THREE ESSAYS IN HEALTH ECONOMICS: THE ROLE OF COORDINATION IN IMPROVING OUTCOMES AND INCREASING VALUE IN HEALTH CARE

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DEDICATION

For my family, friends, and colleagues who have always supported me. For Valerie who endured these six years with grace and anticipation for the day I would be done. Without your encouragement I could not have started this journey, but as Kurt Vonnegut said: "We have to continually be jumping off cliffs and developing our wings on the way down." Thank you all for helping me grow my wings in time.

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THREE ESSAYS IN HEALTH ECONOMICS: THE ROLE OF COORDINATION IN IMPROVING OUTCOMES AND INCREASING VALUE IN HEALTH CARE

Hospital costs are the largest contributor to US health expenditures, making them a common target for cost containment policies. Policies that reduce fragmentation in health care and related systems could increase the value of these expenditures while improving outcomes. Efforts to address fragmentation of health care services, such as Accountable Care Organizations, have typically been enacted at the scale of health systems. However, coordination within health care facilities should also be explored.

In three essays, I analyze the role of coordination in several forms. First, I examine the introduction of interdisciplinary care teams within a hospital. This analysis features care coordination within a health care facility with the potential to reduce resource utilization through improved communication between team members and between patients and their care providers. I find that care coordination reduced length of stay for some patients while maintaining care quality. This combination results in higher value care for patients and hospitals.

Second, I explore whether these interdisciplinary care teams impact resource utilization and patient flow throughout the hospital. The primary outcome is reduction in patient transfers to the ICU. Here, care coordination includes interdisciplinary teams as well as coordination between interdisciplinary teams and intensivists in ICUs. Findings from this analysis suggest that ICU transfers were unaffected by care coordination.

Finally, I examine coordination on a larger scale. I leverage data from a national database of trauma patients to compare mortality among adolescent patients with isolated traumatic brain injury between adult trauma centers and pediatric trauma centers. Previous work has shown that younger pediatric patients with this injury benefit from treatment at pediatric trauma centers. However, it is unclear whether this benefit extends to older pediatric patients on the cusp of adulthood. I find that, after adjusting for differences in injury severity, adolescent patients have no difference in mortality risk when treated at adult or pediatric trauma centers. This finding supports the current regionalized model of trauma care where severely injured patients are taken to the nearest trauma center, regardless of designation as pediatric or adult.

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LIST OF ABBREVIATIONS

ACS – American College of Surgeons
ACU – Accountable Care Unit
AHRQ – Agency for Healthcare Research and Quality
AIS – Abbreviated Injury Scale
ATC – Adult Trauma Center
ATT – Average Treatment Effect on the Treated
CAUTI – Catheter Associated Urinary Tract Infection
CI – Confidence Interval
CLABSI – Central Line Associated Bloodstream Infection
CMI – Case mix index
CMS – Centers for Medicare & Medicaid Services
DRG – Diagnostic Related Group
ED – Emergency Department
EMS – Emergency Medical Services
GCS – Glasgow Coma Scale
GDP – Gross Domestic Product
HAC – Hospital Acquired Condition
HAPU – Hospital Acquired Pressure Ulcer
HCAHPS – Hospital Consumer Assessment of Healthcare Providers and Systems
ICP – Intracranial Pressure Monitor
ICU – Intensive Care Unit
IP – Inpatient
IR – Interdisciplinary Rounding
ISS – Injury Severity Score
LOS – Length of Stay
LPM – Linear Probability Model
MRSA – Methicillin-resistant *Staphylococcus aureus*
MTC – Mixed Trauma Center
OLS – Ordinary Least Squares
OR – Odds Ratio
PCCU – Progressive Care Cardiology Unit
PTC – Pediatric Trauma Center
PUF – Participant Use File
SIBR – Structured Interdisciplinary Bedside Rounding
SNF – Skilled Nursing Facility
SSI – Surgical Site Infection
TBI – Traumatic Brain Injury
TQP – Trauma Quality Programs
VAP – Ventilator Associated Pneumonia
VBP – Value-based Purchasing

INTRODUCTION

1 What is Care Coordination?

Care coordination is the binding theme of this dissertation and is explored in each of the subsequent chapters. Broadly defined, care coordination can be thought of as any policy designed to improve the value of health care by improving efficiency. This definition purposefully includes a wide range of policy interventions, practice models, and technologies that reduce fragmentation in the health care sector.

In general, activities included in care coordination impact efficiency through two channels: encouraging communication and aligning incentives. Communication between members of a patient's care team, between the patient and their clinicians, and between organizations within the health care system influences the value of care a patient receives. For example, miscommunication between care team members can lead to delays in treatment or discharge that can have negative impacts on a patient's recovery and cost of care. Aligning incentives, on the other hand, improves care coordination by encouraging payors to reward high quality care and punish low quality care or inefficient use of resources.

Care coordination, as defined above, is an important topic in health economics because care fragmentation contributes to the high cost of care in the United States. Expenditures on healthcare in the US reached 17.9 percent of GDP in 2017 and hospital care accounted for one-third of those expenditures (Centers for Medicare and Medicaid Services 2018). Thus, policies like care coordination, that target hospital care, can produce significant savings with modest improvements in efficiency.

Strategies to reduce fragmentation (or increase coordination) that rely on contracts alone may succumb to "common agency" problems that result in underpowered incentives and little impact on providers' behavior (Frandsen, Powell, and Rebitzer 2019). Individual hospitals contract with multiple payors who all share the benefits of higher quality care regardless of which payor's contract induces the increase in quality. This means that equilibrium contracts will include underpowered incentives. Enhancing quality improvements from these contracts will require additional efficiency gains from other sources, such as care coordination. In addition to common agency, these types of policies can undercut their goals by inducing additional costs in the form of costly administrative departments (Cutler and Ly 2011).

2 Examples of Care Coordination

Care coordination polices exist at every level of the US healthcare system. At the level of health systems, often regional or national in scope, care coordination can take the form of accountable care organizations (ACOs) or value-based purchasing programs (VBPs) that are designed to improve value of care by aligning incentives between payors and health care providers (Frandsen and Rebitzer 2015; Tanenbaum 2016). These large-scale efforts leverage reimbursement incentives to encourage clinicians to provide high quality care while controlling costs.

Below the federal level, care coordination can occur through collaborative efforts between care facilities, Emergency Medical Services (EMS), and government agencies. Trauma systems are an example of this type of collaboration as they require coordination of services between acute care hospitals and EMS, between health care facilities, and between clinicians who care for trauma patients at different stages of their recovery (van

Rein et al. 2018). Within states, primary care networks using models such as the patient-centered medical home coordinate care to manage population health (David, Saynisch, and Smith-McLallen 2018).

Finally, within a single facility, care coordination can manifest as interdisciplinary rounding schemes that bring together patients' care teams during daily rounds (Pannick et al. 2015). At this most granular scale, care coordination improves efficiency through enhanced communication that can reduce duplication of services and streamline treatment and discharge planning. Interdisciplinary rounding schemes lack the financial incentives of larger scale efforts, but require significantly fewer resources to implement and maintain. Understanding when and where this trade-off is beneficial is of critical importance to the design of holistic care coordination policies.

3 Investigations of Care Coordination

In this dissertation, I analyze two examples of care coordination: interdisciplinary rounding and trauma systems. In the next chapter, I leverage data from a single acute care hospital that implemented an interdisciplinary rounding scheme called Structured Interdisciplinary Bedside Rounding (SIBR) to determine if care coordination in this form can reduce resource utilization while maintaining (or improving) quality of care. This study takes advantage of a staggered roll out of SIBR across seven inpatient units and compares them to a group of 13 units that did not implement the model.

In the following chapter, I revisit the same hospital as the first paper using a more granular data set that tracks patients' movements between units within a single hospital visit. This analysis attempts to estimate additional spillover benefits of SIBR; specifically, whether units that implemented SIBR reduced the occurrence of upstream transfers from lower-acuity units to Intensive Care Units (ICUs). The study also estimates changes at the internal margin by estimating a reduction in patients' length of stay (LOS) on an ICU conditional on transfer from a lower-acuity unit.

Finally, I turn to care coordination at the level of trauma systems in the subsequent chapter. This study compares mortality across pediatric, adult, and mixed (both pediatric and adult) level I trauma centers for adolescent patients with isolated severe traumatic brain injury (TBI). These patients, aged 15 to 17 years old, could conceivably receive high quality care at either pediatric or adult trauma centers, but previous work has yielded mixed results. For younger patients, treatment at pediatric trauma centers has been shown to be beneficial, but it is unclear if this extends to older pediatric patients. The results of this analysis can help policymakers better design trauma systems to deliver high quality care to patients of all ages.

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INTERDISCIPLINARY ROUNDS AS

INPATIENT CARE COORDINATION

1 Introduction

In 2017, US healthcare expenditures reached 17.9 percent of GDP with the largest share (33%) contributed by care delivered at inpatient acute care hospitals (henceforth "inpatient care") (Centers for Medicare and Medicaid Services 2018). The magnitude of these expenditures means that policies targeting inpatient care costs can have a big impact on overall spending. The most common approach to improving the value of inpatient care is to reduce resource utilization and improve quality through reimbursement incentives.

Government and private payors commonly pursue cost reductions through incentives-based contracts. These include Centers for Medicare and Medicaid Services' (CMS) and private insurers' push for value-based purchasing programs (Tanenbaum 2016). These programs incentivize performance on specific quality measures and discourage the use of costly care that returns little value. [1] For example, accountable care organizations allow health systems to keep a portion of the savings they generate from improving care delivery and maintaining quality standards (Frandsen and Rebitzer 2015). Despite their popularity, evidence for the effectiveness of value-based purchasing is mixed (Cutler 1995; Frandsen and Rebitzer 2015; Mellor, Daly, and Smith 2017). Furthermore, value-based purchasing programs are costly to run, requiring hospitals to

[1] VBP programs take on many forms but have in common the idea that the payor takes an active role in distinguishing high-value from low-value care (Tanenbaum 2016). The role of the payor, the measures of value and quality, and the form of reimbursement incentives must be specified either in private contracts or public rule notices. Examples of VBP programs from CMS include the Hospital Readmission Reduction Program (HRRP) and prospective payment systems such as the Inpatient Prospective Payment System (IPPS). Other common VBP initiatives include Accountable Care Organizations (ACOs) and bundled payment programs.

hire additional staff that do not contribute to healthcare provision, but do contribute to administrative costs (Cutler and Ly 2011).

An alternative approach to improving the value of inpatient care, that can complement existing value-based purchasing programs, is care coordination. Fragmentation of services is endemic in the US healthcare system (Agha, Frandsen, and Rebitzer 2017). Care coordination encompasses a variety of policies that address cost and quality by reducing fragmentation. In the context of inpatient care, interdisciplinary medical rounds could address fragmentation arising from the siloed roles of health care personnel in a hospital.

In this study, I analyze an implementation of a new form of interdisciplinary rounding at a hospital in Indianapolis to estimate its effects on care value. Interdisciplinary rounds are not a new idea in hospital medicine (Curley, McEachern, and Speroff 1998). However, a recently developed care model, Accountable Care Units, employs a structured approach to interdisciplinary rounding that formalizes the process: assigning speaking roles to each member, employing a checklist of quality indicators to guide discussion, and emphasizing patient participation (Stein et al. 2015). Called structured interdisciplinary bedside rounds (SIBR), this approach includes physicians, bedside nurses, case managers, and the patient and their family.

To determine whether SIBR improves the value of care, I observe changes in resource utilization and care quality before, during, and after its rollout on several inpatient hospital units. I also observe these measures on several units that did not implement SIBR. Measures of resource utilization include patients' length of stay in the hospital and several measures of cost. Care quality is measured by 30-day readmission and mortality rates as well as central venous catheter usage—all common measures of inpatient care quality. Using these measures, evidence of higher value care would be a combination of 1) reductions in resource utilization while maintaining (or improving) quality measures, or 2) improvement in quality measures while maintaining (or decreasing) resource utilization. If resource utilization is decreased, but quality measures fall as well, overall value may not be improved. Likewise, improving quality at the cost of greater resource utilization may not provide better value.

Overall, my findings indicate that SIBR improved the value of care for some patients, and may be effective for the general patient population. Looking first at resource utilization, patients discharged from the seven units that implemented SIBR left the hospital a half-day sooner, on average, than patients on traditional rounding units. This effect was not consistent across all units that implemented SIBR or all patients treated on SIBR units. Two units (a general medicine unit and an oncology unit) realized statistically significant reductions in length of stay; however, aggregating data for all patients from all seven SIBR units resulted in standard errors too large to rule out a null effect. An event study analysis revealed that, after strong initial reductions in length of stay, SIBR units eventually regressed to their pre-intervention means, wiping out the average effect. SIBR also had heterogeneous effects on patients. Patients discharged to skilled nursing facilities—a more complex group requiring greater resource utilization—were discharged a full day sooner from SIBR units than traditional rounding units. Unlike reductions for the general patient population, this effect remained significant when aggregating data from all SIBR units. Cost measures, another metric of resource utilization, were unchanged by the introduction of SIBR.

Shifting to care quality measures, 30-day readmission and mortality rates were unaffected by SIBR while usage of central venous catheters fell. Central venous catheters are a crucial tool in hospital medicine, but extended periods of catheterization increase the likelihood of a patient developing a dangerous—and costly—bloodstream infection (Gahlot et al. 2014). Therefore, reducing their overall monthly usage is an indicator of improved care quality. Pairing these improvements to care quality with the reductions to resource utilization noted above provides evidence that SIBR can improve the value of inpatient care.

Comparison between the seven treated (i.e. units that implemented SIBR) and thirteen untreated units (i.e. units that did not implement SIBR) using a two-way fixed effects model identify causal relationships under the assumption that outcomes for treated and untreated units would follow parallel paths if not for the introduction of SIBR. Parallel pre-trends are assessed using an event study and provide evidence that this assumption is satisfied. Identification also hinges on control units representing a valid counterfactual to treated units. While the units in each treatment group practice different areas of medicine, the pathways by which SIBR affects outcome measures are the same across all types of units regardless of specialty: improved coordination of clinical care, clear and fast communication, and patient-centered focus of care teams.[2]

This analysis makes several contributions to the literature on interdisciplinary care and value in inpatient care. While previous analyses of interdisciplinary care teams in an inpatient setting have focused on improved patient and staff satisfaction, few have

[2] The 13 control units included 3 cardiology units, 3 OB/GYN or labor & delivery units, 2 intensive care units, 2 oncology units, 1 surgery unit, 1 inpatient rehabilitation unit, and 1 medical/psychiatric unit. The seven treated units included 2 general medicine units, 2 orthopedic units, 1 medical progressive unit, 1 medical oncology unit, and 1 neurology unit.

addressed their impact on resource utilization and quality. No previous studies of interdisciplinary care teams have included the sample size of this analysis nor have they attempted to estimate causal effects. Aside from the novel approach to analysis, this study provides evidence that interdisciplinary rounding schemes, like SIBR, could be added to policymakers—and hospital administrators—toolkits as a means to improve the value of inpatient care.

The rest of the paper proceeds as follows: Section 2 provides additional background on SIBR, accountable care units, and interdisciplinary rounding; Section 3 details the data and methods used for analysis; Section 4 reports the results of this analysis; Section 5 contains a discussion of results; and Section 6 concludes.

2 Background

SIBR, the interdisciplinary rounding model studied in this analysis, is one component of a larger care model called Accountable Care Units. Accountable Care Units is an emerging care model for inpatient hospital units developed at Emory University between 2010 and 2015 (Stein et al. 2015). Since 2015, it has been implemented on over 100 hospital units in the US, Canada, and Australia (1Unit n.d.).

This model reimagines the hospital unit as a "clinical microsystem." There are four elements of the model that encourage coordination: SIBR, unit-level data reporting, co-location of physicians' patients, and co-leadership between physicians and nurses (Stein et al. 2015). SIBR brings together the attending physician, her trainees, and other members of the patient's care team for daily rounds.[3] SIBR differs from traditional

[3] In this study, the patient's care team includes the attending physician, medical residents and interns (if the patient is located on a teaching unit), a bedside nurse, a case manager, a pharmacist, and respiratory or physical therapists as applicable. From interviews with administrators and physicians, I found that care

rounds in several key ways. First, the entire care team is involved in SIBR whereas traditional rounds include only the attending physician and medical trainees. Second, SIBR occurs at the same time each day and is performed at the patient's bedside. And thirdly, SIBR follows a structured checklist that allots speaking roles to each member of the care team, ensures critical quality and safety items are discussed, and provides opportunities for team members—and patients and family members—to ask questions. Consistent daily timing, including the patient and their family, and the structured checklist that map out the conversation set SIBR apart from traditional rounding and other interdisciplinary rounding schemes. While other forms of interdisciplinary rounding include care providers other than the physician, none place the same emphasis on consistent timing and delegate specific roles (Pannick et al. 2015).

Aside from SIBR, the other elements of the ACU model were not emphasized during the implementation in this study. At the hospital where this study was conducted, unit-level data reporting had been in place for all hospital units before, during, and after implementation and remained unchanged. Physician and nurse co-leadership took the form of an alliance between nursing directors and a lead hospitalist (physician) who oversaw the implementation of SIBR. This form of co-leadership is difficult to quantify because so many elements of the physician/nurse-director dyad are unobservable. Finally, co-location of physicians' patients on a single hospital unit—as prescribed by the Accountable Care Units model—did not occur. Typically, physicians have patients located on units throughout the hospital. The Accountable Care Units model places all of a physician's patients on a single unit to create "mutual respect, cohesiveness,

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team composition was fluid and not all members were consistently present. Most often, the care team consisted of the attending physician and her trainees, bedside nurses, and case managers.

communication, timeliness, and face-to-face problem solving" within a unit-based care team (Stein et al. 2015). In this case, physicians' patients remained distributed throughout the hospital due to logistical constraints. Because these elements were not emphasized during implementation, this analysis focuses on the contribution of SIBR to improving the value of inpatient care.

Growth in the use of Accountable Care Units, and SIBR, has been accompanied by research that gives some insight into its effectiveness. Previous studies have found consistent evidence that Accountable Care Units improve patient and staff satisfaction, but mixed evidence for reductions in patients' length of stay. Gausvik et al. (2015) find that job satisfaction for nurses on SIBR units was higher than nurses on a "control" unit. This confirms previous analyses that find SIBR improves nurses' perceptions about teamwork and collaboration (O'Leary et al. 2010, 2011). Interestingly, physicians were indifferent about SIBR; they found it no more collaborative than traditional rounds (O'Leary et al. 2010).

