^{***}	-0.0030	0.0203
	(0.2995)	(0.3196)	(0.0908)	(0.0969)	(0.0268)	(0.0286)
Bed Utilization	1.0732	1.5282	1.5570^{***}	1.5628^{***}	0.0490	0.1158
	(1.7029)	(1.5745)	(0.4139)	(0.3944)	(0.1156)	(0.1080)
Ave Physician Workload	-0.3079^{**}	-0.3766^{***}	-0.1003^{***}	-0.0999^{***}	-0.0191	-0.0297^{**}
	(0.1506)	(0.1396	(0.0368)	(0.0372)	(0.0145)	(0.0142)
Physician Experience	0.1669	0.1952^{*}	-0.0042	-0.0030	-0.0163 ***	-0.0115^{*}
	(0.1143)	(0.1060)	(0.0343)	(0.0341)	(0.0062)	(0.0065)
Number of Obs	15,459	15,459	1 5,096	15,096	1 5,096	15,096

Notes: Cluster robust standard errors in parentheses. ***: $p \leq 0.01$; **: $p \leq 0.05$; *: $p \leq 0.1$. P_{iht} is a vector of the patient level characteristics included in the model: age, age^2, race, gender, admission type, payment type, number of diagnosis, length of stay (for MORT and ReAd), number of procedures, common comorbidities (see Table 1).

Table 9: Moderating effects of teaching status and bed utilization with two-year lagged ABI as IV.

	Teaching Status			Bed utilization		
	Mortality	Readmission	log(LOS)	Mortality	Readmission	log(LOS)
ABI	−4.6605	0.1333	−0.8117**	−7.7357	−2.3869	−1.0034
	(2.9731)	(0.6742)	(0.2420)	(10.5246)	(2.4215)	(0.6434)
ABI^2	6.0131	0.6269	0.9223***	8.7064	3.5186	1.3188**
	(3.9353)	(0.8991)	(0.3140)	(9.1955)	(2.5618)	(0.5726)
Control Variables						
Teaching_Yes	0.2731	0.1124	0.0229	0.3558	0.0197	0.0656**
	(0.5555)	(0.1647)	(0.0451)	(0.3185)	(0.0781)	(0.0261)
Size_Small	−1.9094	−0.4146	−0.0938	−1.9004**	−0.3919**	−0.1169*
	(0.7866)	(0.1865)	(0.0645)	(0.7960)	(0.1676)	(0.0678)
Size_Medium	−0.7629	−0.1474	−0.0029	−0.7603*	−0.1406	−0.0053
	(0.4297)	(0.0959)	(0.0290)	(0.4352)	(0.0916)	(0.0293)
For-Profit_Yes	0.8747***	0.4219***	0.0212	0.8802***	0.4136***	0.0209
	(0.3234)	(0.0957)	(0.0276)	(0.3237)	(0.0954)	(0.0284)
Bed Utilization	1.3473	1.7556***	0.1359	0.5977	1.2030	0.1137
	(1.8376)	(0.3976)	(0.1230)	(3.9053)	(0.8274)	(0.2349)
Ave Physician Workload	−0.3730***	−0.1050***	−0.0309**	−0.3775***	−0.1000***	−0.0296**
	(0.1446)	(0.0366)	(0.0141)	(0.1382)	(0.0378)	(0.0140)
Physician Experience	0.1990*	−0.0079	−0.0097	0.2055 **	−0.0019	−0.0123**
	(0.1034)	(0.0327)	(0.0064)	(0.1009)	(0.0326)	(0.0058)
Interaction effects						
Teaching×ABI	0.3410	−0.0959	0.3809*			
	(2.7507)	(0.8966)	(0.2284)			
Teaching×ABI^2	0.0230	−0.4404	−0.4701*			
	(3.0381)	(1.0078)	(0.2627)			
Bed Utilization×ABI				4.9579	3.9322	0.5694
				(15.4756)	(3.7309)	(1.0158)
Bed Utilization×ABI^2				−3.9248	−5.0039	−0.9686
				(13.9178)	(4.0543)	(0.9526)
P_{iht}	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Cluster robust standard errors are reported in parentheses. ***: $p \leq 0.01$; **: $p \leq 0.05$; *: $p \leq 0.1$. P_{iht} is a vector of the patient level characteristics included in the model: age, age^2, race, gender, admission type, payment type, number of diagnosis, length of stay (for MORT and ReAd), number of procedures, common comorbidities.