Evidence that SIBR can reduce patients' length of stay, or impact measures of care quality, is mixed. Stein et al. (2015), in the paper that introduced the Accountable Care Units model, found that units implementing the model reduced patients' length of stay and mortality. However, this was a pre-/post-implementation comparison of patients on the same unit and could not account for existing secular trends in outcomes. Several subsequent analyses of SIBR found no effect on length of stay or 30-day readmission rates (Huynh et al. 2017; Jala et al. 2019; Sunkara et al. 2020). Though one study did find a reduction in 7-day readmissions (Sunkara et al. 2020). On the other hand, Kara et al. (2015) found that implementing the elements of the Accountable Care Units model reduced length of stay and cost. This analysis differed from other because, rather than using patient-level outcomes from “treated” and “control” units, implementation was tracked using an index measuring eight dimensions of Accountable Care Unit implementation each scored from one (least implemented) to five (most implemented). This study also found no reduction in 30-day readmissions.

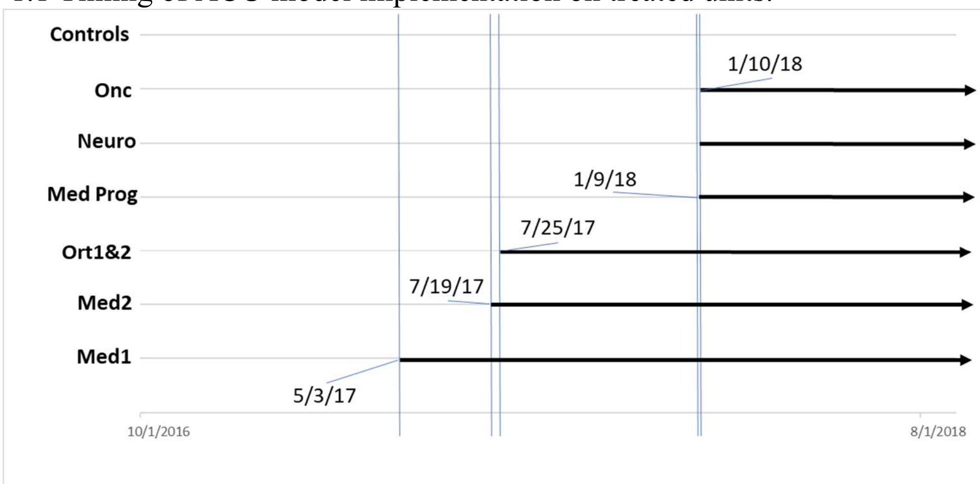
3 Data & Methods

3.1 Data

This is a retrospective study of patients admitted to adult inpatient units at a single acute care teaching hospital. SIBR adoption was staggered across hospital units over a 10-month period from April 2017 – January 2018. The study timeframe from which patient records were pulled runs from 10/1/2016 through 8/31/2018 (23 months). In total, 20 inpatient units were included in the analysis, seven of which implemented the SIBR model. Figure 1.1 shows the implementation schedule for treated units. Hospital unit-day panel data sets were constructed from patient-encounter data. The study sample was drawn from the complete universe of IP discharges, 63,099 patient-encounters, between October 1, 2016 and August 31, 2018. Using these patient-encounters, unit-day panels were constructed for analysis.

Observations were subjected to a set of basic inclusion criteria designed to preserve the integrity of the treatment effect and its causal interpretation. Patients who stayed on multiple units during a single admission were excluded from the analysis to ensure no observations contained patients seen on both treated and control units. Additionally, patients were excluded if they stayed on a control unit but were cared for by an attending physician who had previously seen patients on a treated unit.[4] Finally, patients whose LOS or cost was above the 99th percentile were excluded from the analysis to reduce the impact of extremely influential observations (>10 standard deviations from the mean) in the analysis.

Figure 1.1 Timing of ACU model implementation on treated units.



Note: ACU implementation was staggered over approximately 9 months starting with Med1 (a general medicine unit) in May 2017, followed by Med2 (general medicine) and Ort1 and Ort2 (both orthopedics units) in July 2017, and finally Med Prog (a medical progressive unit), Neuro (neurology), and Onc (medical oncology) in January 2018. ACU implementation "switched on" in a single day and remained active for the remainder of the study timeframe.

Data obtained for each patient-encounter include dates of admission and discharge, patient demographics, all hospital units on which the patient incurred room and board charges, the unit from which the patient was discharged, discharge disposition, source and type of admission, diagnostic related group (DRG) information, attending physician, attending physician specialty, direct cost and variable supply cost associated with the patient-encounter. LOS for each patient-encounter was constructed by

[4] Additional exclusion criteria included pediatric patients (pediatric units previously implemented a different interdisciplinary care scheme), uncomplicated pregnancies, and encounters with length of stay less than one day.

subtracting a patient's date of discharge from their date of admission to obtain an integer number of days. LOS was chosen as a dependent variable as a proxy for resource utilization and due to its use as a clinical and organizational performance metric and inclusion in previous studies of IR schemes. Like all other dependent variables used in this study, it is a common quality measure used by insurers (including CMS) and hospital administrations. Patients who had a readmission to the hospital within 30 days of discharge from a previous stay were coded as a readmission. Patient-encounters with a discharge disposition of 'Expired' were coded as mortalities. Readmission and mortality rates are key quality measures for many VBP programs.

Costs associated with hospital stays are notoriously difficult to calculate and interpret (Jena and Philipson 2013; Roberts et al. 1999). In this study, "cost" can be interpreted as a measure of the price paid by the hospital in the case of supplies or as wages in the case of labor. A patient's total cost of care is then the sum of the cost of supplies and wages needed during their visit.[5] This number measures the marginal utilization of hospital resources required to provide care for a patient-encounter. Daily total costs divide this number by a patient's length of stay to measure intensity of resource utilization throughout a patient's visit.

Additional covariates were included in the analysis to account for hospital unit characteristics that vary over time both between and within units and could affect patients' resource utilization and quality of care. These include patient demographics,

[5] Supply costs were determined using patient account information, charge description master codes, and ICD-10 procedure codes indicating the treatments a patient received during their visit. Wage costs were determined using payroll data for staff, contract details for external clinicians, and relative value unit conversions for ICD-10 procedure codes. Total costs also include indirect costs accounting for administrative, management, and non-clinical labor required for care. These calculations were performed by the hospital's finance department.

payor mix, physician panel size, and proxies for patient acuity. Patient acuity is approximated by averaging the DRG weights of patients discharged from a unit in a given time-frame. This measure is referred to as case mix index (CMI) and is commonly used as a proxy for acuity (Mendez et al. 2014). Accounting for patient acuity is important in this context because it is strongly associated with patients' LOS and costs. Patients' admission route is also included as a covariate using a dummy variable for admission through the emergency department (ED). Admission through the ED indicates a higher acuity than non-ED admits. Physician panel size is an important covariate because it determines the amount of time and energy a physician can devote to each patient under their care. Physicians with fewer simultaneous patients can spend a greater amount of time on their care, potentially diluting the coordination and communication benefits of an intervention like SIBR. Physician panel size for a given patient-encounter was calculated by averaging the daily number of patients being seen by the reference patient's attending physician over the days that the reference patient was hospitalized. The payor for each patient-encounter was included, using a dummy for Medicare patients, due to differences in reimbursement generosity and incentives that could affect care decisions for the patient.

Several alternative measures of quality, measured at the unit-level rather than patient-encounter level, were included. Central line (central venous catheter) usage on each unit was included as a quality measure for several reasons. First, it is included as an item on the SIBR discussion checklist that care teams used to structure their conversations during rounding. Second, reducing central line usage has been shown to be an effective way to reduce central line associated bloodstream infections (CLABSIs) which are a preventable, and costly, complication of Inpatient care (Xiong and Chen 2018). Thirdly, CLABSIs are used by insurers as a quality measure that can affect reimbursement (Calderwood et al. 2018). Central line usage was measured as the total number of days that patients on a given unit had a central venous catheter in use.

Units' monthly number of adverse events were also included as a quality measure. Adverse events include unintentional patient falls as well as several hospital-acquired conditions (HACs): CLABSIs, catheter associated urinary tract infections (CAUTIs), hospital-acquired pressure ulcers (HAPUs), ventilator associated pneumonias (VAPs), Methicillin-resistant *Staphylococcus aureus* (MRSA) infections, and surgical site infections (SSIs). These are costly and preventable events that also affect hospitals' reimbursement through pay-for-performance insurance schemes. Because these events are rare, the measure used in the analysis sums all types of events together over a month in a given unit.

Post-discharge surveys of patients' perceptions of their Inpatient care were also used as a quality measure. The Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) survey is administered to a random sample of adult patients after they have been discharged from their hospital stay. These surveys were developed by CMS and the Agency for Healthcare Research and Quality (AHRQ) to assess patients' perceptions of care quality and to publicly report these findings[6]. Data from these surveys include several different dimensions of care quality (Centers for Medicare and Medicaid Services 2020). In this analysis, three dimensions of care were considered from HCAHPS data that may have been affected by SIBR implementation: nurses'

[6] Summaries of HCAHPS data can be found at the Department of Health and Human Services' Hospital Compare website (www.hospitalcompare.hhs.gov).

communication with patients, doctors' communication with patients, and overall quality of care rating.

After applying inclusion criteria, 29,485 patient-encounters were collapsed into a panel of 8,841 unit-day observations. SIBR was implemented at the level of hospital units making them the appropriate unit of observation for this analysis. Data for all patients discharged from a given hospital unit in a given day were aggregated to form each observation. In total, 700 days of data were observed for 20 inpatient units. Each unit did not discharge patients on every day of the analysis time period. Because the number of units is fixed, collapsing data to discharge days rather than a longer time unit such as months allows for a larger number of unit-time cells, improving the consistency of standard errors (Donald and Lang 2007).

A second, more restrictive, data set was created that included only patients discharged to SNFs. This data set was created to evaluate the effect of increased care coordination on a sub-population likely to benefit from advanced discharge planning. Additional data sets were created that isolated each treated unit (excluding observations from all treated units but one) to determine if there was heterogeneity in effectiveness of care coordination on different types of units.

3.2 Analysis

The main analysis was carried out using a two-way fixed effect approach analogous to the specification suggested by Bertrand, Duflo, & Mullainathan (2004) and discussed in greater detail in Goodman-Bacon (2018). The two-way fixed effects model, with the inclusion of a dummy variable for units that have implemented SIBR, can be thought of as an extension of the classic two-period difference-in-differences (DD) model which allows for multiple treatment timings and more than two time periods. Reducing the number of units to two (a treated unit and a control unit) and the number of time periods to two (a pre-treatment period and a post-treatment period) would result in exactly the simple two-period DD model.

The primary specification is shown in equation (1). The outcome for a hospital unit-day observation (e.g. average LOS for patients discharged from unit *u* on day *t*), Y_{ut}, is predicted by a treatment dummy, T_{ut}, set to 1 if unit *u* had implemented SIBR on or before day t. The right-hand side also includes a vector of independent hospital unit covariates, X_{ut}, an unobserved hospital unit effect, μ_u, and a time fixed effect, γ_w, where *w* indexes weeks. The average treatment effect on the treated (ATT) is captured by β.

$$Y_{ut} = \beta T_{ut} + \delta X_{ut} + \mu_u + \gamma_w + \varepsilon_{ut} \quad (1)$$

Estimation of (1) was carried out using an ordinary least squares (OLS) estimator with robust standard errors clustered at the unit level, weekly time fixed effects, and hospital unit fixed effects. Distributions of cost variables were heavily skewed to the left with a long tail, so logs of cost variables were used as outcomes to normalize their distribution and to enable estimation of percent changes. No other variables were transformed prior to analysis[7]. Mortality and 30-day readmission rates were estimated as linear probability models (LPM).

Data were originally in the form of a cross-sectional time-series of patient-encounter observations but were transformed to a panel of unit-day observations for analysis. A unit-day observation was formed by averaging the values for each covariate across all *n* patients discharged from a given unit, *u*, in a given day, *t*, as shown in (2).

[7] LOS outcomes were also heavily left-skewed with a long right tail. Therefore, logged LOS outcomes were considered as a robustness check.

Covariate values for individual *i* discharged from unit *u* on day *t* are given by X_{iut}. On days where a unit did not discharge any patients, the value of X_{ut} is recorded as missing.

$$X_{ut} = \frac{1}{n}\sum_{i=1}^{n} X_{iut} \quad u = 1, \ldots, 20; t = 1, \ldots, 700 \qquad (2)$$

The vector of patient characteristics for each unit-day observation, X_{ut}, was included in the model to account for differences that varied over time and across units. Of greatest import are covariates accounting for differences in patient acuity and physician panel size. Case mix index and an indicator variable for admission through the emergency room proxy for acuity and complexity of care. Physician panel size was calculated using patient-level data which included each patient's attending physician. The patient's insurance status, which affects LOS and cost due to differences in reimbursement structure and generosity of plans, was also included.[8]

The analysis is supplemented with an event study specification (3). This specification estimates dynamic treatment effects based on dummy variables indicating relative time since SIBR implementation. Furthermore, pre-trends can be directly compared between treated and control units to assess the identifying assumption of parallel trends in outcomes.

Estimating dynamic treatment effects may be particularly useful to assess the impact of SIBR on patient outcomes. SIBR must be learned by staff members who likely become better at utilizing the intervention as time goes on. Therefore, the effectiveness of SIBR likely increases as members of a given care team work together more often. The treatment effect of SIBR likely does not manifest as an instantaneous level-shift in

[8] Additional covariates included demographic variables (race, ethnicity, sex, and age) and dummy variables for the day of the week that a patient was admitted as this can affect LOS (LEW 1966).

patients' LOS or cost, but rather an ongoing improvement in patient outcomes that changes over time.

$$Y_{um} = \sum_{j \neq -1} \beta_j T_{u,m+j} + \mu_u + \gamma_m + \varepsilon_{um} \quad u = 1, \dots, 20; m = 1, \dots, 23;$$

$$j = -7, \dots, -2, 0, \dots, 7 \quad (3)$$

The event study specification shown in (3) swaps out the binary treatment indicator, T_{ut}, used in (1) for a set of relative-time dummies, $T_{u,m+j}$, that indicate leads and lags of treatment timing.[9] Data used to estimate (3) were aggregated to unit-months to show a longer time trend with a manageable number of relative-time dummies. There were 23 months in the study timeframe, with all treated units having values for up to 7 leads and 7 lags from implementation.

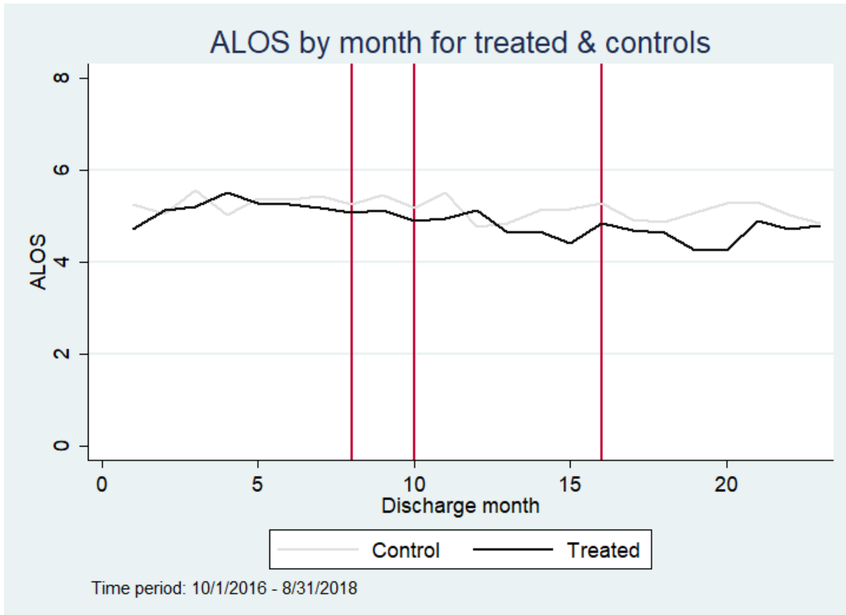
3.3 Identification

The assumption of parallel trends in outcomes between treated and untreated units implies that, if not for the implementation of SIBR, the treated units would have continued on the same path as control units. But why should one assume that the control units operate as valid counterfactuals to the treated units when the treatment groups are not comprised of identical types of units? Because the control units are not proxying for differences in the content of treatment, but rather for differences in the manner in which treatment is delivered. SIBR affects resource utilization through improved coordination of care and communication between care team members; a pathway that is not reliant on the type of care a patient received. For example, a cardiology unit can function as a

[9] Covariates are not included in the event study specification. Estimation was carried out using robust standard errors clustered at the unit level.

counterfactual to an oncology unit because the differences in outcomes from SIBR are not due to changes specific to cardiology or oncology practice.

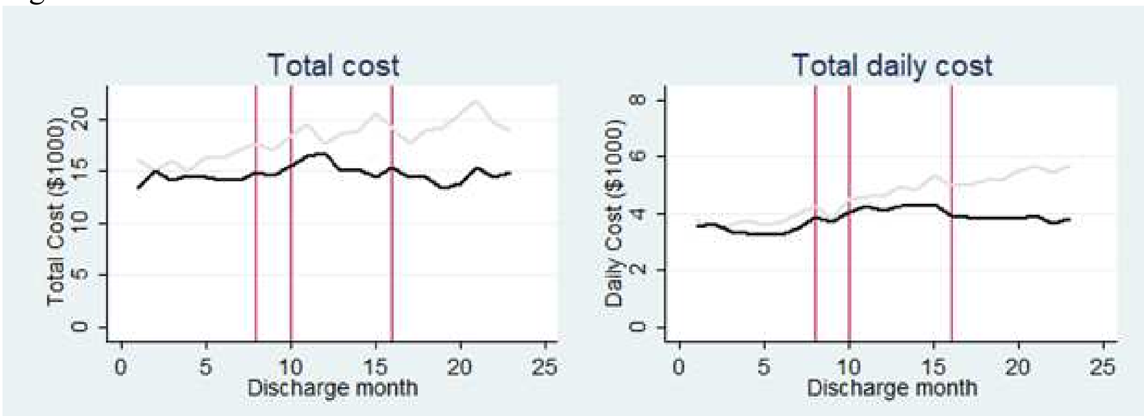
Figure 1.2 Time trend of LOS for treated and control units.



Note: The black and grey lines indicate average length of stay (ALOS) for patients discharged from treated and control units and are based on LOS data from patients discharged across all units in a treatment group for a given month. The three vertical bands give approximate timings of ACU implementation on treated units. Discharge month starts from 1 (October 2016) and runs through 23 (August 2018).

Figure 1.2 provides evidence that, prior to implementation of SIBR, the LOS of patients on treated and control units were not only on parallel trends, but were of similar levels. This implies that the difference in average LOS between treated and control units post-implementation may be informative on its own. Figure 1.3 compares trends between treatment groups for total cost (left panel) and total daily cost (right panel). While the trend in total cost of care may begin diverging prior to the first implementation of SIBR, the trend for daily total cost of care is very similar for treated and control units prior to implementation. Like LOS, the levels of daily total cost of care between treatment groups is similar in the pre-treatment era.

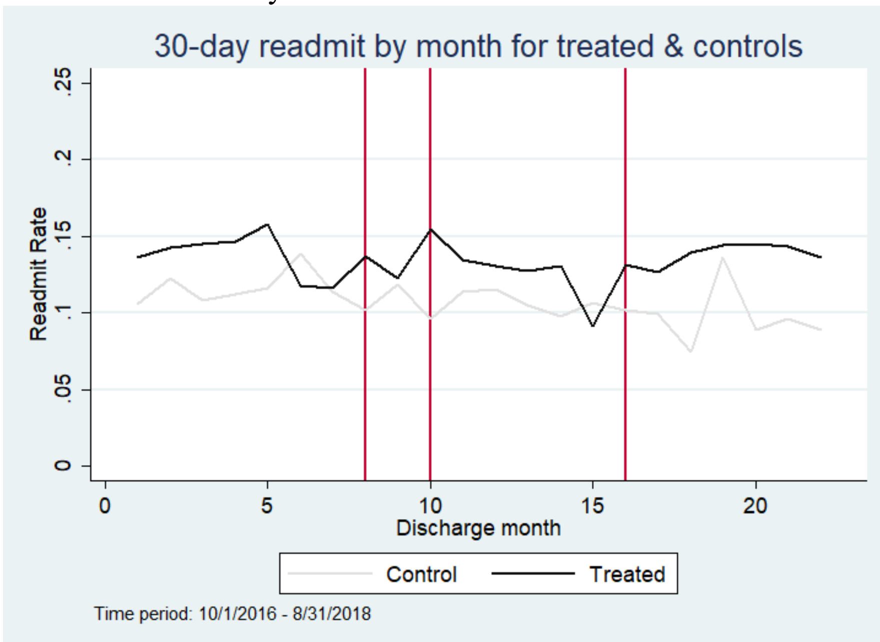
Figure 1.3 Time trend of cost outcomes for treated and control units.



Note: The black and grey lines indicate monthly average cost for patients discharged from treated and control units and are based on cost data from patients discharged across all units in a treatment group for a given month. The three vertical bands give approximate timings of ACU implementation on treated units. Discharge month starts from 1 (October 2016) and runs through 23 (August 2018).

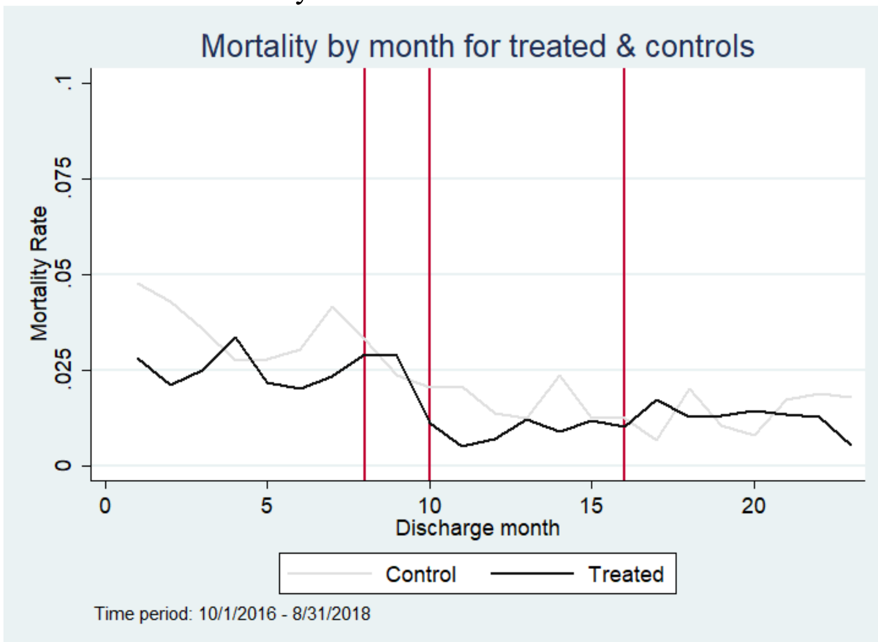
Trends in quality of care measures are shown in Figures 1.4 and 1.5. Pre-trends in 30-day readmissions (Figure 1.4) are initially parallel—though at different levels—but diverge in the months immediately preceding the first implementation of SIBR. Similarly, Figure 1.5 shows pre-trends for mortality begin at different levels between treatment groups and trends do not appear parallel due to a spike in mortality among treated units during a time when mortality fell among control units.

Figure 1.4 Time trend of 30-day readmits for treated and control units.



Note: The black and grey lines indicate monthly 30-day readmission rates for patients discharged from treated and control units and are based on readmission data from patients discharged across all units in a treatment group for a given month. The three vertical bands give approximate timings of ACU implementation on treated units. Discharge month starts from 1 (October 2016) and runs through 23 (August 2018).

Figure 1.5 Time trend of mortality rate for treated and control units.



Note: The black and grey lines indicate monthly mortality rates for patients discharged from treated and control units and are based on mortality data from patients discharged across all units in a treatment group for a given month. The three vertical bands give approximate timings of ACU implementation on treated units. Discharge month starts from 1 (October 2016) and runs through 23 (August 2018).

4 Results

4.1 Descriptive Results

Table 1.1 summarizes key variables for treated and control units. Unless otherwise noted, all differences mentioned below are statistically significant. Treated units saw a greater weekly volume of patients (27.3 vs. 10.2 weekly discharges for treated and control units, respectively). The difference in patient volumes between treatment groups is driven by the inclusion of general medicine units in the treated group which are the busiest, and largest, units in the hospital[10]. Patients discharged from treated units had slightly greater LOS than those on control units (4.84 and 5.34 days,

[10] Appendix A contains additional tables displaying unit level descriptive information on outcomes and covariates for treated units and the same data grouped by unit specialty for control units.

respectively). Quality measures included 30-day readmissions, which were similar between the groups, and mortality which was greater in control units (3.8% vs. 1.1%). The elevated mortality rate in control units is due to a combination of two factors: 1) inclusion of ICUs in the control group and 2) the restriction that patients in this study must stay on a single unit during their entire admission[11]. Units' use of central venous catheters did not differ significantly between treatment groups. Control units had higher HCAHPS survey ratings in all three included categories: nursing communication, doctor communication, and overall rating.

[11] One of the criteria for inclusion in the study sample is that patients must have stayed on a single unit during their entire admission. This criterion ensures that patients who stayed on treated units benefited from SIBR during their entire stay and patients who stayed on control units were not "partially treated." Patients who stay on the ICU during their admission typically transfer to a lower acuity unit (e.g. general medicine or medical progressive unit) as their condition improves. Limiting ICU patients to those who stayed *only* on the ICU during their admission selects for a group with higher mortality. These patients are often transferred in serious condition from other facilities and expire in the ICU. I have included a specification that excludes ICU patients from the analysis to address this possibility of this population impacting estimation.

Table 1.1 Descriptive statistics of treated and untreated units.

Measure	Overall	Treated Units	Control Units	p-value
N	29,485	18,891	10,594	
Weekly discharges	16.98 (13.61)	27.26 (10.94)	10.16 (10.59)	< 0.001
LOS	5.02 (4.82)	4.84 (4.53)	5.34 (5.29)	< 0.001
Quality outcomes				
30-day readmission	0.12 (0.33)	0.12 (0.33)	0.11 (0.32)	0.003
Mortality	0.02 (0.14)	0.01 (0.11)	0.04 (0.19)	< 0.001
Weekly central line use	179 (165)	174 (116)	182 (189)	0.321
HCAHPS summary				
Nurse communication	82.02 (10.16)	80 (7.97)	83.77 (11.45)	< 0.001
Doctor communication	82.08 (9.88)	79.13 (8.02)	84.63 (10.6)	< 0.001
Overall rating	75.92 (13.86)	72.44 (8.96)	78.93 (16.41)	< 0.001
Cost outcomes				
Total cost	15,868 (15,332)	15,265 (14,200)	16,942 (17,115)	< 0.001
Daily cost	4,009 (3,839)	3,951 (3,728)	4,113 (4,029)	0.001
Patient details				
MD panel size	5.79 (3.84)	6.11 (3.64)	5.22 (4.13)	< 0.001
Case mix index	1.77 (1.46)	1.72 (1.17)	1.87 (1.85)	< 0.001
Discharged home	0.58 (0.49)	0.53 (0.5)	0.67 (0.47)	< 0.001
Discharged to SNF	0.19 (0.39)	0.24 (0.43)	0.1 (0.3)	< 0.001
Medicare	0.42 (0.49)	0.43 (0.5)	0.39 (0.49)	< 0.001
Age	62.07 (18.52)	63.16 (18.67)	60.14 (18.09)	< 0.001
Female	0.54 (0.5)	0.55 (0.5)	0.53 (0.5)	0.002
White	0.79 (0.4)	0.78 (0.41)	0.82 (0.38)	< 0.001
Hispanic	0.02 (0.15)	0.02 (0.15)	0.02 (0.15)	0.496

Other notable differences between the treated and control units include the percentage of patients discharged to SNFs, CMI, and proportion of patients on Medicare. These differences are driven by the mix of units in the treated and control groups. Treated units had a greater proportion of patients who were discharged to SNFs (24% vs. 10%). This difference is due to the inclusion of orthopedic units, which discharge patients to SNFs at a much higher rate than typical units, in the treated group. Case mix index, a measure of patients' complexity of care, was greater among control units than treated (1.87 vs. 1.72, respectively). Control units included cardiology units (CMI =

2.01) and ICUs (CMI = 3.93) that treat patients with high acuity conditions requiring complex treatment. Finally, the proportion of patients on Medicare was greater for treated units than controls (43% vs. 39%, respectively). This difference was driven by the inclusion of the OB/GYN units in the control group which treat a much younger population that is almost never (3%) on Medicare. Total cost of care was greater for patients who stayed on control units ($16,942 vs. $15,265 for treated units). Similarly, daily cost of care was greater for control units as well.

4.2 Length of Stay

Table 1.2 contains estimates of the effect of SIBR on LOS. This table (as well as Tables 1.3 & 1.5) shows four iterations of the specification in equation (1). Model 1 contains no covariates, no weighting of observations, and no restrictions on units included in the control group. Model 2 includes covariates without weighting or unit restrictions. Model 3 includes covariates and weights observations by the number of discharges from each unit in a given day. Model 4 is identical to 3 but excludes ICUs from the control group. Due to significant baseline differences in covariates among the treatment groups and variance in weekly discharge volume, model 3 is the preferred specification. All results mentioned moving forward are based on 3 unless otherwise noted. The top panel of each table shows results for the entire sample, the bottom panel shows results for only patients who were discharged to SNFs.

Table 1.2 Effect of SIBR on LOS.

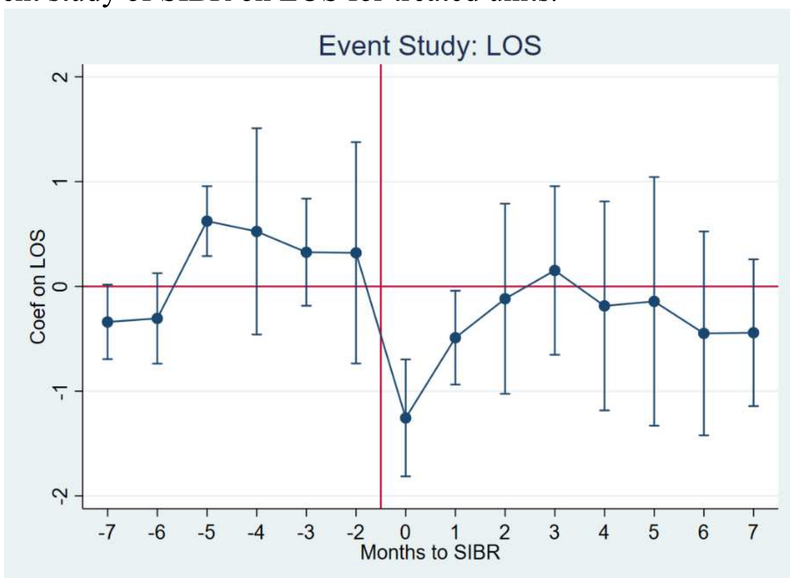
	Mean	(1)	(2)	(3)	(4)
Panel A: Full Sample					
LOS	5.02	-0.475	-0.411	-0.275	-0.335
		(0.344)	(0.297)	(0.246)	(0.255)
N		*8,841*	*8,841*	*8,841*	*8,088*
Panel B: SNF Discharges					
LOS	6.998	-1.746**	-1.081	-1.067*	-1.085*
		(0.544)	(0.547)	(0.463)	(0.475)
N		*3,453*	*3,453*	*3,453*	*3,378*
Specification					
Includes covariates			x	x	x
Weighted observations				x	x
Excludes ICUs					x

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Observations are unit-days. Weighting indicates that observations are weighted by the daily number of discharges from a given unit. Standard errors are shown below point estimates in parenthesis and are clustered at the unit level. Panel A includes all 29,485 patient-encounters (aggregated to a panel of unit-day observations) and Panel B includes 5,579 patient-encounters that resulted in the patient being transferred to a skilled nursing facility (SNF).

On average, SIBR reduced patients' LOS by approximately 6 hours (0.275 days) from an average LOS of 5 days. Though this reduction is not statistically significant, the economic impact could be quite large considering the high daily cost of care and the large number of patients impacted. For patients discharged to SNFs, SIBR had a much greater effect, reducing LOS by approximately one day (-1.067 days) from an average LOS of 7 days.

As noted in Section 3.3, Figure 1.2 shows that LOS not only followed parallel paths between treatment groups prior to SIBR implementation, but also remained at similar levels. The average LOS in the pre-SIBR era was 5.1 days (std. dev. = 4.8) for treated units and 5.4 days (std. dev. = 5.2) for control units. Average LOS in the period after all SIBR implementations had occurred was 4.6 days (std. dev. = 4.2) for treated units and 5.3 days (std. dev. = 5.4) for control units. This corresponds to a half-day reduction in average LOS for treated units and less than a 0.1 day reduction in average LOS for control units from the beginning to the end of the study period. This difference in reductions, while not as rigorously estimated as regression results, does suggest that SIBR impacted patients' LOS.

Figure 1.6 Event study of SIBR on LOS for treated units.



Note: The figure displays coefficients and clustered standard errors for an event study, based on equation (3) in Section 3.2, showing dynamic treatment effects of SIBR on LOS. The marks represent point estimates and the vertical capped bars represent standard errors which have been clustered at the unit level. The y-axis gives the coefficients' values and the x-axis shows relative time to initial SIBR implementation in months. Negative values on the x-axis represent months prior to treatment and positive values represent months after treatment. The vertical line shows approximate treatment timing (treatment actually occurs during month zero, but the bar is offset to more clearly show the coefficient estimate in month zero).

Figure 1.6 presents an alternate approach to estimating the effect of SIBR on LOS by allowing the effect to vary over time. First, Figure 1.6 adds additional evidence that no pre-trends exist for LOS among treated units. Coefficients on "leads" in treatment (i.e. months that preceded treatment in the figure) are not significantly different than zero, indicating that LOS evolved in parallel for treated and control units prior to implementation. Second, SIBR induced a strong reduction on LOS immediately following implementation. This effect was strongest in the first month of implementation, a reduction in LOS of greater than one day compared to the baseline. The effect tapered in the second month post-implementation, and was indistinguishable from baseline levels after the third month. These results contextualize the insignificant overall effect of SIBR on LOS shown in Table 1.2 (Panel A): SIBR may have had a strong initial effect on LOS, but over time outcomes returned to baseline.

4.3 Quality Outcomes

Reductions in patients' LOS were not accompanied by any change in 30-day readmission rates or mortality (Table 1.3). Table 1.4 shows that HCAHPS survey scores reflecting patient satisfaction in three categories (nursing communication, doctor communication, and overall rating) remained unchanged by SIBR. However, Table 1.4 provides evidence that. SIBR implementation decreased units' usage of central lines by approximately 45 days per month (-45.89). The mean number of days per month that patients spent with a central line was 180.6 on each unit. A 45-day reduction represents a 25% reduction from the mean. The notable reduction in central line usage after SIBR is likely attributable to the inclusion of central lines as an explicit topic of conversation on the checklist that care teams used during SIBR.

Table 1.3 Effect of SIBR on patient-level quality outcomes.

	Mean	(1)	(2)	(3)	(4)
Panel A: Full Sample					
30-day readmit	12.1%	0.0171	0.0169	0.0148	0.0127
		(0.0100)	(0.00979)	(0.00872)	(0.00857)
Mortality	2.1%	-0.00524	-0.00538	-0.00411	0.00497
		(0.0112)	(0.0120)	(0.00875)	(0.00264)
N		*8,841*	*8,841*	*8,841*	*8,088*
Panel B: SNF Discharges					
30-day readmit	11.5%	-0.00201	-0.00226	0.00184	0.00194
		(0.0223)	(0.0222)	(0.0185)	(0.0187)
N		*3,453*	*3,453*	*3,453*	*3,378*
Specification					
Includes covariates			x	x	x
Weighted observations				x	x
Excludes ICUs					x

Note: * p < 0.05, ** p < 0.01 , *** p < 0.001. Observations are unit-days. Weighting indicates that observations are weighted by the daily number of discharges from a given unit. Standard errors are shown below point estimates in parenthesis and are clustered at the unit level. Panel A includes all 29,485 patient-encounters (aggregated to a panel of unit-day observations) and Panel B includes 5,579 patient-encounters that resulted in the patient being transferred to a skilled nursing facility (SNF). Mortality outcomes are not applicable to patients discharged to SNFs because all patients were discharged alive by definition.

Table 1.4 Effect of SIBR on unit-level quality outcomes.