Table 10: Effect of hospital-physician integration on patient care outcome measures, namely log(LOS), Mortality and Readmission. Results correspond to the alternative definition, namely: $ABI_{ht} = \frac{VolOfFullSurgerons_{ht}}{VolOfTotalSugery_{ht}}$.

	log(LOS)		Mortality		Readmission	
ABI_Volume	-0.1280^{***}	-0.3379^{***}	-0.3816	-1.1127	-0.0781	0.0511
	(0.0369)	(0.1270)	(0.2751)	(0.7417)	(0.1655)	(0.4807)
ABI_Volume^2		0.3176^{**}		0.9461		-0.1985
		(0.1642)		(0.8972)		(0.5263)
Control Variables						
Teaching_Yes	0.0258	0.0383^{*}	0.0575	0.0739	-0.0649	-0.0733
	(0.0246)	(0.0224)	(0.1141)	(0.1194)	(0.0804)	(0.0801)
Size Medium	0.0267	0.0255	-0.2125	-0.2084	-0.0672	-0.0664
	(0.0305)	(0.0291)	(0.1477)	(0.1458)	(0.0733)	(0.0737)
Size Small	0.0089	-0.0320	-0.4219	-0.5287	-0.3163^{**}	-0.2909^{**}
	(0.0461)	(0.0534)	(0.3341)	(0.3343)	(0.0829)	(0.1024)
For-Profit_Yes	-0.0152	0.0021	0.1282	0.1479	0.2337^{**}	0.2221^{**}
	(0.0216)	(0.0232)	(0.1270)	(0.1208)	(0.0711)	(0.0751)
Bed Utilization	-0.0283	0.0490	0.1102	0.2238	0.9752^{**}	0.9305^{**}
	(0.1081)	(0.1044)	(0.6050)	(0.6943)	(0.3373)	(0.3405)
P_{iht}	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs	24,105	24,105	24,679	24,679	24,105	24,105
R^2	0.408	0.410				
AIC			2250	2238	17511	17511

The *Notes*: Cluster robust standard errors are reported in parentheses. ***: $p \leq 0.01$; **: $p \leq 0.05$; *: $p \leq 0.1$. P_{iht} is a vector of the patient level characteristics included in the model: age, age^2, race, gender, admission type, payment type, number of diagnosis, length of stay (for MORT and ReAd), number of procedures, common comorbidities.

Table 11: Results for ABI measured at the hospital system level.

	LOS		Mortality	
ABI_System	1.1848	−3.0562	−0.0681	0.3870
	(1.0228)	(3.4450)	(0.2049)	(0.8368)
ABI_System^2		2.8910		−0.3202
		(2.7724)		(0.6372)
Control Variables				
Size_Medium	−0.5300*	−0.5134*	0.0032	0.0010
	(0.2947)	(0.2937)	(0.0632)	(0.0630)
Size_Small	−0.5577	−0.6562**	−0.0651	−0.0489
	(0.3440)	(0.3159)	(0.1241)	(0.1188)
Teaching_Yes	0.2766	0.2951	0.1361**	0.1331**
	(0.2365)	(0.2407)	(0.0575)	(0.0583)
Bed_Utilization	0.3815	0.2847	0.1245	0.1431
	(1.1476)	(1.1449)	(0.2152)	(0.2129)
For-Profit_Yes	0.1613	0.0495	0.0349	0.0473
	(0.3025)	(0.3517)	(0.0698)	(0.0831)
Ave Physician Workload	−0.2442***	−0.2472***	−0.0428	−0.0430
	(0.0803)	(0.0822)	(0.0272)	(0.0268)
Physician Experience	0.0563	0.0533	−0.0240 *	−0.0233
	(0.0822)	(0.0798)	(0.0143)	(0.0146)
P_{iht}	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: Cluster robust standard errors in parentheses. ***: $p \leq 0.01$; **: $p \leq 0.05$; *: $p \leq 0.1$. P_{iht} is a vector of the patient level characteristics included in the model: age, age^2, race, gender, admission type, payment type, number of diagnosis, length of stay (for Mortality), number of procedures, common comorbidities (see Table 1). Time fixed effects are also included in the model.

B Appendix: Figures and tables in chapter 3

B.1 Tables

Table 12: Related literature in healthcare

	Simultaneous teamwork	Sequential teamwork
Familiarity	Avgerinos and Gokpinar (2017) Avgerinos et al. (2020) Niewoehner and KC (2022) Aksin et al ,(2021)	Senot, (2019) Lu and Lu (2018)
Partner exposure	Kim et al. (2022) Aksin et al,(2021)	

Table 13: Summary Statistics at patient level

Variable	N	Mean	Std. Dev.	Min	Max
Duration in ED (hours)	35,987	29.246	25.844	0	236
Number of Procedures	43,273	1.212	1.401	0	5
Age	43,273	55.421	15.643	3	101
Severity	43,273	3.57	2.059	0	9
Categorical variable	N	%			
Female	24,742	57.2%			
Admission time					
Afternoon	20,396	47.1%			
Morning	15,306	35.4%			
Night	7,571	17.5%			
Admission day					
Weekday	33,309	77%			
Weekend	9,964	23%			
Insurance					
Medicare & Medicaid	21,855	50.5%			
Private	12,492	28.9%			
Self-pay	5,881	13.6%			
No charge & Others	3,045	7%			
YEAR					
2011	7,050	16.3%			
2012	11,261	26%			
2013	12,673	29.3%			
2014	12,289	28.4%			
Quarter					
1	8,714	20.1%			
2	11,340	26.2%			
3	11,991	27.7%			
4	11,228	25.9%			