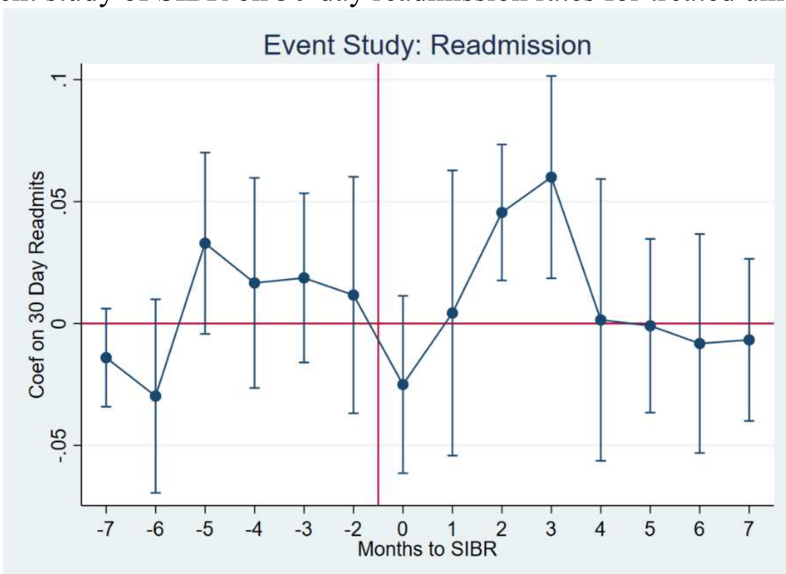
	Mean	SIBR
Panel A: Adverse Events		
Central line days	180.6	-45.89*
		(21.14)
Num. adverse events	0.6	0.116
		(0.135)
N		*436*
Panel B: HCAHPS Measures		
Nurses' communication	81.7%	-0.0137
		(0.0227)
Doctor's communication	81.7%	0.0078
		(0.0278)
Overall care quality	75.7%	-0.0074
		(0.0182)
N		*355*

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Observations are unit-months. All outcome variables represent separate regressions. Central line days are the total number of patient days spent with a central line in use in a given unit-month. Adverse events include patient falls and HACs. HCAHPS scores are measured in percentage of patients responding “Excellent” to the category. All regressions included covariates and were weighted by the monthly number of discharges from a given unit. Standard errors are shown below point estimates in parenthesis and are clustered at the unit level.

Taken together with the reduced LOS in the previous section (especially for SNF patients), improved (or unchanged) quality outcomes indicate an overall increase in value for patients. If SIBR had caused LOS to decrease and readmissions to increase, then the reduction in LOS may, ultimately, lead to increased resource utilization and lower value for patients due to subsequent rehospitalization.

An event study was also performed for 30-day readmissions (Figure 1.7) and mortality (Figure 1.8). Coefficients on leads of SIBR implementation for 30-day readmission and mortality do not differ significantly from zero indicating pre-trends in outcomes were approximately parallel. Figure 1.7 also shows that, two to three months after implementation, readmission rates may have actually risen in SIBR units compared to control units. Although this spike in 30-day readmission rates may be statistically significant, it corresponds to only a 0.6 percentage point increase in readmission rates, or approximately one additional readmission per month.[12] This trend is not sustained as estimates return to zero in the fourth month after implementation and remain there. Mortality (Figure 1.8) showed no difference between treatment groups at any point in the study timeframe.

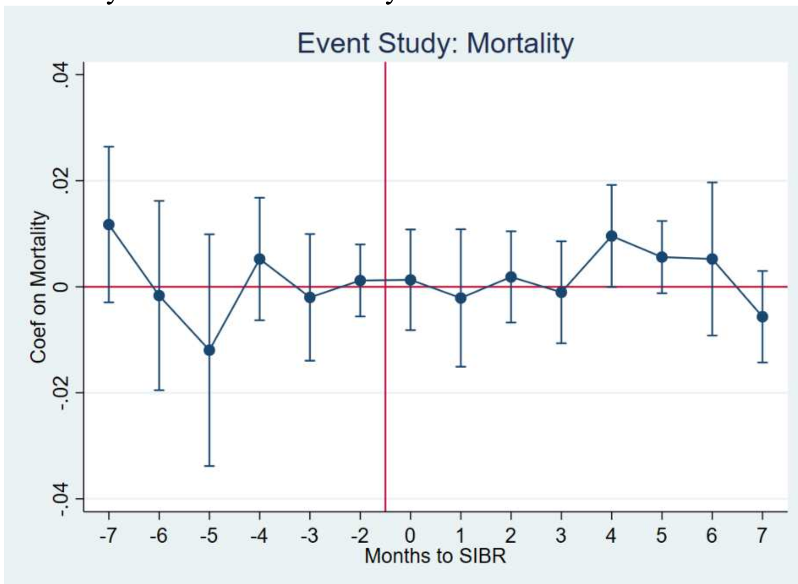
Figure 1.7 Event study of SIBR on 30-day readmission rates for treated units.



Note: The figure displays coefficients and clustered standard errors for an event study, based on equation (3) in Section 3.2, showing dynamic treatment effects of SIBR on patients' 30-day readmission rates. The marks represent point estimates and the vertical capped bars represent standard errors which have been clustered at the unit level. The y-axis gives the coefficients' values and the x-axis shows relative time to initial SIBR implementation in months. Negative values on the x-axis represent months prior to treatment and positive values represent months after treatment. The vertical line shows approximate treatment timing (treatment actually occurs during month zero, but the bar is offset to more clearly show the coefficient estimate in month zero).

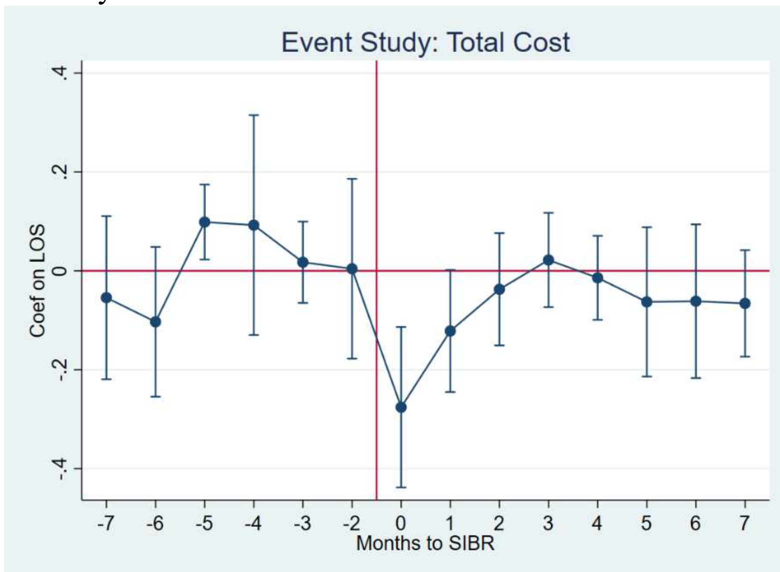
[12] Treated units averaged 117 discharges per month. The mean 30-day readmission rate for treated units was 12.48% which corresponds to 14.6 readmission cases per month. Increasing the readmission rate to 13.11% (a 5% increase) would result in 15.4 readmission cases per month.

Figure 1.8 Event study of SIBR on mortality rates for treated units.



Note: The figure displays coefficients and clustered standard errors for an event study, based on equation (3) in Section 3.2, showing dynamic treatment effects of SIBR on patients' mortality. The marks represent point estimates and the vertical capped bars represent standard errors which have been clustered at the unit level. The y-axis gives the coefficients' values and the x-axis shows relative time to initial SIBR implementation in months. Negative values on the x-axis represent months prior to treatment and positive values represent months after treatment. The vertical line shows approximate treatment timing (treatment actually occurs during month zero, but the bar is offset to more clearly show the coefficient estimate in month zero).

Figure 1.9 Event study of SIBR on total cost for treated units.



Note: The figure displays coefficients and clustered standard errors for an event study, based on equation (3) in Section 3.2, showing dynamic treatment effects of SIBR on patients' total cost of care. The marks represent point estimates and the vertical capped bars represent standard errors which have been clustered at the unit level. The y-axis gives the coefficients' values and the x-axis shows relative time to initial SIBR implementation in months. Negative values on the x-axis represent months prior to treatment and positive values represent months after treatment. The vertical line shows approximate treatment timing (treatment actually occurs during month zero, but the bar is offset to more clearly show the coefficient estimate in month zero).

4.4 Cost Outcomes

The impact of SIBR on cost outcomes is described in Table 1.5. Overall, SIBR did not impact total costs or daily costs in a meaningful way. However, when the effect of SIBR was allowed to vary over time, there does appear to be a strong initial reduction in total cost following implementation (Figure 1.9). The effect follows a similar pattern to the dynamic effect of SIBR on LOS (Figure 1.6) where the effect is strongest in the first month following implementation and tapers to zero by the third month. Figure 1.9 also shows that pre-trends were insignificant for total cost as coefficients on treatment leads were insignificant.

Table 1.5 Effect of SIBR on cost outcomes.

	Mean	(1)	(2)	(3)	(4)
Panel A: Full Sample					
Total Cost	$15,868	-0.0178	0.0298	0.0288	0.0187
		(0.0471)	(0.0407)	(0.0326)	(0.0323)
Daily Total Cost	$4,275	-0.0534	-0.000121	-0.00464	0.00401
		(0.0463)	(0.0372)	(0.0323)	(0.0333)
N		*8,841*	*8,841*	*8,841*	*8,088*
Panel B: SNF Discharges					
Total Cost	$19,941	-0.155*	-0.0314	-0.0282	-0.0251
		(0.0551)	(0.0525)	(0.0505)	(0.0518)
Daily Total Cost	$3,149	-0.00518	0.0308	0.0461	0.0525
		(0.0359)	(0.0352)	(0.0353)	(0.0360)
N		*3,453*	*3,453*	*3,453*	*3,378*
Specification					
Includes covariates			x	x	x
Weighted observations				x	x
Excludes ICUs					x

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Observations are unit-days. Weighting indicates that observations are weighted by the daily number of discharges from a given unit. Standard errors are shown below point estimates in parenthesis and are clustered at the unit level. Panel A includes all 29,485 patient-encounters (aggregated to a panel of unit-day observations) and Panel B includes 5,579 patient-encounters that resulted in the patient being transferred to a skilled nursing facility (SNF). Cost outcome variables were logged in each regression so coefficients approximate percent changes in outcome variables due to SIBR implementation. Means of outcome variables are given in levels.

Comparing the trends in cost between treatment groups in Figure 1.3, it is interesting that no cost savings are identified by the regression models as the control group trend appears to rise while the treated group's cost measures remain stable.[13] The distributions of total cost and total daily cost were skewed strongly to the left with a long right tail, making it possible that differences noted in Figure 1.3 were driven by a small

[13] Figure 3 also shows that daily cost measures were at similar levels for both treatment groups prior to SIBR implementation (mean daily cost for treated units = $3,484, mean for control units = $3,633). Post-implementation, patients on treated units had an average daily cost of $4,091 and those on control units averaged $4,991. Daily costs for treated units rose only $607 compared to $1,358 for control units, suggesting that SIBR may have some impact on cost.

number of influential observations. However, the analysis sample excludes patients with costs above the 99th percentile which should mitigate this effect.

4.5 Effects on Individual SIBR Units

Up to this point, all analyses lumped together the seven units that implemented SIBR. Table 1.6 provides estimates of SIBR's effect on outcomes for individual treated units and reveals additional subpopulations that may have benefitted from SIBR. Among the treated units, SIBR reduced LOS on 5 of the 7 units with reductions on two units (Med2, a general medicine unit; and Onc, a medical oncology unit) large enough to rule out a null effect.   The reduction in LOS on the medical oncology unit was of similar magnitude (-0.589). As with reductions to LOS for SNF patients, the shorter LOS on Med2 and Onc were not accompanied by increased readmissions or mortalities. This is further confirmation that the reduction in resource utilization from SIBR is not occurring at the cost of quality of care.

Table 1.6 Effect of SIBR on individual treated units' outcomes.

Outcome	**3MP**	**4EW**	**5E**	**5S**	**6S**	**Ort1**	**Ort2**
LOS	-0.331	0.0672	-0.0520	-0.504	-0.589*	0.218	-0.194
	(0.260)	(0.210)	(0.213)	(0.239)	(0.259)	(0.221)	(0.231)
Total Cost	-0.0680	0.0836*	0.0391	0.0185	0.0193	0.0014	0.147**
	(0.0421)	(0.0322)	(0.0362)	(0.0404)	(0.0428)	(0.0390)	(0.0389)
30-day readmit	0.0337	0.0251*	0.0306	0.0050	0.0143	0.0115	0.0006
	(0.0180)	(0.00836)	(0.0162)	(0.0112)	(0.0170)	(0.0102)	(0.0126)
Mortality	0.0026	-0.0155	-0.0025	-0.0105	-0.0160	-0.0003	-0.0007
	(0.0154)	(0.0137)	(0.0144)	(0.0124)	(0.0148)	(0.0118)	(0.0121)
N	*4,838*	*5,038*	*4,992*	*5,024*	*4,984*	*4,997*	*4,993*

Note: + p = 0.057, * p < 0.05, ** p < 0.01 , *** p < 0.001. Observations are unit-days. All units and outcome variables represent separate regressions. Regressions for a given unit include all control units and no additional treated units. All regressions included covariates and were weighted by the daily number of discharges from a given unit. Standard errors are shown below point estimates in parenthesis and are clustered at the unit level. Total cost was logged so coefficients represent approximate percent change due to SIBR implementation.

4.6 Robustness

Variations in the specification tested as robustness checks did not make a substantive difference to results as point estimates remained stable and standard errors changed in small ways. Furthermore, when data were aggregated to unit-week and unit-month observations, both Med2 and Onc showed strongly significant reductions in LOS under all specifications. Taken together, these results support the conclusion that SIBR was able to reduce patients' LOS on these units.

Another result with strong statistical significance, LOS reduction for SNF patients, was also robust to these variations in models. While the model containing no covariates had a significantly greater magnitude (1.75 day reduction in LOS), the other three models remained statistically significant and had similar point estimates.

Regression results for patients' LOS, readmission rates, mortality, and cost of care were checked for robustness with a several variations in model specifications. The secondary models included in regression tables (models 1, 2, and 4 in Tables 1.2, 1.3, and 1.5) account for several concerns raised by differences in the treatment groups found in Table 1.1. The first of these alternate models assesses the impact of removing covariates which differed significantly between units. Model 2 contains covariates but does not weight observations by their discharge volume (which was found to differ significantly between groups in Table 1.1). Finally, Model 4 removes intensive care units (ICUs) from the analysis. This is an important test as ICUs were only included in the control group and may operate differently from lower acuity units. Additional checks included aggregating observations to weeks and months rather than days.

5 Conclusions

Overall, this study provides evidence that SIBR can improve the value of inpatient care in some populations. Though SIBR did not appear to reduce costs, it did reduce resource utilization for some patients through shorter LOS. Furthermore, event study analysis showed that SIBR had strong initial reductions in LOS and cost that, had they been sustained, could drastically increase its impact on resource utilization. Patients who reaped the greatest benefits from SIBR included those discharged to SNFs and patients on two of the seven units that implemented SIBR: a general medicine unit (Med2) and a medical oncology unit (Onc). SIBR reduced units' use of central venous catheters, though it did not affect two of the most common measures of inpatient care quality: 30-day readmission rates and mortality rates. The reduction in resource utilization accompanied by improvements in quality measures (central line usage) shows the promise of SIBR as a policy that is capable of improving value in hospital care.

For inpatient care coordination schemes, like SIBR, to offer a viable alternative to contract-based solutions to the high cost of hospital care, like VBP programs, identifying where it is most effective is crucial. There are two dimensions of SIBR effectiveness to consider: the patient population for which SIBR is effective and the type of care team that is effective. The evidence in this study suggests two patient populations that might benefit from SIBR: patients who were discharged to SNFs and patients who have complex, chronic conditions like cancer. Patients discharged to SNFs had their LOS reduced by approximately one day. SNF patients require greater discharge planning than patients who are discharged home because case managers must find a facility that has capacity and accepts the patient's insurance. SIBR may have enabled earlier discharge planning by involving the case manager in daily rounds. Giving case managers extra time to contact facilities and payors can avoid situations where the patient is ready to be discharged but must stay additional days before an opening can be found at an appropriate long-term care facility.

The other patient group who benefited from SIBR are cancer patients. One of the units that implemented SIBR was a medical oncology unit which reduced patients' LOS by 0.6 days. The improved care coordination from SIBR could benefit these patients through more efficient treatment. SIBR can improve the efficiency of treatment plans through reduced delays in treatment, such as faster drug administration through daily collaboration between patients' attending physician and pharmacist. Patients with complex care plans, like cancer patients, could especially benefit from the improved communication and coordination among care team members as there are simply more opportunities for SIBR to improve coordination. These types of improvements do not only depend on patients' needs, but on how SIBR is carried out by care teams.

Another difference in outcomes that could be due to care teams' effectiveness in practicing SIBR comes from its impact on individual units. Two general medicine units implemented SIBR, Med1 and Med2. Patients' LOS on Med1 was not affected by SIBR implementation while patients who stayed on Med2 had a modest reduction in LOS. Additionally, 30-day readmissions and total cost of care slightly increased on Med1 and were unaffected on Med2. These units treat very similar patient populations, but had quite different results from SIBR. The difference between them comes down to staffing. Med1 is staffed by a private hospitalist service that consists entirely of attending physicians who have completed their training and residency. The staff of Med2 includes residents who are still completing their training. Residents, who have not had years of experience with traditional rounding schemes, may be more likely to accept SIBR and practice it consistently.

This leads to a promising avenue for future research investigating whether earlier introduction of SIBR during a physician's training could improve its impact on care. A prospective study pairing teams of physicians—one practicing SIBR and the other traditional rounding—at various levels of training could identify if physicians earlier in their career perform better using SIBR. These results would inform a policy recommendation for when SIBR should be introduced to physicians to produce the greatest impact on care.

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THE EFFECT OF CARE COORDINATION ON ICU TRANSFERS

1 Introduction

Care coordination models are proliferating through the US healthcare system on the promise of improved patient and provider satisfaction, improved clinical outcomes, and reduced costs (Cao et al. 2018; Gausvik et al. 2015; Halm et al. 2003; Kara et al. 2015; O'Leary et al. 2010; Stein et al. 2015; Vazirani et al. 2005). In inpatient settings, care coordination often takes the form of interdisciplinary care teams. The benefits of care coordination models in inpatient acute care hospitals align with the Centers for Medicare & Medicaid Services (CMS) push to incentivize care quality as outlined in the CMS Quality Strategy (Centers for Medicare & Medicaid Services 2015). However, previous studies of inpatient care coordination models have returned mixed results and focused on a narrow set of clinical outcomes (Huynh et al. 2017; Jala et al. 2019; Pannick et al. 2015). Pannick et al. (2015), conducting a systematic review of 30 papers on interdisciplinary care teams, found that most studies included length of stay (LOS), hospital readmission, and in-hospital mortality as primary outcomes. I investigate an additional avenue along which care coordination models could generate value for patients, hospital systems, and insurers: reducing intra-hospital transfers to intensive care units (ICUs).

Limiting the number of patients who experience an avoidable "upstream" transfer from a low-acuity unit to a high-acuity one, like an ICU, could improve patient outcomes while preserving ICU capacity for the sickest patients. For some patients, ICU resources can be lifesaving. These are the most critically ill patients who require close monitoring, specialized interventions, or are deteriorating rapidly on low-acuity hospital units

(Simchen et al. 2007). Allocating ICU capacity to these patients provides the highest-value use of ICU beds. Guidelines for admission and triage emphasize the autonomy of the intensivist(s) overseeing the ICU to assess patients on an individual basis (Nates et al. 2016). However, in practice, this results in substantial variation from these guidelines (Walter, Siegler, and Hall 2008).

Care coordination on low-acuity units could aid in ICU admission decisions by providing more accurate information on patients' conditions. Better understanding the conditions of patients throughout the hospital allows intensivists to make an informed decision about which patients would most benefit from an ICU stay and to preserve capacity appropriately. Furthermore, care coordination could reduce upstream transfers by providing better care for patients on low-acuity units, decreasing the likelihood of an unexpected decompensation requiring critical care.

In inpatient acute care settings, care coordination usually takes the form of interdisciplinary care teams. Team composition varies, but most include physicians, physician trainees, nurses, and case managers (Pannick et al. 2015). In this paper, the typical interdisciplinary team was accompanied by pharmacists, respiratory therapists, and other allied health professionals. The implementation studied here is called structured interdisciplinary bedside rounding (SIBR). SIBR is one element of a care coordination model called Accountable Care Units developed by Dr. Jason Stein at Emory University starting in 2010 (Stein et al. 2015).

I estimate the effect of SIBR, implemented at the level of hospital units, on utilization of ICU resources using a rich and novel data set from a 500+ bed teaching hospital. Following patient movements within a hospital admission requires granular data. I leverage administrative data from the hospital system's enterprise data warehouse to reconstruct 23,707 inpatient admissions tracking patients' daily movement within the hospital. Using these data and a staggered roll-out of SIBR on several hospital units between May 2017 and January 2018, I focus on three "pathways" within the hospital to identify changes in transfers from low-acuity units to ICUs.[14] The pathways used in this study are: general medicine, cardiology, and neurology. These pathways were chosen because they represent a large proportion of patients seen in the hospital, they each contain an ICU, and they contain hospital units that implemented SIBR.

I follow patients who were admitted to non-ICUs and estimate the effect of being admitted to a unit that implemented SIBR on the likelihood of being transferred to an ICU. As an additional measure, I estimate the change in patients' length of stay in an ICU after transfer from SIBR units versus non-SIBR units. Though it is a relatively rare occurrence—6% of patients experienced an upstream transfer to the ICU—these patients put additional demand on ICU beds and are among the most critically ill patients in the hospital.

I find that initial admission to a care coordinated unit does not reduce the likelihood of transfer to an ICU. Conditional on being transferred from an initial stay on a low-acuity unit, patients' length of stay in the ICU was also unaffected by care coordination in the initial unit. Taken together, these results suggest that SIBR does not affect ICU transfers on the external margin or the internal margin.

Identifying these effects relies on a difference-in-differences approach that compares the trends in ICU transfers between and within two groups of units: those that

[14] A pathway is a group of units among which patients are frequently transferred.

implemented SIBR and those that did not. This comparison yields causally interpretable effects assuming: 1) these two groups of units were on similar paths prior to implementation of SIBR, and 2) there were no additional policies that affected individual units' ICU transfer rate. I present figures suggesting that both groups' ICU transfer rate followed a parallel trend prior to the implementation of SIBR. Hospital administrators and physicians were interviewed during the analysis and were unaware of any unit-level policies that would have affected ICU transfers. Thus, a causal interpretation of the results is possible.

The paper proceeds as follows: Section 2 provides background on care coordination implementation and ICU utilization, Section 3 details data and methods used in this paper, Section 4 contains the results of the analysis, Section 5 discusses the results, and Section 6 concludes.

2 Background

2.1 Structured Interdisciplinary Bedside Rounding

The care coordination model, Accountable Care Units, features SIBR as a means to improve communication between care team members and patients. The Accountable Care Units model was developed at Emory University and has since been adopted at hospital systems throughout the US, Canada, and Australia (Chadwick 2018). This model emphasizes several key elements that treat a hospital unit as a "clinical microsystem." These elements include: SIBR, care teams dedicated to an individual hospital unit, performance reporting focused on the unit, and co-leadership between nurses and physicians (Stein et al. 2015). The goal of the model is to improve the experience of patients—and clinicians.

Like other interdisciplinary care coordination models, evidence for the effectiveness of the ACU model is mixed. Previous work indicates that the ACU model can reduces patients' LOS, variable costs, and improve patient and provider satisfaction (Gausvik et al. 2015; Kara et al. 2015; Stein et al. 2015). However, these effects were not confirmed in all studies (Huynh et al. 2017; Jala et al. 2019; O'Leary et al. 2010, 2011; Pannick et al. 2015).

While the Accountable Care Units model encompasses several elements, SIBR is the focus of this analysis. In the hospital at which this study took place, the only element of Accountable Care Units that was consistently implemented was SIBR. Unit level data reporting had been a standard before, during, and after the analysis. Co-location of a physician's patients on a single unit did not occur due to logistical constraints. Nurse and physician co-leadership existed in various forms, but was not emphasized by hospital administration nor given a large role in SIBR implementation.

SIBR differs from traditional medical rounding in several key ways. Communication between the members of a patient's care team is emphasized by requiring all members to be present during the rounds. Furthermore, the structured conversation that occurs during SIBR allots each care team member a speaking role and ensures that all voices are heard. SIBR also improves communication between the care team, the patient, and the patient's family. Locating SIBR at the bedside, in front of the patient and their family, invites more communication between the care team and the patient. Care teams are encouraged to round at the same time each day so the family can plan ahead to attend.

The communication fostered by SIBR offers potential to reduce upstream transfers to the ICU. Within the care team, interactions across specialty and profession enable faster diagnosis and response to an unexpected deterioration in patients' health. This knowledge could help avoiding a rapid decompensation requiring ICU care.

The benefits of improved communication within the care team are augmented by improved communication with the patient and their family. Distrust between patients and physicians, especially in the impersonal setting of hospitals, is a longstanding obstacle to good care (Baron and Berinsky 2019; Peabody 1927). Though SIBR is not a panacea for doctor-patient relations, it is a step toward more personalized care. That patients and their families prefer this approach is borne out in previous literature showing higher patient satisfaction on units using SIBR (Cao et al. 2018; Halm et al. 2003). Better rapport between the patient, the family, and the care team, fostered during SIBR, builds trust and interpersonal relationships. Trust, in turn, allows patients—and clinicians—to be candid about health concerns, treatment options, discharge plans, emotional and psychological context, and family situations all of which paint a more accurate and holistic picture of a patient's current health status. This picture could reveal details that help avoid a transfer to the ICU.

2.2 Intensive Care Units

The evolution of modern ICUs as centers of specialized therapies and near-constant monitoring of high-risk patients follows from a history of increasing specialization in medical care. A polio outbreak in Denmark in 1952 is often cited as the first implementation that inspired the concept of the modern ICU (Kelly et al. 2014). Though details vary from facility to facility, ICUs have several defining shared features.

First, ICU patients are typically the most critically ill and unstable of any in the hospital. Exceptions include patients offered palliative care who are so ill that their prognosis cannot be improved with more intensive care. Second, the ratio of patients to nurses is much lower on ICUs. A general medicine ward (the lowest acuity type of unit) may have five patients per nurse whereas an ICU has between one and two patients per nurse. Thirdly, ICUs offer specialized interventions not found in other hospital units such as cerebral spinal fluid drains, invasive mechanical ventilation, and extracorporeal membrane oxygenation (Nates et al. 2016).

The combination of high staffing requirements and complex medical interventions makes ICU care expensive. ICUs account for 15 – 40 percent of hospitals' operating costs, despite making up a small proportion of total hospital beds. To offset their high cost, ICUs tend to operate at, or near, full capacity (Kim et al. 2015; Meisami et al. 2019). Managing ICU capacity is a balancing act between offsetting the costs of operating an ICU by maintaining high utilization and preserving capacity for incoming patients (Kc and Terwiesch 2011).

Capacity constraints in the ICU can disrupt patient flow throughout a hospital, negatively impacting patient outcomes across all hospital units. Patients admitted to acute care hospitals are typically transferred from high-acuity units (e.g. ICUs) to lower-acuity units (e.g. progressive care or general medicine units) as their condition improves (Kim et al. 2015). However, incoming patients who would ideally be placed in ICU beds may be temporarily placed on lower acuity floors when there are no ICU beds available. These patients are then transferred "upstream" when an ICU bed opens (Louriz et al. 2012). Previous research indicates that patients transferred from low-acuity to high-acuity units experience greater mortality and longer LOS than patients who are admitted to the ICU and transfer "downstream" and those who never enter the ICU (Escobar et al. 2011). Furthermore, delaying transfer to the ICU from a low-acuity unit increases patients' risk of death (Sankey et al. 2016).

3 Data & Methods

3.1 Data

Assessing changes in rates of intra-hospital transfers within a single patient admission requires granular data. It is not sufficient to know the hospital unit from which a patient was discharged or even the complete set of hospital units on which a patient stayed. The data must show the order in which the patient stayed on each unit of their admission, and, ideally, the amount of time (and money) spent at each unit.

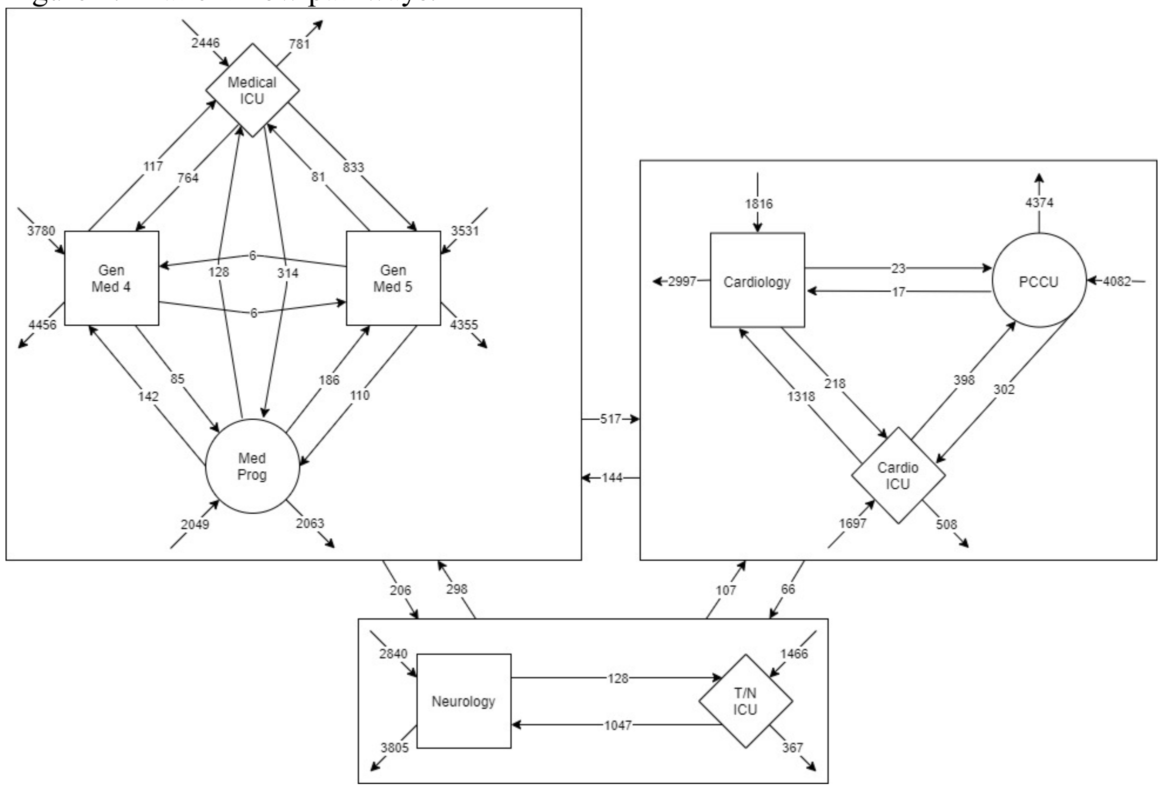
To produce this data set I abstracted patient-level demographic, clinical, and financial data from an enterprise data warehouse for a 500+ bed teaching hospital. For each patient-admission, a list of daily charges was pulled that indicate the unit on which each charge was incurred. From these data a patient's intra-hospital movement within a single admission can be reconstructed.

Every inpatient discharge that occurred between April 1, 2017 and December 31, 2018 was included in the data abstraction.[15] Demographic data include patient age, sex, race and ethnicity. Clinical and administrative data include the billed diagnostic related group (DRG), locations within the hospital (hospital units), discharge disposition, and attending physician. Financial data include hospital unit-level charges for imaging, diagnostic, pharmacy, and laboratory services as well as labor costs for nursing services.

[15] Originally, data were pulled going back to October 1, 2016 (to allow for a longer pre-intervention period), but data fidelity issues made the first six months of data unusable.

Though data were pulled for every IP discharge during the study timeframe, the sample used for analysis was restricted to units that interacted with ICUs. Patient movement within the hospital generally follows distinct pathways that are defined along two dimensions: specialty and acuity. Patients do not move between specialties (i.e. a cardiology patient tends to stay on cardiology units, a neurology patient tends to stay on neurology units, etc.). A possible exception to this is general medicine patients who are capable of being treated on more specialized units. This may occur when general medicine units are at capacity. In addition to staying on units within a single specialty, patients tend to stay on units of decreasing acuity. The highest acuity units are ICUs followed by progressive care units followed by acute care units which are the lowest acuity level. Figure 2.1 shows the patient flow within the three pathways.

Figure 2.1 Patient flow pathways.



Note: The figure shows patient flow between units in each of the three pathways included in the analysis: general medicine, cardiology, and neurology (clockwise from top left). The shape outlining each unit indicates its acuity level: squares are low acuity units, circles are intermediate/progressive units, and diamonds are ICUs. The numbers displayed on each arrow indicate the total number of patients who moved from one unit to another. For example, 117 patients were transferred from Gen Med 4 to the Medical ICU. Arrows with their tail not connected to any unit indicate direct admissions to a given unit, arrows with their head not connected to any unit indicate discharges from a given unit. Finally, the arrows between pathways indicate patients that transferred from any unit within a given pathway to any unit in another pathway; a rare occurrence.

The patient-admissions included in the analysis sample respected the patient flow pathways explained above. Three specialties were chosen that each correspond to a distinct ICU: general medicine, cardiology, and neurology. The general medicine pathway includes two acute care general medicine units, one progressive care general medicine unit, and one medical ICU. The cardiology pathway includes two progressive care cardiology units, and one cardiology ICU. The neurology pathway includes a neurology unit with a mix of acute and progressive care beds and a trauma/neuro ICU. To be included in the analysis sample patients' entire admission must have taken place on some combination of these units. This excludes pediatric patients, labor and delivery, oncology services, orthopedic surgery patients, and psychiatric patients.

Within the three pathways that were included in this analysis, four lower acuity units implemented SIBR. In the general medicine pathway, the two general medicine wards and progressive care unit implemented SIBR. In the neurology pathway, the neurology unit implemented SIBR. None of the units in the cardiology pathway implemented SIBR. The specifications used in this analysis, discussed in the section below, are able to take advantage of both the staggered timing of SIBR implementation and the inclusion of lower acuity units that did not implement SIBR as "controls."

Ultimately, 23,707 patient-admissions were included in the analysis that occurred between April 1, 2017 to December 31, 2018. This time period was chosen to capture discharges both pre- and post-implementation of SIBR which was staggered across four units over a period of 10 months. The first unit to implement SIBR was a general medicine ward (Gen Med 4) on 5/3/17 followed by another general medicine ward (Gen Med 5) on 7/19/17, a medical progressive ward on 1/9/18, and a neurology ward on 1/10/18. Each observation indicates unit(s) on which a patient stayed during their admission, the order in which they stayed on those units, and the amount of time (in days) they spent on each unit.

Though the majority (74.5%) of patients stay on only a single unit during their entire admission, a significant proportion of patients do move between units. Because the care coordination treatment, SIBR, was implemented at the level of hospital units it can be difficult to classify observations as “treated” or “untreated” when the admission includes units that implemented the ACU model and some that did not. I chose to define treatment status using the initial unit on which a patient stayed. This seems like a logical choice because it can be enforced for all observations (even those who stay on a single unit), and the initial unit has the greatest influence on the treatment plan of a patient’s entire admission. There is one sub-analysis in which treatment status is classified using the second unit on which a patient stayed to assess the impact of care coordination after an initial stay on an ICU.

3.2 Analysis

The effect of SIBR on ICU transfers is examined at both external and internal margins. This is expressed as two primary research questions: 1) does an initial stay on a unit that has implemented SIBR reduce the likelihood of transfer to ICU? And 2) conditional on being transferred to an ICU from a non-ICU unit, does an initial stay on a SIBR unit reduce length of stay in the ICU? To estimate the effects of SIBR implementation on ICU transfers and length of stay I use a two-way fixed effects estimator that exploits the staggered implementation of SIBR on hospital units to identify its effect.

Two-way fixed effects estimators generalize the concept of difference-in-differences (DD) to account for multiple timings of treatment (SIBR) implementation.[16] Following Goodman-Bacon (2018) there are two key identifying assumptions in the two-way FE estimator specification: “variance weighted common trends”—a weaker version

[16] Recent work on two-way FE estimators such as Goodman-Bacon (2018), de Chaisemartin & D’Haultfoeuile (2020), and Callaway & Sant’Anna (2020) provides background on the method and detailed discussions of its strengths, weaknesses, and identifying assumptions.

of the classic parallel trends assumption—and time-constant treatment effects. In this analysis, I opt to show that the transfer rate from low-acuity units to ICUs does follow a parallel path for units that implemented SIBR and those that did not.

The second identifying assumption, time-constant treatment effects, is unlikely to hold in this case. Goodman-Bacon (2018) shows that when treatment effects vary over time the estimate is biased away from the true treatment effect. There are several remedies to this problem. First, an event-study specification can be employed to estimate the treatment effect. Second, the treatment effect can be modeled as a linear trend-break rather than a level-shift (Meer & West, 2013). Finally, because the bias introduced by violating this assumption leads to attenuation of the estimated treatment effect, the estimand returned by the two-way FE estimator can be interpreted as a lower bound on the true treatment effect. I employ the first strategy by additionally estimating an event-study specification and proceed with two-way FE estimation under the caveat that the estimate is likely a lower bound on the true treatment effect. In this case, a linear trend-break does not seem realistic given that the treatment effect likely levels off after a period of time rather than continuing on a changed slope.