Table 14: Summary Statistics for physician level variables

Variable	N	Mean	Sd	Min	Max
Joint physician variable					
Familiarity	35,740	7.307	19.372	1	322
Attending physician variables					
PartnerExposure	17,661	0.338	0.292	0.015	1
Fraction_coop	17,661	0.564	0.366	0.001	1
Total_volume_acc	17,661	980	2,960	0	68,826
Multisiting	7,513	42.5%			
Operating physician variables					
PartnerExposure	14,861	0.356	0.299	0.015	1
Fraction_coop	14,861	0.798	0.332	0.001	1
Total_volume_acc	14,861	1,180	3,600	0	68,826
Multisiting	5,947	40%			

Table 15: Summary Statistics for hospital level variables

Variable	N	Mean	Sd	Min	Max
Total visit	2,365	9,880.176	5,893.781	669	39,978
Utilization	2,365	137.477	64.977	26.76	989.692
Fraction of chest pain visits	2,365	0.035	0.016	0.004	0.084
Categorical variable	N	%			
Teaching hospital	671	31.1%			
Rural	156	7.2%			
Ownership					
Profit	1,019	47.2%			
Government	244	11.3%			
Nonprofit	894	41.4%			

Table 16: Correlation table

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Duration													
Procedure	0.44****												
AGE	0.21****	0.12****											
Severity	0.35****	0.24****	0.37****										
Familiarity	-0.51****	-0.40****	-0.23****	-0.33****									
PartnerExposure.x	0.28****	0.24****	0.11****	0.13****	-0.33****								
PartnerExposurep.y	0.27****	0.22****	0.08****	0.12****	-0.35****	0.25****							
Experience.x	-0.27****	-0.27****	-0.11****	-0.17****	0.51****	-0.28****	-0.18****						
Experience.y	-0.45****	-0.37****	-0.17****	-0.29****	0.61****	-0.24****	-0.31****	0.37****					
Faction_coop.x	-0.24****	-0.19****	0.00	-0.06****	0.29****	-0.19****	-0.29****	0.09****	0.32****				
Fraction_coop.y	0.16****	0.20****	0.04****	0.10****	-0.05****	-0.01	0.03****	0.01*	-0.18****	0.06****			
Chestpain_perc	0.20****	0.00	0.04****	0.07****	-0.03****	-0.11****	-0.08****	0.01*	0.03****	0.00	0.12****		
ED_utilizaiton	0.29****	0.36****	0.04****	0.14****	-0.31****	0.18****	0.18****	-0.17****	-0.33****	-0.41****	-0.02**	-0.28****	
ED_visit	0.16****	0.18****	0.01	0.09****	-0.14****	-0.01**	0.00	-0.06****	-0.09****	-0.15****	0.10****	0.11****	0.38****

Table 17: Effect of last quarter shared working experience and partner exposure on care efficiency

	log(Duration)			Number of Procedures		
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Familiarity)	−0.2977***	−0.2722***	−0.2845***	−0.2285***	−0.1960***	−0.2190***
	(0.0173)	(0.0177)	(0.0165)	(0.0290)	(0.0295)	(0.0306)
PartnerExposure.x		0.4416***	0.4337***		0.5284***	0.5141***
		(0.0431)	(0.0408)		(0.0864)	(0.0855)
PartnerExposure.y		0.2656***	0.2576***		0.2991***	0.2864***
		(0.0459)	(0.0440)		(0.0976)	(0.0969)
Log(Familiarity)×Severity			−0.0136**			−0.0263***
			(0.0057)			(0.0037)
Patient control variable						
Severity	0.0838***	0.0820***	0.1026***	0.0540***	0.0517***	0.0893***
	(0.0046)	(0.0044)	(0.0111)	(0.0058)	(0.0058)	(0.0092)
ED control variables						
Chest_perc	0.8288***	0.8874***	0.8776***	0.3684**	0.4527***	0.4469***
	(0.1100)	(0.1032)	(0.1003)	(0.1679)	(0.1681)	(0.1676)
Utilization	9.4462***	9.2083***	9.2108***	14.2949***	14.2055***	14.2108***
	(0.9842)	(0.9496)	(0.9438)	(1.8834)	(1.8667)	(1.8543)
Total_visits	−0.2390**	−0.1492	−0.1436	−0.6871***	−0.5775***	−0.5701***
	(0.0963)	(0.0949)	(0.0945)	(0.2001)	(0.2022)	(0.2015)
Urban	−0.3459***	−0.3461***	−0.3373***	−0.2724**	−0.2773**	−0.2640**
	(0.1030)	(0.0964)	(0.0967)	(0.1214)	(0.1151)	(0.1131)
Ownership						
Government	−0.0079	0.0261	0.0235	0.6027***	0.6271***	0.6227***
	(0.0498)	(0.0485)	(0.0494)	(0.1335)	(0.1333)	(0.1344)
Nonprofit	−0.0382	−0.0233	−0.0228	0.0288	0.0517	0.0493
	(0.0487)	(0.0458)	(0.0458)	(0.0991)	(0.0987)	(0.0988)
Teaching	0.1694***	0.1293***	0.1319***	0.2148**	0.1851**	0.1875**
	(0.0365)	(0.0343)	(0.0349)	(0.0846)	(0.0849)	(0.0846)
Physician control variables						
Total_experience.x	−0.4350	−0.2675	−0.3189	−1.4214**	−1.2119*	−1.3180**
	(0.4632)	(0.4367)	(0.4168)	(0.6732)	(0.6297)	(0.6198)
Total_experience.y	−3.4633***	−3.5311***	−3.5235***	−0.5297	−0.5861	−0.5970
	(0.6052)	(0.5985)	(0.5956)	(0.4749)	(0.4593)	(0.4574)
Multisiting.x	0.0791***	0.1001***	0.0987***	−0.0679	−0.0380	−0.0400
	(0.0210)	(0.0204)	(0.0202)	(0.0466)	(0.0467)	(0.0467)
Multisiting.y	−0.0476	−0.0057	−0.0074	−0.1600***	−0.1122*	−0.1146**
	(0.0297)	(0.0281)	(0.0283)	(0.0549)	(0.0573)	(0.0571)
Freq_coop.x	−0.0496	0.0020	0.0011	−0.0366	0.0171	0.0168
	(0.0572)	(0.0540)	(0.0543)	(0.1084)	(0.1069)	(0.1073)
Freq_coop.y	0.4264***	0.4084***	0.4062***	0.8456***	0.8347***	0.8305***
	(0.0719)	(0.0675)	(0.0670)	(0.0671)	(0.0695)	(0.0693)
Number of Obs	33,500	33,500	33,500	39,950	39,950	39,950
R^2	0.5897	0.5980	0.5988	0.3140	0.3224	0.3241