3.2.1 Two-way Fixed Effects Specification

The two-way FE model employed in this analysis is a standard implementation shown in equation (1) below. This specification includes a treatment dummy, a vector of covariates, a hospital unit fixed effect, calendar time fixed effect, and an error term that is assumed to be normally distributed.

$$Y_{iut} = \beta T_{iut} + \delta X_{iut} + \theta_u + \mu_t + \varepsilon_{ut} \qquad (1)$$

The left-hand side of (1) contains the dependent variable for individual i seen initially on unit u and discharged from the hospital at time t. The right-hand side contains a treatment dummy, T_{iut}, which equals 1 if the patient was admitted to a unit that had implemented SIBR and 0 otherwise; fixed-effects for hospital unit, θ_u, and calendar time in months, μ_t; a vector of covariates, X_{iut}; and an error term that is clustered at the hospital unit level. The coefficient on the treatment dummy, β, estimates the average treatment effect. Equation (1) is estimated using OLS with standard errors clustered at the hospital unit level to account for correlated patient-level error terms within hospital units.

For analysis of ICU transfers, the dependent variable, Y_{iut}, takes on a value of 1 if the patient experienced a transfer to an ICU following an initial stay on a lower acuity unit. Therefore, OLS estimation of (1) yields a linear probability model (LPM) in which β approximates the change in a patient's likelihood of experiencing an upstream transfer if they stayed on a unit that implemented SIBR. When analyzing patients' length of stay in the ICU, the dependent variable takes on positive integer values corresponding to the number of days spent in the ICU. In this case, OLS returns an estimate of the change in ICU length of stay, measured in days, if a patient stayed on a unit that implemented SIBR.

3.2.2 Event Study Specification

Estimation of the event-study model is carried out using the specification in equation (2) below. I follow the standard event study approach which excludes the time period prior to implementation (in this case the month prior to SIBR implementation) as a baseline against which monthly effects are calculated (Sun and Abraham 2020). The model includes a set of dummy variables indicating relative time to implementation (negative time periods indicate months prior to implementation, positive time periods indicate months since implementation), a hospital unit fixed effect, a calendar time fixed effect, and an error term that is assumed to be normally distributed.

$$Y_{ium} = \sum_{j \neq -1} \beta_j T_{iu,m+j} + \theta_u + \mu_m + \varepsilon_{um} \quad (2)$$

The left-hand side of (2) contains the dependent variable for individual *i* seen initially on unit *u* and discharged from the hospital in month m. The right-hand side contains a set of relative time indicators, $T_{iu,t+j}$, that equal 1 if patient *i*'s stay on unit *u* in month *m* occurred *j* months from SIBR implementation and 0 otherwise. Corresponding to each relative time indicator is a coefficient, β_j, that estimates the difference in the dependent variable from the baseline period. The relative time indicators exclude the month prior to SIBR implementation (*j* = -1) which becomes the baseline against which the effects are estimated. The right-hand side also includes fixed effects for hospital unit, θ_u, and calendar time, μ_m, and an error term clustered at the hospital unit level. In addition to providing dynamic treatment effect estimates for each hospital unit that implemented SIBR, (2) also provides a convenient test for pre-trends in outcomes using the β_j coefficients for which *j* < -1.

4 Results

4.1 Descriptive Results

Table 2.1 shows descriptive statistics for patients for whom the initial unit of their visit was not an ICU (left column) and those whose initial unit was an ICU (right column). The majority (76.3%) of patients do not begin their stay on the ICU: this is the group which could potentially avoid an upstream transfer to the ICU later. Of those, approximately six percent (1,084 patients) experienced a transfer to an intensive care unit. Patients who initially stayed on an ICU also experienced transfers to *other* ICU units, or returned to the ICU after an initial transfer to a lower acuity unit, but did so at a lower rate (3%). Patients initially admitted to lower acuity units had a longer length of stay (LOS) on their first unit than those admitted directly to an ICU (4.24 days vs. 3.45 days; p-value < 0.001), but had shorter overall visits than those initially admitted to an ICU (5.04 days vs. 7.51 days; p-value < 0.001). Unsurprisingly, patients admitted to lower acuity units had a lower case mix index[17] (CMI) than ICU patients (1.69 vs. 3.08; p-value < 0.001) as well as lower mortality (0.02 vs. 0.13; p-value < 0.001) and a greater proportion of patients discharged to home (0.56 vs. 0.43; p-value < 0.001). Demographic information differed slightly between these groups: patients who did not initiate their visit with an ICU stay were older (64.9 years vs. 62.7 years; p-value < 0.001), less likely to be female (0.49 vs. 0.54; p-value < 0.001), and less likely to be white (0.77 vs. 0.84; p-value < 0.001).

[17] Case mix index is a measure of the severity and complexity of medical cases. A higher number indicates more severe and complex patients. Case mix index is determined by patients' diagnostic related group (DRG) weight calculated and updated on an annual basis by CMS.

Table 2.1 Descriptive statistics for visits initiated on a non-ICU versus those on an ICU.

	Non-ICU	**ICU**
N	18,098	5,609
Transferred to ICU	0.06 (0.23)	0.03 (0.17)
Units in visit	1.16 (0.53)	1.87 (0.66)
Unit 1 LOS	4.24 (3.46)	3.45 (3.78)
Visit LOS	5.04 (4.87)	7.51 (7.25)
Case mix index	1.69 (1.52)	3.08 (2.77)
Discharged home	0.56 (0.50)	0.43 (0.49)
Mortality	0.02 (0.13)	0.13 (0.34)
Medicare	0.46 (0.50)	0.43 (0.49)
Age	64.9 (17.7)	62.7 (16.5)
Female	0.49 (0.50)	0.54 (0.50)
White	0.77 (0.42)	0.84 (0.36)
Hispanic	0.02 (0.15)	0.02 (0.13)

Note: The table shows descriptive statistics for patients whose stay was initiated on a non-ICU (left column) and whose stay was initiated on an ICU (right column). "Transferred to ICU" indicates patients who experienced a stay on an ICU after an initial stay on any unit (including an ICU). "Unit 1 LOS" is the length of stay, in days, that a patient spent on the first unit of their visit. "Visit LOS" is the length of stay, in days, of the patient's entire hospital visit. Means are given with standard deviations in parenthesis. Differences between group means were compared using a t-test and found to be significant for all variables at the 95% confidence level.

Table 2.2 Descriptive statistics for patients transferred to an ICU versus initial ICU stays.

	Transferred to ICU	**Initial stay on ICU**	**P-value of difference**
N	1,084	5,609	
ICU LOS	4.02 (3.88)	3.47 (3.71)	0.000
Units in visit	2.96 (0.78)	1.87 (0.66)	0.000
Visit LOS	13.45 (9.55)	7.51 (7.25)	0.000
Case mix index	4.57 (3.70)	3.08 (2.77)	0.000
Discharged home	0.28 (0.45)	0.43 (0.49)	0.000
Mortality	0.13 (0.33)	0.13 (0.34)	0.760
Medicare	0.44 (0.50)	0.43 (0.49)	0.319
Age	64.5 (15.0)	62.7 (16.5)	0.001
Female	0.60 (0.49)	0.54 (0.50)	0.001
White	0.81 (0.39)	0.84 (0.36)	0.010
Hispanic	0.01 (0.11)	0.02 (0.13)	0.184

Note: The table shows descriptive statistics for patients who were transferred to an ICU from a lower acuity unit (left column) and whose stay was initiated on an ICU (middle column). "ICU LOS" is the length of stay, in days, that a patient spent in the ICU. Means are given with standard deviations in parenthesis. Differences between group means were compared using a t-test with p-values listed in the right-most column.

The data in Table 2.2 compare patients who were transferred to the ICU (left column) with patients who initiated their visit in the ICU (right column). The group represented in the right column is the same as that in the right column of Table 2.1. Overall, fewer patients were transferred to the ICU than began their visit there. However, patients transferred to the ICU had longer ICU stays than those who started there (4.02 days vs. 3.47 years; p-value < 0.001) and longer overall visits (13.45 days vs. 7.51 days; p-value < 0.001). Transfer patients also had a greater CMI than initial ICU patients (4.57 vs. 3.08; p-value < 0.001) indicating more severe diagnoses. A lower proportion of transfer patients were discharged home (0.28 vs. 0.43; p-value < 0.001) though mortality was similar between the groups (0.13 vs. 0.13; p-value = 0.319). Demographic characteristics also differed between the groups: transfer patients were older (64.5 years vs. 62.7 years; p-value = 0.001), more likely to be female (0.60 vs. 0.54; p-value = 0.001), and less likely to be white (0.81 vs. 0.84; p-value = 0.010).

Information on the number of units on which patients stayed during their visits is displayed in Table 2.3. The majority of patients (74.8%) spent their entire visit on a single unit. Overall, 28% of patients had a visit that included a stay on the ICU. The proportion of patients with an ICU stay during their visit increases as the number of units in a patient's visit increases: 8% of patients who stayed on a single unit during their visit stayed on an ICU, 87% of patients who stayed on two units during their visit stayed on an ICU, 96% of patients who stayed on three units during their visit stayed on an ICU, and 100% of patients with four or more units involved in their visit stayed on an ICU. Length of stay and CMI followed similar patterns in which patients who stayed on more units had longer stays and greater CMI.

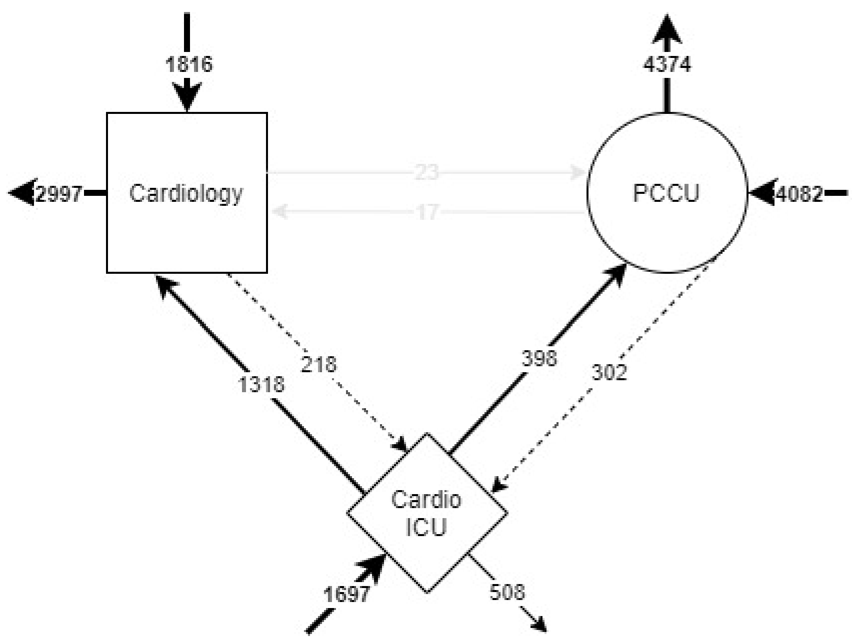
Table 2.3 Descriptive statistics by number of units in a visit.

Units in Visit	**N**	**ICU**	**LOS**	**CMI**
1	17,736	0.08 (0.27)	4.40 (4.20)	1.64 (1.54)
2	4,657	0.87 (0.34)	7.75 (5.85)	2.85 (2.38)
3	1,024	0.96 (0.19)	12.84 (7.87)	4.15 (2.94)
4+	290	1.00 (0.00)	20.64 (12.84)	4.60 (3.53)
Total	23,707	0.28 (0.45)	5.62 (5.62)	2.02 (1.98)

Note: The table shows descriptive statistics for patients whose visit included 1, 2, 3, or 4 or more stays on separate units. Overall measures are included in the bottom row. "ICU" indicates the proportion of patients in a row that experienced a stay on an ICU during their visit. "LOS" is the length of stay, in days, for a patient's entire visit. Means are given with standard deviations in parenthesis. Differences between group means were compared using a t-test with p-values listed in the right-most column.

4.2 Pathway Results

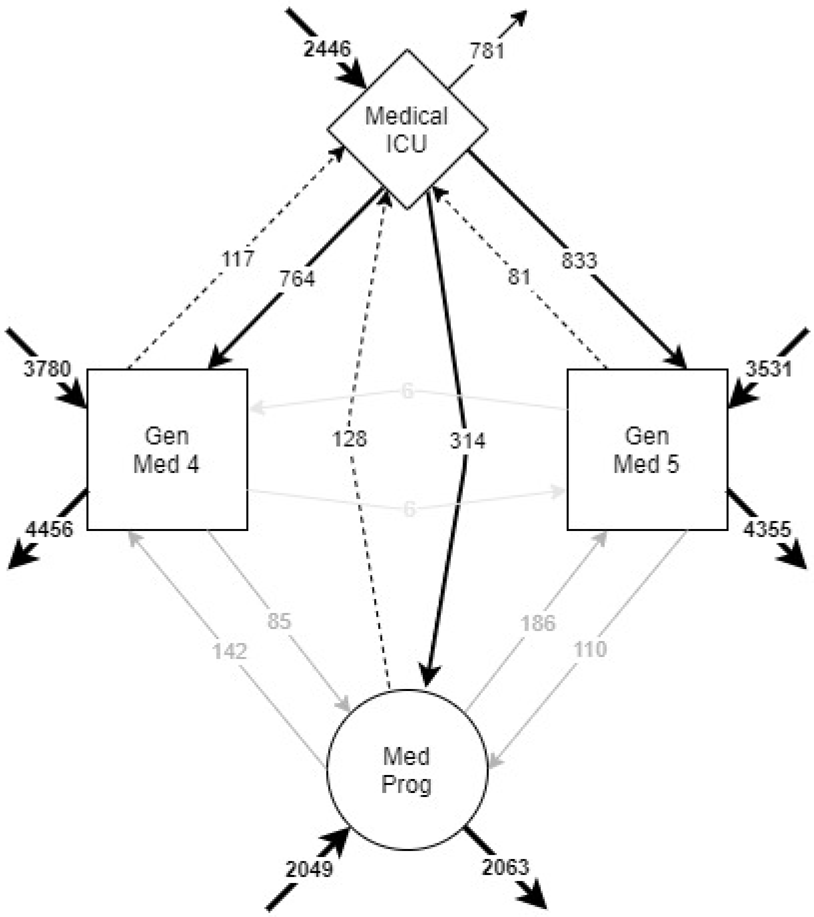
Figure 2.2 Cardiology unit pathway detail.



Note: The figure shows patient flow between units in the cardiology pathway. The shape outlining each unit indicates its acuity level: squares are low acuity units, circles are intermediate/progressive units, and diamonds are ICUs. The numbers displayed on each arrow indicate the total number of patients who moved from one unit to another. Darker shaded arrows indicate a greater number of patients, lighter shaded arrows represent fewer patients. Arrows with dotted lines represent upstream transfers of patients from lower acuity units to ICUs. Arrows with their tail not connected to any unit indicate direct admissions to a given unit, arrows with their head not connected to any unit indicate discharges from a given unit.

Figures 2.2, 2.3, and 2.4 detail patient movement within the three pathways used in this analysis. Figure 2.2 depicts the three units involved in the cardiology pathway: cardiology (a low acuity general ward), a progressive cardiology unit (PCCU) providing intermediate level care, and the cardiology ICU providing critical care. The typical patient flow is from high acuity (ICU) to low acuity (cardiology) to discharge. However, many patients also were admitted and discharged directly from the PCCU. The dotted lines indicate pathways that represent upstream transfers of patients from lower acuity units to an ICU. While these transfers are less common than the typical pathways, they occur relatively frequently between the PCCU and cardiology ICU and less frequently between the cardiology unit and the cardiology ICU. Patients were very rarely transferred between the two lower acuity units.

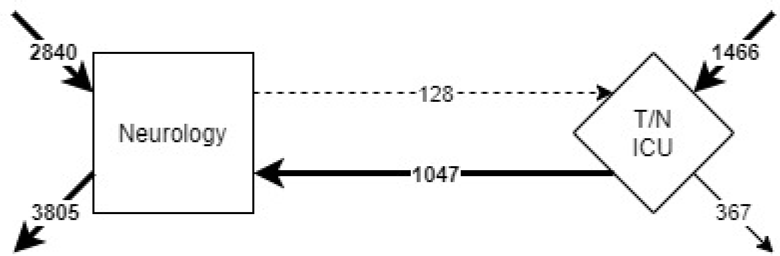
Figure 2.3 General medicine unit pathway detail.



Note: The figure shows patient flow between units in the general medicine pathway. The shape outlining each unit indicates its acuity level: squares are low acuity units, circles are intermediate/progressive units, and diamonds are ICUs. The numbers displayed on each arrow indicate the total number of patients who moved from one unit to another. Darker shaded arrows indicate a greater number of patients, lighter shaded arrows represent fewer patients. Arrows with dotted lines represent upstream transfers of patients from lower acuity units to ICUs. Arrows with their tail not connected to any unit indicate direct admissions to a given unit, arrows with their head not connected to any unit indicate discharges from a given unit.

Figure 2.3 shows the four units involved in the general medicine pathway: two lower acuity general medicine units (4^{th} floor and 5^{th} floor), a medical progressive unit offering intermediate level care, and the medical ICU providing critical care. The most common pathways are, again, from high acuity to low acuity units. It is also common for patients to be admitted directly to lower acuity units and discharged without interacting with the ICU. Dotted lines indicate upstream transfers and occur relatively infrequently for the general medicine units and more frequently for the medical progressive unit. As with cardiology, transfers between lower acuity units are uncommon though some patients seen on general medicine floors are transferred to the medical progressive unit for more intensive care.

Figure 2.4 Neurology unit pathway detail.

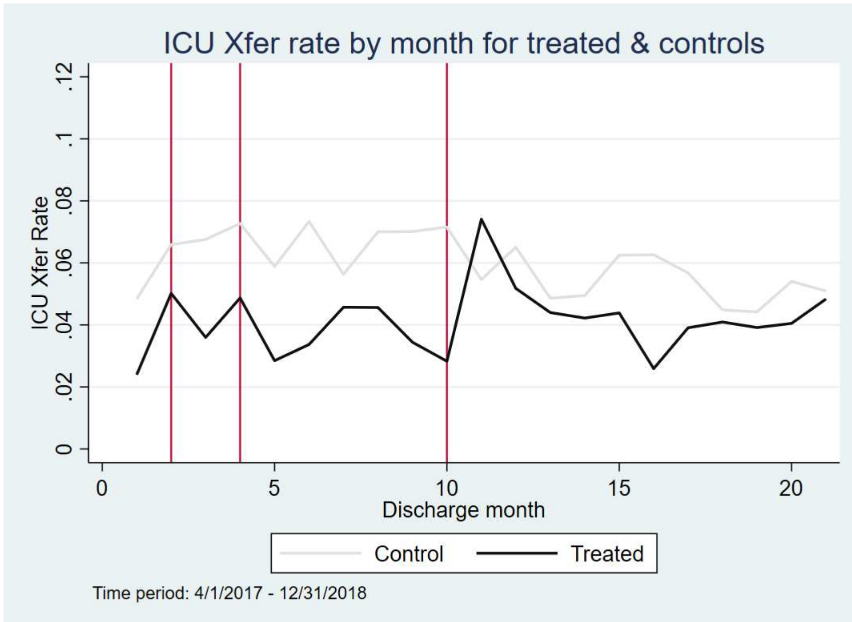


Note: The figure shows patient flow between units in the neurology pathway. The shape outlining each unit indicates its acuity level: squares are low acuity units and diamonds are ICUs. The numbers displayed on each arrow indicate the total number of patients who moved from one unit to another. Darker shaded arrows indicate a greater number of patients, lighter shaded arrows represent fewer patients. Arrows with dotted lines represent upstream transfers of patients from lower acuity units to ICUs. Arrows with their tail not connected to any unit indicate direct admissions to a given unit, arrows with their head not connected to any unit indicate discharges from a given unit.