Notes: Cluster robust standard errors based on paired physicians are reported in parentheses. ***: $p \leq 0.01$; **: $p \leq 0.05$; *: $p \leq 0.1$.

Table 18: Effect of accumulated shared working experience and partner exposure on care efficiency

	log(Duration)			Number of Procedures		
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Familiarity)	−0.1662***	−0.1569***	−0.1631***	−0.1039***	−0.0923***	−0.0999***
	(0.0116)	(0.0116)	(0.0123)	(0.0177)	(0.0177)	(0.0187)
PartnerExposure.x		0.3520***	0.3417***		0.4510***	0.4388***
		(0.0544)	(0.0530)		(0.0949)	(0.0937)
PartnerExposure.y		0.1841***	0.1773***		0.1894*	0.1792
		(0.0646)	(0.0627)		(0.1100)	(0.1091)
Log(Familiarity)×Severity			−0.0097***			−0.0139***
			(0.0035)			(0.0027)
Patient control variable						
Severity	0.0895***	0.0893***	0.1054***	0.0594***	0.0591***	0.0802***
	(0.0048)	(0.0048)	(0.0088)	(0.0059)	(0.0059)	(0.0081)
ED control variables						
Chest_perc	0.8841***	0.9123***	0.9004***	0.3861**	0.4223**	0.4162**
	(0.1098)	(0.1076)	(0.1042)	(0.1719)	(0.1713)	(0.1710)
Utilization	9.0726***	8.8959***	8.8841***	14.3610***	14.2176***	14.2278***
	(1.0560)	(1.0422)	(1.0356)	(1.9126)	(1.9017)	(1.8927)
Total_visits	−0.2025*	−0.1556	−0.1461	−0.6635***	−0.6126***	−0.6025***
	(0.1051)	(0.1039)	(0.1038)	(0.2065)	(0.2076)	(0.2077)
Urban	−0.3602***	−0.3678***	−0.3633***	−0.3171**	−0.3277**	−0.3243**
	(0.1021)	(0.1013)	(0.1019)	(0.1325)	(0.1316)	(0.1306)
Ownership						
Government	0.0302	0.0373	0.0405	0.6143***	0.6192***	0.6205***
	(0.0558)	(0.0548)	(0.0552)	(0.1358)	(0.1356)	(0.1368)
Nonprofit	−0.0674	−0.0602	−0.0594	0.0196	0.0301	0.0291
	(0.0531)	(0.0528)	(0.0528)	(0.1023)	(0.1019)	(0.1022)
Teaching	0.1502***	0.1373***	0.1380***	0.2180**	0.2121**	0.2125**
	(0.0394)	(0.0388)	(0.0390)	(0.0873)	(0.0875)	(0.0874)
Physician control variables						
Total_experience.x	−0.6623	−0.6730	−0.7325	−1.8898***	−1.8915***	−1.9911***
	(0.5404)	(0.5321)	(0.5169)	(0.6896)	(0.6762)	(0.6629)
Total_experience.y	−3.1341***	−3.2852***	−3.3542***	−0.6677	−0.8423	−0.9698*
	(0.6343)	(0.6381)	(0.6334)	(0.5494)	(0.5335)	(0.5317)
Multisiting.x	0.0802***	0.0889***	0.0885***	−0.0722	−0.0600	−0.0602
	(0.0213)	(0.0211)	(0.0210)	(0.0481)	(0.0481)	(0.0482)
Multisiting.y	−0.0518	−0.0375	−0.0386	−0.1697***	−0.1547***	−0.1562***
	(0.0320)	(0.0307)	(0.0308)	(0.0563)	(0.0561)	(0.0561)
Freq_coop.x	−0.0450	−0.0365	−0.0384	−0.0378	−0.0294	−0.0310
	(0.0628)	(0.0615)	(0.0620)	(0.1092)	(0.1086)	(0.1091)
Freq_coop.y	0.4848***	0.4704***	0.4642***	0.8765***	0.8617***	0.8532***
	(0.0707)	(0.0691)	(0.0684)	(0.0687)	(0.0697)	(0.0694)
Number of Obs	33,500	33,500	33,500	39,950	39,950	39,950
R^2	0.5889	0.5911	0.5923	0.3003	0.3030	0.3100

Notes: Cluster robust standard errors based on paired physicians are reported in parentheses. ***: $p \leq 0.01$; **: $p \leq 0.05$; *: $p \leq 0.1$.

Table 19: Effect of last quarter shared working experience and partner exposure on care efficiency. Partner exposure defined as the number of past co-workers.

	log(Duration)			Number of Procedures		
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Familiarity)	−0.2977***	−0.1939***	−0.2081***	−0.2285***	−0.0517	−0.0768*
	(0.0173)	(0.0274)	(0.0254)	(0.0290)	(0.0401)	(0.0405)
Total_coworker.x		−0.0036***	−0.0036***		−0.0061***	−0.0061***
		(0.0005)	(0.0005)		(0.0006)	(0.0006)
Total_coworker.y		−0.0033***	−0.0033***		−0.0057***	−0.0057***
		(0.0006)	(0.0006)		(0.0006)	(0.0006)
Log(Familiarity)×Severity			−0.0162***			−0.0309***
			(0.0053)			(0.0036)
Patient control variable						
Severity	0.0838***	0.0817***	0.1063***	0.0540***	0.0501***	0.0941***
	(0.0046)	(0.0047)	(0.0109)	(0.0058)	(0.0053)	(0.0084)
ED control variable						
Chest_perc	0.8288***	0.7765***	0.7665***	0.3684**	0.3505**	0.3467**
	(0.1100)	(0.1040)	(0.1018)	(0.1679)	(0.1569)	(0.1565)
Utilization	9.4462***	6.7327***	6.7349***	14.29497***	10.2585***	10.2501***
	(0.9842)	(1.0210)	(1.8834)	(1.0169)	(1.9282)	(1.9164)
Total_visit	−0.2390**	−0.0193	−0.0104	−0.68710***	−0.3603*	−0.3462*
	(0.0963)	(0.0941)	(0.0939)	(0.2001)	(0.1975)	(0.1968)
Urban	−0.3459***	−0.4983***	−0.4875***	−0.2724***	−0.4690***	−0.4541***
	(0.10301)	(0.1241)	(0.1229)	(0.1214)	(0.1597)	(0.1557)
Ownership						
Government	−0.0079	−0.0159	−0.0181	0.6027***	0.5896***	0.5854***
	(0.0498)	(0.0488)	(0.0496)	(0.1335)	(0.1300)	(0.1312)
Nonprofit	−0.0382	−0.0312	−0.0302	0.0288	0.0563	0.0544
	(0.0487)	(0.0473)	(0.0471)	(0.0991)	(0.0942)	(0.0942)
Teaching	0.1694***	0.1193***	0.1214***	0.2148***	0.1284	0.1296
	(0.0365)	(0.0341)	(0.0345)	(0.0846)	(0.0852)	(0.0850)
Physician control variable						
Total_experience.x	−0.4350***	0.9995**	0.9383**	−1.4214**	1.0763**	0.9652*
	(0.4632)	(0.4692)	(0.4470)	(0.6732)	(0.5301)	(0.5157)
Total_experience.y	−3.4633***	−2.4876***	−2.4814***	−0.5297	1.2308***	1.2228***
	(0.6052)	(0.5313)	(0.5250)	(0.4749)	(0.4035)	(0.3915)
Multisiting.x	0.0791***	0.1066***	0.1054***	−0.0679	−0.0178	−0.0190
	(0.0210)	(0.0223)	(0.0221)	(0.0466)	(0.0480)	(0.0480)
Multisiting.y	−0.0476	0.0227	0.0219	−0.1600***	−0.0517	−0.0520
	(0.0297)	(0.0267)	(0.0267)	(0.0549)	(0.0542)	(0.0540)
Freq_coop.x	−0.0496***	0.0292	0.0293	−0.0366***	0.0816	0.0838
	(0.0572)	(0.0570)	(0.0571)	(0.1084)	(0.1072)	(0.1077)
Freq_coop.y	0.4264***	0.5181***	0.5149***	0.8456***	0.9863***	0.9814***
	(0.0719)	(0.0730)	(0.0723)	(0.0671)	(0.0668)	(0.0670)
Number of Obs	33,500	33,500	33,500	39,950	39,950	39,950
R^2	0.5897	0.6018	0.6029	0.3140	0.3361	0.3385

Notes: Cluster robust standard errors based on paired physicians are reported in parentheses. ***: $p \leq 0.01$; **: $p \leq 0.05$; *: $p \leq 0.1$.