Figure 2.4 shows the neurology pathway which consists of only two units: a lower acuity neurology unit and a high acuity trauma/neurology ICU. Patients typically admitted to the trauma/neuro ICU are typically transferred to the neurology floor and then discharged. Some patients are admitted and discharged from the neurology unit without interacting with the trauma/neuro ICU. Upstream transfers are less common, occurring at about one tenth the rate of downstream transfers.

4.3 ICU Transfers

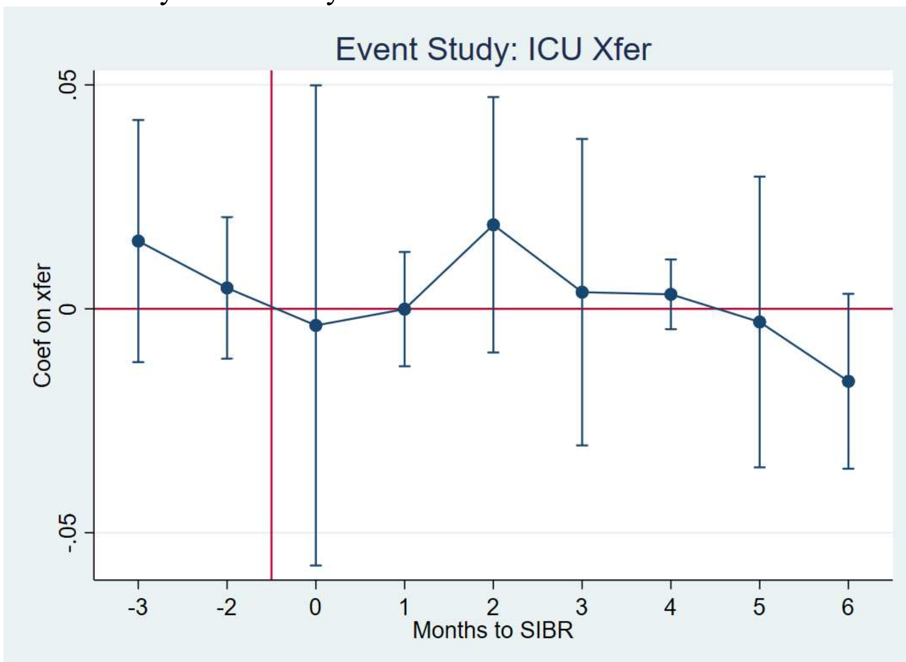
Figure 2.5 ICU transfer rate over time.



Note: The figure shows trends in ICU transfers for units that implemented SIBR (treated) and those that did not (control). The x-axis indicates the number of months since initiation of the study timeframe (month 1 is April 2017 and month 21 is December 2018). The y-axis indicates the proportion of patients transferred to an ICU. The three vertical lines indicate the implementation timings of SIBR.

Figure 2.5 shows the monthly rate of transfers from lower acuity units to ICUs for units that implemented SIBR (treated) and those that did not (control). The x-axis indicates time using the number of months since the beginning of the study time frame (month 1 is April 2017 and month 21 is December 2018) and the y-axis indicates the proportion of patients transferred to the ICU in a given month. The three vertical lines indicate the three dates of SIBR implementation. Although the control units have a consistently higher level of ICU transfers than the treated group, the two groups' trends follow parallel paths prior to the first, second, and third implementations of SIBR. The parallel trend shown in Figure 2.5 is critical to the identification of SIBR's effect on ICU transfers. Additional evidence against the existence of pre-implementation differences in trends is discussed below in Figure 2.6.

Figure 2.6 Event study results of dynamic treatment effect of SIBR on ICU transfer rate.



Note: The figure shows the results of the event study analysis of SIBR implementation on ICU transfers. The x-axis indicates relative time periods (months) prior to (negative numbers) and after (positive numbers) SIBR implementation. The y-axis indicates the magnitude of change in ICU transfer rate compared to the baseline period. The baseline period is the month prior to SIBR implementation (month -1; coefficient excluded). The dots indicate point estimates of the effect of SIBR implementation over time. Positive coefficients (above the horizontal line) indicate an increase in ICU transfers compared to baseline and negative coefficients (below the horizontal line) indicate a decrease in ICU transfers compared to baseline. Error bars indicate 95% confidence intervals on coefficients.

Table 2.4 provides the results of the primary regression used in this analysis (specification in equation (1) in section 3.2). The first two columns (left panel) show the coefficient estimating the effect of an initial stay on a unit that implemented SIBR on the likelihood of a patient being transferred to an ICU for the second unit of their visit. The second two columns (right panel) show this same coefficient's impact on the likelihood of being transferred to an ICU at any point after an initial stay on a non-ICU. The first coefficient in each panel shows the results of the two way fixed effects estimator without any covariates included in the model and the second includes covariates. In all cases, I find no effect of SIBR on the likelihood of transfer to the ICU. Table 2.5 also includes the average rate of transfers to the ICU (6%) and the number of observations used in this analysis (n = 18,098) which includes any patient in the sample whose initial unit was not an ICU. Sub-analyses of the effect of SIBR on ICU transfer rates within individual pathways were also carried out and yielded no effect.

Table 2.4 Effect of SIBR on ICU transfers.

	2nd unit ICU	**2nd unit ICU**	**2nd+ unit ICU**	**2nd+ unit ICU**
SIBR	0.003 (0.005)	0.001 (0.007)	0.003 (0.005)	0.001 (0.007)
Covariates?	No	Yes	No	Yes
Overall ICU transfer rate	0.06			
N	18,098			

Note: *** indicates p-value < 0.001, ** indicates p-value < 0.05, and * indicates p-value < 0.10. The table shows the results of regressions using transfer to an ICU from a lower acuity unit as the dependent variable and stay on a unit that had already implemented SIBR as the primary independent variable. Coefficients on the primary independent variable are reported with standard errors in parenthesis. The left panel uses a dependent variable that considers only the second unit of a patient's visit when determining if they were transferred to an ICU. The right panel uses a dependent variable that considers any ICU stay beyond the initial unit when determining if the patient was transferred to the ICU.

Table 2.5 ICU LOS under different circumstances.

	N	LOS
Initial unit ICU	5,609	3.5 (3.8)
Second unit ICU	1,018	4.0 (3.9)
Second unit ICU + Initial SIBR	363	4.1 (4.3)
Second unit ICU + initial not SIBR	655	3.9 (3.7)
Second unit ICU + initial pre-SIBR	138	4.1 (4.3)

Note: The table shows patients' length of stay, in days, in the ICU under several different circumstances. The top row indicates patients who stayed on the ICU for the first unit of their visit. The second row indicates patients who stayed on the ICU for the second unit of their visit (i.e. were transferred to the ICU). The subsequent rows in the bottom panel provide breakdowns of patients who stayed on the ICU for the second unit of their visit. In descending order, these rows indicate: patients who were transferred to the ICU following an initial stay on a unit that had already implemented SIBR, patients who were transferred to the ICU following an initial stay on a unit that never implemented SIBR, and patients who were transferred to the ICU following an initial stay on a unit prior to it implementing SIBR. Means are given with standard deviations in parenthesis.

These results are augmented by an event study analysis (following the specification in equation (2) in section 3.2) measuring the dynamic treatment effect of SIBR on the likelihood of ICU transfer. Event study results are shown in Figure 2.6. In Figure 2.6, the x-axis indicates relative time before (negative numbers) and after (positive numbers) implementation of SIBR (at zero) in months. The vertical line indicates the month prior to SIBR implementation which is serves as the baseline against which monthly changes in ICU transfer rates are measured. The y-axis indicates the magnitude of change in monthly ICU transfer rate compared to the baseline period (i.e. one month prior to SIBR implementation). Positive coefficients represent an increase in ICU transfer rate and negative coefficients represent a decrease. The point estimates of each month's change from the baseline are shown as dots with error bars representing the 95% confidence interval of each estimate.

There are two key results in Figure 2.6. The first result is that there are no time periods with a statistically significant change in ICU transfer rate compared to the baseline (i.e. all error bars overlap the horizontal zero line). This indicates that not only did the average treatment effect of SIBR (given in Table 2.4) not capture an effect on ICU transfers, but that there was no temporary decrease (or increase) in transfer rate lost in the average. By six months post-implementation the trend in ICU transfers seems to be dropping, but is not statistically significant. The second result is that neither of the pre-periods (i.e. the coefficient values at -3 months and -2 months in Figure 2.6) indicate a pre-existing trend in results. This complements the findings from Figure 2.5 which showed no differences in pre-implementation trends of ICU transfer rates between SIBR and non-SIBR units. This result provides further evidence that the identifying assumptions of the model are valid.

4.4 ICU Length of Stay

Table 2.5 provides several raw measures of patients' length of stay in ICUs based on how they arrived in the ICU. Patients whose visit was initiated with a stay on the ICU had an average length of stay of 3.5 days (SD = 3.8 days). This was the most common (n = 5,690) manner in which a patient received care in the ICU. Patients transferred from a lower acuity unit to the ICU as the second unit of their stay had an average length of stay of 4.0 days (SD = 3.9 days). Beneath the average length of stay for all patients transferred to the ICU are several breakdowns of this group divided by whether they had previously stayed on a unit that implemented SIBR or not. Patients whose initial unit implemented SIBR are further divided into patients whose stay occurred pre-implementation and post-implementation. Overall, patients transferred from SIBR units had slightly longer ICU stays than those from units not implementing SIBR (4.1 days vs. 3.9 days; p-value = 0.641) but this difference was small enough not to be statistically significant. Comparing patients who stayed on units implementing SIBR prior to implementation to those who stayed post-implementation shows no change in ICU length of stay (4.1 days vs. 4.1 days; p-value = 0.946).

The results shown in Table 2.6 are derived from the two-way fixed effects model specified in equation (2) in section 3.2 using ICU length of stay conditional on ICU transfer as the dependent variable. These results include only those patients who initially stayed on a non-ICU and were then transferred to the ICU in the same visit. The first two columns (left panel) use only patients transferred to the ICU as the second unit of their stay while the second two columns (right panel) consider the ICU length of stay for any ICU stay after an initial stay on a lower acuity unit. In all cases, SIBR had no significant effect on patients' length of stay in the ICU.

Table 2.6 Effect of SIBR on ICU LOS conditional on transfer to ICU.

	2nd unit ICU	**2nd unit ICU**	**2nd+ unit ICU**	**2nd+ unit ICU**
SIBR	-0.409 (0.491)	-0.281 (0.453)	-0.412 (0.463)	-0.295 (0.430)
Covariates?	No	Yes	No	Yes
Overall ALOS on ICU	3.98			
N	1,018			

Note: *** indicates p-value < 0.001, ** indicates p-value < 0.05, and * indicates p-value < 0.10. The table shows the results of regressions using the number of days spent in the ICU as the dependent variable and stay on a unit that had already implemented SIBR as the primary independent variable. Coefficients on the primary independent variable are reported with standard errors in parenthesis. The left panel uses a dependent variable that considers only the second unit of a patient's visit when determining ICU length of stay. The right panel uses a dependent variable that considers any ICU stay beyond the initial unit when determining total ICU length of stay.

5 Discussion

5.1 Interpretation of Results

The results of this analysis show that an interdisciplinary rounding scheme, like SIBR, implemented on lower acuity units does not affect the rate of upstream transfers to critical care units. Furthermore, SIBR does not have an impact at the internal margin: transfer patients' length of stay on the ICU. These results were robust to multiple specifications and the inclusion of covariates meant to control for potentially confounding differences in patients seen across a heterogenous set of trial units.

Patients transferred from lower acuity units to ICUs were older, more complex (higher CMI), and had longer stays in the hospital than patients admitted directly to an ICU. This conforms with previous work showing that upstream transfer patients are often some of the most complex and high acuity in the hospital (Escobar et al. 2011). The high acuity of this patient population may indicate that these types of transfers are, in many cases, unavoidable decompensations that no amount of observational diligence or care coordination could overcome.

Alternatively, the persistence of upstream transfers to the ICU may be due to patient flow dynamics that result from capacity constraints in the ICU, operating rooms, and intermediate care units (Kc and Terwiesch 2011). These constraints would not be responsive to improved care coordination on lower acuity units because they originate in higher acuity areas. A shortcoming of this analysis is its inability to account for each unit's capacity. Future work could incorporate a measure of whether ICU beds were available when a patient is admitted who ultimately experiences an upstream transfer. Indeed, previous research has shown that free ICU capacity—at least in a perinatal context—is put to use when marginal cases present (Freedman 2016). An analog to this could be that patients are transferred from lower acuity units to the ICU to ensure high utilization of an expensive resource.

Though not tested directly, several results undercut the idea that patients may be opportunistically transferred from low acuity units to fill ICU beds. First, transfer patients had longer ICU stays than patients who were admitted directly to the ICU. Second, patients transferred to the ICU were of higher severity and complexity than direct admits (as measured by CMI). Third, the mortality rate for transfer patients was the same as patient admitted directly to the ICU. If patients were transferred only to fill ICU beds, then their mortality should be lower than patients directly admitted to the ICU. Taken together, it seems unlikely that a substantial proportion of upstream transfers are a result of business decisions rather than clinical ones.

5.2 Limitations

This analysis faces several limitations. Measuring upstream transfers of patients to the ICU required the sample to be limited to three pathways within the hospital in which lower acuity units routinely interacted with higher acuity ones. This led to a small number of units involved and meant that all but two units ultimately implemented SIBR. While identification is still possible given the staggered timing of SIBR implementation and the inclusion of units that never implemented SIBR, a more sensitive study would include a greater number of hospital units. Furthermore, the units included in this study were heterogenous. The reasons a patient in a general medicine unit might be transferred to the ICU are different than the reasons a patient in a cardiology unit might be transferred to the ICU.

6 Conclusion

Care coordination is a growing trend in health care with much promise. SIBR, and models like it, have benefits that justify their use: improved patient and clinician satisfaction, reduced resource utilization, and reduced length of stay. While it is likely that SIBR has benefits beyond those that have been documented in the literature, these results indicate that SIBR may not be able to prevent patient transfers from low acuity units to ICUs. Determining where care coordination schemes, like SIBR, can have the greatest impact is critical to developing new policies that do not simply add to the massive expenditure already occurring in healthcare, but return value for patients, clinicians, and health systems. These results aid in that determination.

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MORTALITY OF ADOLESCENTS WITH ISOLATED TRAUMATIC BRAIN INJURY DOES NOT VARY WITH TYPE OF LEVEL I TRAUMA CENTER

1 Introduction

Unintentional injuries are the leading cause of death among children and adolescents.(Centers for Disease Control and Prevention 2021) Traumatic brain injury (TBI) is the most common type of injury sustained among pediatric trauma patients.(Mendelson and Fallat 2007) Adolescents (ages 15 – 17) are at particularly high risk of experiencing a TBI due to involvement in motor vehicle collisions and participation in contact sports.(Centers for Disease Control and Prevention 2021; Kuehn 2019) Therefore, defining the best treatment of severe head injuries in adolescents is of crucial importance.

Pediatric patients are generally defined as those less than 18 years of age, although that age limit is raised to 21 years in some areas. For trauma patients, the American College of Surgeons (ACS) Committee on Trauma defines a pediatric patient as less than 15 years of age while those 15 years and older are defined as adults. While it is expected that most children less than 15 years old will be cared for at Pediatric Trauma Centers (PTCs), adolescent trauma patients between 15 to 17 years straddle the boundary between Pediatric and Adult Trauma Centers (ATCs) and may receive definitive care at either type of trauma center depending upon institutional and regional resources and preferences. Hospitals that are designated as both an ATC and a PTC (Mixed Trauma Centers - MTC) each determine whether these adolescent patients will receive care within the ATC or PTC based on available resources such as pediatric surgeons, adult trauma surgeons, surgical intensive care units (ICUs), or pediatric ICUs.

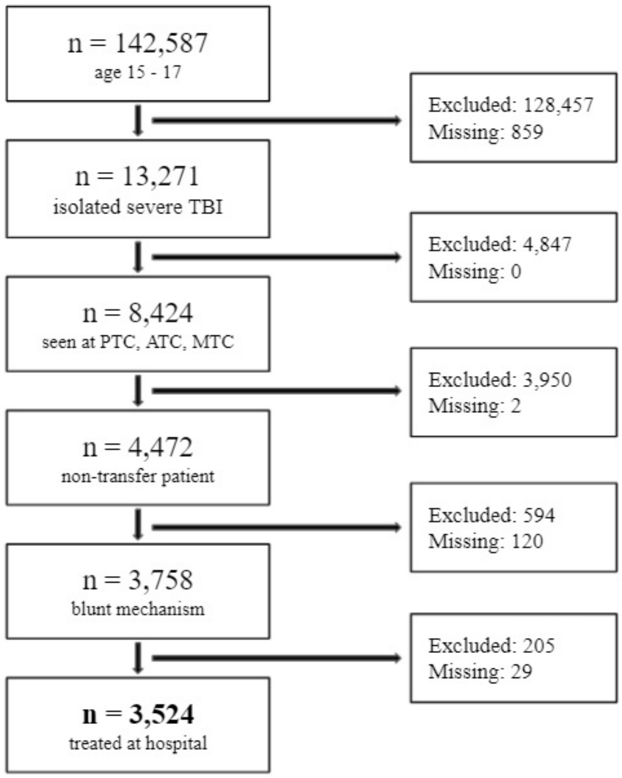
Several studies have compared the outcomes of pediatric trauma patients treated at ATCs, PTCs and MTCs(Miyata et al. 2015; Oyetunji et al. 2011; Sathya et al. 2015) while other studies have specifically focused on the outcomes of adolescent trauma patients treated at these different centers.(Matsushima et al. 2013; Rogers et al. 2017; Walther et al. 2014, 2016; Webman et al. 2016) Bardes et al. (2018) evaluated the difference in outcomes for pediatric trauma patients less than 15 years of age with isolated severe traumatic brain injury (TBI) treated at ATCs, PTCs and MTCs and found better survival at PTCs compared to ATCs, but not compared to MTC.(Bardes et al. 2018) The goal of this study was to evaluate the outcome differences for adolescent patients (15-17 years) with isolated severe TBI cared for at ATCs, PTCs and MTCs. Of primary interest were differences in survival between center types. Secondary outcomes included discharge disposition, utilization of craniotomy/craniectomy, ICU utilization, ICU length of stay (LOS), and hospital LOS.