Table 20: Post-Hoc Analyses: interaction between the partner exposure variables.

	log(Duration)	Number of Procedure	log(Duration)	Number of Procedure
	(1)	(2)	(3)	(4)
Log(Familiarity)	-0.2673^{***}	-0.1881^{***}		
	(0.0178)	(0.0299)		
PartnerExposure.x	0.6277^{***}	0.8077^{***}		
	(0.0661)	(0.1258)		
PartnerExposure.y	0.4518^{***}	0.5835^{***}		
	(0.0669)	(0.1346)		
PartnerExposure.x × PartnerExposure.y	-0.6184^{***}	-0.9469^{***}		
	(0.1179)	(0.2115)		
Alternative measure of partner exposure				
Log(Familiarity)			-0.2418^{***}	-0.1913^{***}
			(0.0239)	(0.0302)
Total coworker.x			-0.0750	-2.0997^{***}
			(0.1222)	(0.2102)
Total coworker.y			-2.3554^{***}	-1.9466^{***}
			(0.1489)	(0.1984)
Total coworker.x×Total coworker.y			1.7878^{***}	3.4651^{***}
			(0.1663)	(0.2426)
Control variables				
Patient control variables	Yes	Yes	Yes	Yes
ED control variables	Yes	Yes	Yes	Yes
Physician control variables	Yes	Yes	Yes	Yes
Time factors	Yes	Yes	Yes	Yes
Number of Obs	33,500	39,950	33,500	39,950
R^2	0.5989	0.3238	0.6361	0.3651

Notes: Cluster robust standard errors based on paired physicians are reported in parentheses. ***: $p \leq 0.01$; **: $p \leq 0.05$; *: $p \leq 0.1$.

Table 21: Post-Hoc Analyses: moderating role of multisiting status.

	log(Duration)	Number of Procedure
	(1)	(2)
log(Familiarity)	-0.3234^{***}	-0.2995^{***}
	(0.0322)	(0.0427)
PartnerExposure.x	0.3535^{***}	0.2810^{***}
	(0.0569)	(0.0850)
PartnerExposure.y	0.0100	0.0209
	(0.0491)	(0.0952)
Paired_multisiting_Mixed	-0.1269^{**}	-0.1854^{**}
	(0.0577)	(0.0895)
Paired_multisiting_Multi	-0.2568^{***}	-0.8465^{***}
	(0.0862)	(0.1354)
Interaction Effects		
Paired_multisiting_Mixed×log(Familiarity)	0.0149	0.0041
	(0.0295)	(0.0369)
Paired_multisiting_Mixed×PartnerExposure.x	0.0605	0.1953^{*}
	(0.0651)	(0.1065)
Paired_multisiting_Mixed×PartnerExposure.y	0.3811^{***}	0.3212^{***}
	(0.0763)	(0.1187)
Paired_multisiting_Multi × Log(Familiarity)	0.0892^{**}	0.2137^{***}
	(0.0376)	(0.0480)
Paired_multisiting_Multi×PartnerExposure.x	0.2464^{**}	0.8297^{***}
	(0.0981)	(0.1793)
Paired_multisiting_Multi×PartnerExposure.y	0.9384^{***}	1.2760^{***}
	(0.1882)	(0.2422)
Control variables		
Patient control variables	Yes	Yes
ED control variables	Yes	Yes
Physician control variables	Yes	Yes
Time factors	Yes	Yes
Number of Obs	33,500	39,950
R^2	0.6005	0.3295

Notes:Cluster robust standard errors based on paired physicians are reported in parentheses. ***: $p \leq 0.01$; **: $p \leq 0.05$; *: $p \leq 0.1$.

B.2 Figures

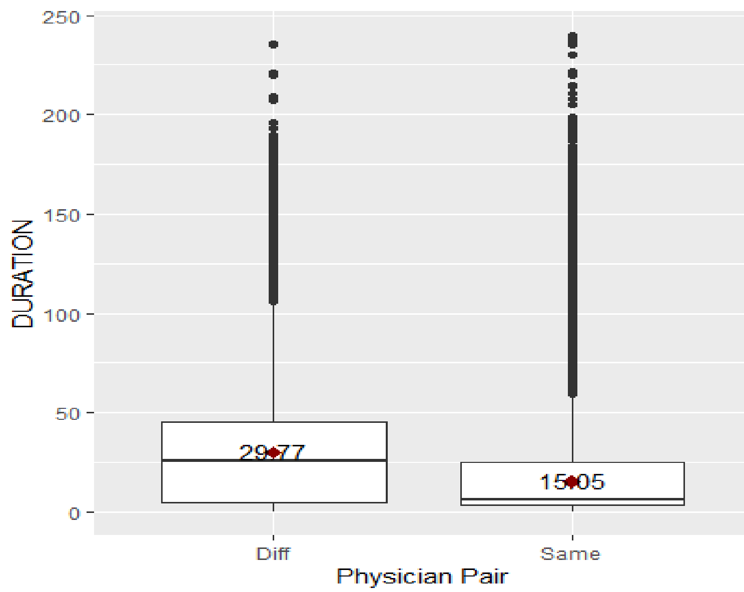

Figure 5: Difference between two or more than one physicians

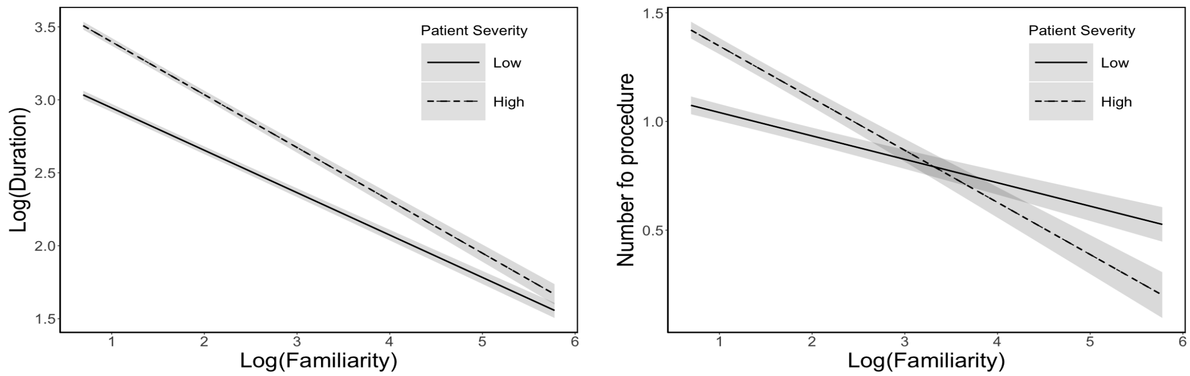

Figure 6: Partial effect plots of Familiarity X Patient Severity level

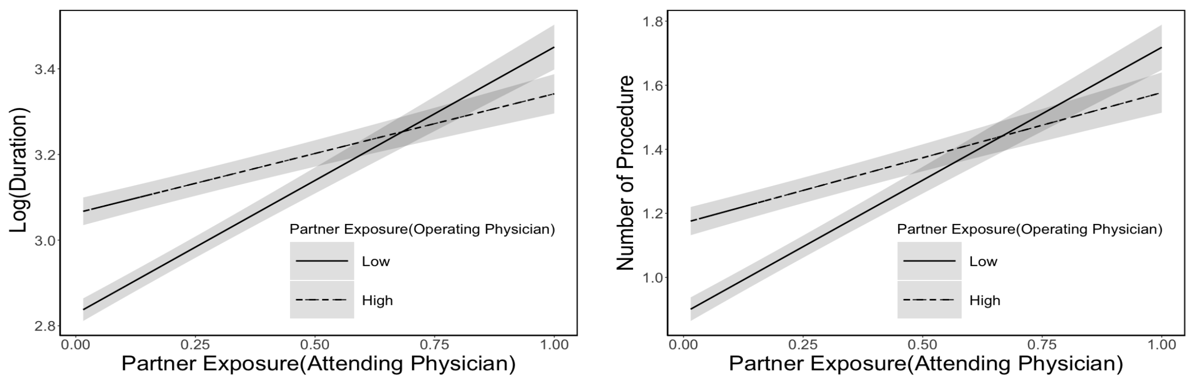

Figure 7: Partial effect plots of partner exposure for Attending Physician

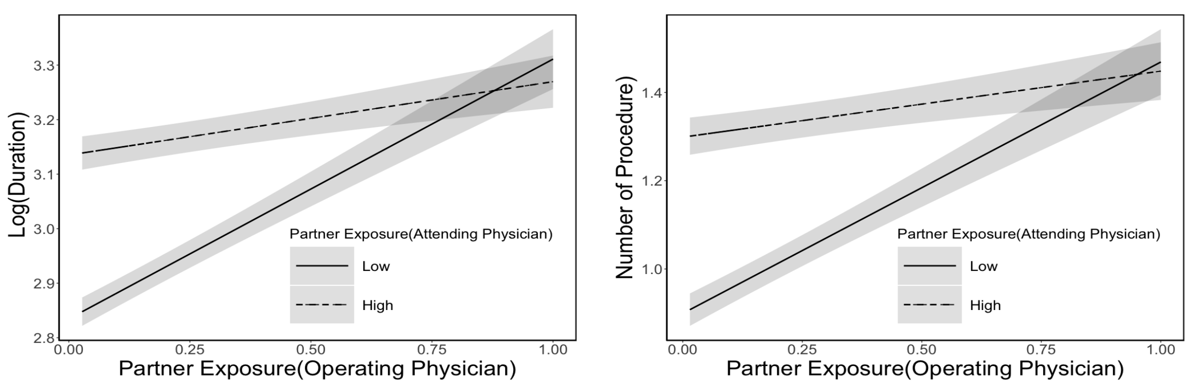

Figure 8: Partial effect plots of partner exposure for Operating Physician

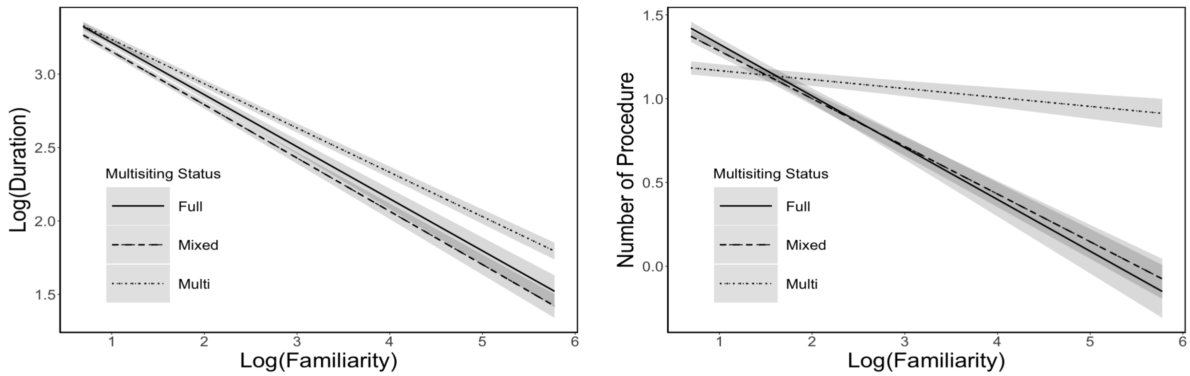

Figure 9: Partial effect plots of physician multisiting status on relationship between familiarity and operational performance

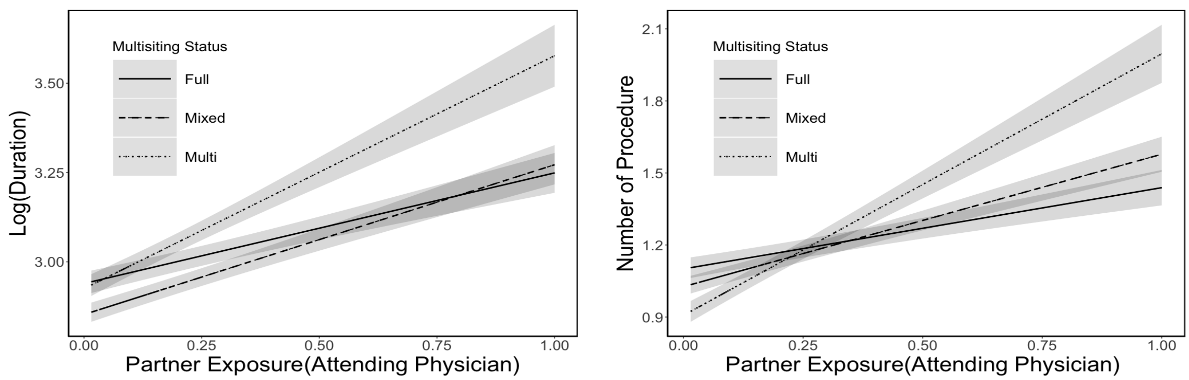

Figure 10: Partial effect plots of physician multisiting status on relationship between partner exposure and operational performance for Attending Physician

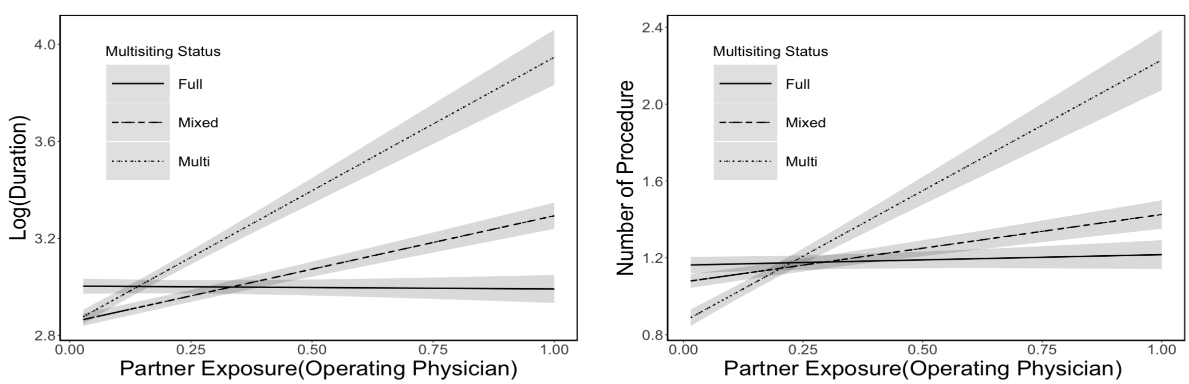

Figure 11: Partial effect plots of physician multisiting status on relationship between partner exposure and operational performance for Operating Physician

Vita

Hui Jia is a doctoral student in business analytics and statistics at the Haslam College of Business, University of Tennessee, Knoxville. Prior to joining the PhD. program, she earned her bachelor's degree in mechanical engineering from the Beijing University of Chemical Technology in China, and her master's degree in industrial and systems engineering from Lehigh University in Pennsylvania. Her research interests lies in data-driven operations management and analytics in the healthcare industry. Her works mainly focus on two areas: (i) applying quantitative methods (e.g., econometrics models) to study individual and organizational behaviors, interventional healthcare policy, and quantify their impacts on care outcomes to inform policy making; (ii) using data analytics skills (e.g., machining learning and statistics models) to customize treatment/decision-making for personalized medicine plans and offer patient-level predictions.