2 Data & Methods

This is a cross-sectional analysis of a national sample of trauma patient data abstracted from the American College of Surgeons (ACS) Trauma Quality Programs (TQP) Participant Use Files (PUFs) from 2013 – 2017. Results were reported according to Enhancing the QUAlity and Transparency Of health Research (EQUATOR) Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) guidelines (see Supplemental Digital Content 1 for completed STROBE checklist). Patient records were included if they were 15 - 17 years old at the time of their injury; had an Abbreviated Injury Scale (AIS) head severity ≥ 3 with no severe injury in another body region (all other AIS severity < 3); were seen at an ACS or state verified Level I

PTC, ATC, or MTC; were not an interfacility transfer patient; had a blunt mechanism of injury; arrived at the facility with signs of life; and did not leave the emergency department prior to receiving care. Overall, 3,524 patients met these inclusion criteria (Figure 3.1).

Figure 3.1 Inclusion and exclusion.



Note: The figure displays the sequential exclusion criteria used to define the analysis sample. Between each stage, the numbers of subjects excluded due to not meeting the exclusion criteria ("Excluded") or excluded for missing data ("Missing") are noted in the boxes on the right. Patients were considered to have isolated severe traumatic brain injury (TBI) if they had a head injury with abbreviated injury scale (AIS) severity > 2 and no other body region with an AIS severity > 2. The final exclusion criterion ("treated at hospital") removes patients discharged home from the emergency department (ED), those who arrived with no signs of life, those who expired in the ED, those who left against medical advice, and those who were missing data for discharge disposition.

Centers were classified as PTCs if they were designated as a Level I pediatric trauma center and had no ATC designation of any level. Similarly, centers were classified as ATCs if they were designated as a Level I adult trauma center and had no PTC designation of any level. Finally, centers that had both adult and pediatric trauma center designations—at least one of which was Level I—were classified as MTCs.

The primary outcome—mortality—was defined as any patient who met the inclusion criteria above and had a hospital discharge disposition of "Expired." Secondary outcomes for patient discharge disposition were similarly defined. Patients were discharged "Home" if they had a hospital discharge disposition indicating a routine discharge home or home with health services. Patients were discharged to "Rehab" if they had a hospital discharge disposition indicating transfer to an outside facility to continue recovery. Remaining secondary outcomes were defined by procedure codes (craniotomy/craniectomy) or hospital resource utilization data from TQP (ICU LOS, hospital LOS, and ICU admission). LOS measures were given as an integer number of days.

Covariates were included in regression models to address differences in injury severity across center types: AIS head severity, initial Glasgow Coma Scale (GCS), use of intracranial pressure (ICP) monitoring, or craniotomy/craniectomy). AIS head severity was defined as the highest severity score of a patient's head injuries and took integer values of three, four, five, or six. Patients' initial GCS was the GCS recorded in the emergency department. Patients were considered to have ICP monitoring in place if they had an intraventricular drain or catheter, intraparenchymal pressure monitor, or an intraparenchymal oxygen monitor. Age and patient insurance status were also included as covariates to control for differences in patient population by center type. Insurance status—a proxy for socioeconomic status—was categorized as private, public, self-pay, or other. Public insurance included Medicare or Medicaid and "other" included a small number of patients who paid through worker's compensation or other uncommon arrangements.

Descriptive statistics were calculated using univariate analysis comparing patients' characteristics across center types (PTC, ATC, and MTC). Chi-square and ANOVA tests were used, as appropriate, to determine differences in patients' demographic (age, race, sex, ethnicity), clinical (initial GCS, injury severity score (ISS), head AIS severity, hypotension), and visit (discharge disposition, insurance type, LOS, ICU admission, procedures) data. The primary outcome of interest was in-hospital mortality. Secondary outcomes were discharge disposition, craniotomy/craniectomy, ICU utilization, ICU LOS, and hospital LOS. The primary covariate in all analyses was center type. The association between center type and binary outcomes, like mortality, was assessed using a multivariate logistic regression controlling for age, insurance type, initial GCS, AIS head severity, ICP monitor, and craniotomy/craniectomy. Associations between center type and continuous outcomes—hospital LOS and ICU LOS—were assessed using multiple linear regression including the same covariates as above. Patients missing data for any variable included in the model were excluded from regression analysis.

A preliminary power analysis, performed using the WebPower package in R version 4.0.1, found that the logistic regression of the primary outcome (mortality) had an approximate power of 93% to detect a difference of 5 percent mortality rate between center types at the 95% confidence level with an overall sample size of 3,000.

3 Results

Table 3.1 shows descriptive statistics of the analysis sample across center types. A total of 3,524 patients with isolated severe blunt head traumas were included in the analysis sample. These patients were unevenly distributed across PTCs (n = 430, 12.2%

of sample), ATCs (n = 1,430, 40.6% of sample), and MTCs (n = 1,664, 47.2% of sample). Patients seen at ATCs and MTCs were slightly older than those seen at PTCs, with a greater proportion of 15 year olds seen at PTCs (vs. ATCs and MTCs) and a greater proportion of 17 year olds seen at ATCs and MTCs.

Patients' race, ethnicity, and insurance status differed between center types. A greater proportion of PTC patients were Black or African American than ATC/MTC patients (PTC = 22.7%, ATC = 15.5%, and MTC = 15.3%; $p < 0.001$); conversely, a lower proportion of PTC patients were of Hispanic or Latino ethnicity than ATC/MTC patients (PTC = 15.0%, ATC = 22.2%, and MTC = 19.7%; $p = 0.003$). Patients, at all center types, were predominately male (overall = 73.7%). Public insurance was more common among PTC patients than ATC/MTC patients (PTC = 40.1%, ATC = 35.7%, and MTC = 33.0%; $p = 0.017$).

Table 3.1 Descriptive statistics of analysis sample by center type.

	PTC	ATC	MTC	Overall	p-value
	n = 430	*n = 1,430*	*n = 1,664*	*n = 3,524*	
Mean age	15.9 (0.8)	16.2 (0.8)	16.1 (0.8)	16.1 (0.8)	< 0.001
15 y/o	171	347	475	993	< 0.001
16 y/o	152	484	576	1,212	0.631
17 y/o	112	626	623	1,361	< 0.001
Male	303 (70.5)	1,077 (75.4)	1,217 (73.1)	2,597 (73.7)	0.098
Hispanic or Latino	61 (15.0)	291 (22.2)	288 (18.8)	640 (19.7)	0.003
Race					< 0.001
White	247 (59.1)	855 (62.0)	996 (61.2)	2,098 (61.3)	0.574
Black or African American	95 (22.7)	214 (15.5)	249 (15.3)	558 (16.3)	< 0.001
Other race	76 (17.7)	311 (21.7)	382 (23.0)	769 (21.8)	0.061
Insurance					0.001
Private	229 (53.4)	690 (51.1)	895 (56.0)	1,814 (53.7)	0.029
Public	172 (40.1)	482 (35.7)	527 (33.0)	1,181 (35.0)	0.017
Self-pay	20 (4.7)	109 (8.1)	106 (6.6)	235 (7.0)	0.042
Discharge disposition					< 0.001
Discharged home	385 (89.5)	1,142 (79.9)	1,373 (82.5)	2,900 (82.3)	< 0.001
Discharged to rehab	40 (9.3)	243 (17.0)	246 (14.8)	529 (15.0)	< 0.001
Hospital stay					
Mean Hospital LOS	5.0 (7.4)	6.0 (8.4)	5.9 (8.2)	5.8 (8.2)	0.056†
ICU during stay	217 (50.5)	1,000 (69.9)	1,122 (67.4)	2,339 (66.4)	< 0.001
Mean ICU LOS	4.3 (6.3)	4.7 (5.6)	4.8 (6.6)	4.7 (6.1)	0.564†
Procedures					
ICP monitor	16 (3.7)	94 (6.6)	116 (7.0)	226 (6.4)	0.047
Craniotomy	41 (9.5)	169 (11.8)	170 (10.2)	380 (10.8)	0.241
Tracheostomy	1 (0.2)	54 (3.8)	48 (2.9)	103 (2.9)	< 0.001
Head AIS severity	3.7 (0.6)	3.8 (0.7)	3.8 (0.7)	3.8 (0.7)	0.038
AIS head 3	166 (38.6)	493 (34.5)	593 (35.6)	1,252 (35.5)	0.290
AIS head 4	223 (51.9)	720 (50.3)	821 (49.3)	1,764 (50.1)	0.621
AIS head 5	41 (9.5)	216 (15.1)	249 (15.0)	506 (14.4)	0.010
ISS	13.3 (6.0)	14.6 (6.9)	14.6 (6.8)	14.5 (6.8)	0.001†
GCS	13.5 (3.2)	12.1 (4.3)	12.3 (4.3)	12.4 (4.2)	< 0.001†
GCS < 9	43 (10.2)	307 (21.9)	336 (20.6)	686 (19.9)	< 0.001
Hypotension	4 (0.9)	15 (1.1)	18 (1.1)	37 (1.1)	0.966
Mortality	5 (1.2)	45 (3.1)	45 (2.7)	95 (2.7)	0.084

Note: Counts are given except where row is noted as a mean. Numbers in parenthesis are within center type percentages or standard deviations for means. † indicates a p-value from an ANOVA test, all other p-values are from Chi-Square tests.

Hospital visit characteristics also differed between center types. PTC patients were more commonly discharged home (PTC = 89.5%, ATC = 79.9%, and MTC = 82.5%; $p < 0.001$), less likely to stay in the ICU during their visit (PTC = 50.5%, ATC = 69.9%, and MTC = 66.4%; $p < 0.001$), and had a shorter overall length of stay (PTC = 5.0 days, ATC = 6.0 days, MTC = 5.9 days; $p = 0.056$). Only one PTC patient underwent a tracheostomy, much fewer than at ATCs and MTCs—although statistical inference is difficult from such a small sample. Craniotomies and craniectomies were performed at similar rates between center types (PTC = 9.5%, ATC = 11.8%, MTC = 10.2%; $p = 0.241$).

Mortality was low throughout the sample (2.7%) and showed some variation across center types: 1.2% at PTCs, 3.1% at ATCs, and 2.7% at MTCs ($p = 0.084$). Mean AIS head severity varied significantly across center types. This difference was driven by a greater proportion of AIS head severity 5 patients being seen at ATCs and MTCs compared to PTCs (PTC = 9.5%, ATC = 15.1%, and MTC = 15.0%; $p = 0.010$). Mean ISS (PTC = 13.3, ATC = 14.6, and MTC = 14.6; $p = 0.001$) and mean GCS (PTC = 13.5, ATC = 12.1, and MTC = 12.3; $p < 0.001$) also differed significantly between center types. By all measures of injury severity (mean AIS head severity, ISS, and GCS), PTC patients were found to be less severely injured than patients seen at ATCs and MTCs.

Among patients included in the analysis, the most common missing variables were ethnicity ($n = 274$) and race ($n = 99$), neither of which were included in regression models. Data missingness resulted in 271 (7.7%) observations being excluded from regression models.

Table 3.2 breaks down the mortality data further by center type and AIS head severity. Of the 94 mortalities that occurred among AIS head severity 3, 4, and 5 patients (one mortality occurred for a patient with AIS head severity 6), 79 (84%) were from patients with AIS head severity 5. Sub-analysis of mortality among AIS head severity 5 patients (not shown) yielded insignificant differences between PTCs, ATCs, and MTCs.

Table 3.2 Mortality by center type and AIS head severity.

	PTC	**ATC**	**MTC**
AIS head = 3			
N	166	493	593
Mortality	0 (0.0)	1 (0.2)	2 (0.3)
AIS head = 4			
N	223	720	821
Mortality	1 (0.4)	8 (1.1)	3 (0.4)
AIS head = 5			
N	41	216	249
Mortality	4 (9.8)	35 (16.2)	40 (16.1)

Note: Two patients (1 at ATC, 1 at MTC) had head AIS severity 6, one expired and one was transferred to hospice.

Risk of mortality for patients with severe TBI was greater at ATCs compared to PTCs (OR = 2.76, 95% CI = 1.20 – 8.01, p = 0.032) in the simple logistic regression model (Table 3.3). Similarly, the risk of mortality for patients treated at MTCs compared to PTCs was also higher in the unadjusted model, but this did not reach statistical significance (OR = 2.36, 95% CI = 1.03 – 6.85, p = 0.070). However, when models included covariates adjusting for patient injury severity and insurance type, there was no difference in mortality risk at ATCs or MTCs vs. PTCs (ATC OR = 1.21, p = 0.733; MTC OR = 0.95, p = 0.919).

Table 3.3 Multivariate logistic regression of center type on mortality.

	Unadjusted O.R.	Unadjusted p-value	Adjusted O.R.	Adjusted p-value
PTC	1	-	1	-
ATC	2.76 (1.20 - 8.01)	0.032	1.21 (0.43 - 4.06)	0.733
MTC	2.36 (1.03 - 6.85)	0.070	0.95 (0.34 - 3.14)	0.919
Insurance - Private	-	-	1	-
Insurance - Public	-	-	0.62 (0.34 - 1.08)	0.098
Insurance - Self Pay	-	-	2.94 (1.33 - 6.27)	0.006
Age	-	-	0.92 (0.68 - 1.26)	0.600
GCS	-	-	0.70 (0.64 - 0.76)	< 0.001
ICP monitor	-	-	1.70 (0.99 - 2.90)	0.054
Craniotomy	-	-	0.70 (0.40 - 1.20)	0.200
AIS head severity	-	-	6.80 (4.18 - 11.72)	< 0.001

Note: Logistic regression with PTC as reference category for center type and private insurance as reference category for insurance type. Odds ratios are presented in the table with 95% confidence intervals in parenthesis. Unadjusted model contains only center type with no covariates.

Additional differences in treatment patterns between PTCs, ATCs, and MTCs were explored with multivariate logistic and linear regression of secondary outcomes (Table 3.4). There was higher proportion of patients admitted to an ICU at ATCs (adjusted OR = 2.12, 95% CI = 1.64 – 2.75, $p < 0.001$) and MTCs (adjusted OR = 1.91, 95% CI = 1.49 – 2.46, $p < 0.001$) compared to PTCs; however, patients who were admitted to an ICU did not have a longer LOS at ATCs. There was no significant variation in hospital LOS, the proportion of patients discharged home or to other facilities to continue rehabilitation, or the use of craniotomy/craniectomy between center types. This difference was robust to the inclusion of covariates controlling for severity and insurance type. Self-pay patients had lower odds of an ICU stay than private pay patients; more severely injured patients were more likely to experience an ICU stay as measured by initial GCS, use of craniotomy/craniectomy, and AIS head severity (Table 3.5).

Table 3.4 Regression results for secondary outcomes.

Panel A: Logistic regressions				
Outcome	**O.R. ATC**	**p-value**	**O.R. MTC**	**p-value**
Mortality	1.21 (0.43 - 4.06)	0.733	0.95 (0.34 - 3.14)	0.919
DC Home	0.80 (0.52 - 1.21)	0.297	0.98 (0.64 - 1.48)	0.933
DC Rehab	1.21 (0.81 - 1.84)	0.362	1.02 (0.69 - 1.56)	0.911
Craniotomy	0.95 (0.63 - 1.45)	0.796	0.79 (0.52 - 1.20)	0.250
ICU stay	2.12 (1.64 - 2.75)	< 0.001	1.91 (1.49 - 2.46)	< 0.001
Panel B: Linear regressions				
Outcome	**ATC**	**p-value**	**MTC**	**p-value**
ICU LOS	-0.27 (-1.01 - 0.48)	0.482	-0.10 (-0.83 - 0.64)	0.791
LOS	-0.45 (-1.14 - 0.23)	0.195	-0.40 (-1.07 - 0.26)	0.235

Note: Adjusted models include insurance type, age, GCS, AIS head severity, ICP monitor, and craniotomy/craniectomy as covariates. Odds ratios are reported for logistic regressions and linear coefficients are reported for linear regressions. Coefficients are displayed only for center type, all coefficients on additional covariates are suppressed. PTC is the reference category in both logistic and linear models. 95% confidence intervals are given in parenthesis for each estimate.

Table 3.5 Multivariate logistic regression of center type on ICU stays.

	Unadjusted O.R.	**Unadjusted p-value**	**Adjusted O.R.**	**Adjusted p-value**
PTC	1	-	1	-
ATC	2.28 (1.83 - 2.85)	< 0.001	2.12 (1.64 - 2.75)	< 0.001
MTC	2.03 (1.64 - 2.52)	< 0.001	1.91 (1.49 - 2.46)	< 0.001
Insurance - Private	-	-	1	-
Insurance - Public	-	-	0.95 (0.79 - 1.14)	0.570
Insurance - Self Pay	-	-	0.63 (0.45 - 0.88)	0.007
Age	-	-	1.00 (0.90 - 1.11)	0.976
GCS	-	-	0.72 (0.68 - 0.76)	< 0.001
ICP monitor	-	-	2.17 (0.83 - 7.49)	0.157
Craniotomy	-	-	4.60 (2.75 - 8.20)	< 0.001
AIS head severity	-	-	2.69 (2.32 - 3.12)	< 0.001

Note: Logistic regression with PTC as reference category for center type and private insurance as reference category for insurance type. Odds ratios are presented in the table with 95% confidence intervals in parenthesis. Unadjusted model contains only center type with no covariates.

4 Discussion

Investigating differences in outcomes for pediatric patients when treated at PTCs versus ATCs or MTCs is an ongoing topic in the literature. Previous work has found lower mortality among younger pediatric patients—including those with TBIs—treated at PTCs versus ATCs and MTCs.(Bardes et al. 2018; Hall et al. 1996; Potoka et al. 2000; Sathya et al. 2015) However, this benefit does not seem to extend to adolescent patients.(Gross et al. 2017; Matsushima et al. 2013; Rogers et al. 2017; Walther et al. 2014; Webman et al. 2016) The analysis by Gross et al. (2017), the closest comparison to this study, looked at the same patient population and arrived at similar conclusions, but used data from only a single state (Pennsylvania) instead of the national sample used here. In comparison with Gross et al. (2017), this study also considers MTCs rather than classifying all facilities as either ATCs or PTCs. This additional level of detail in this analysis may provide a better estimate of the impact of treatment at a facility staffed by clinicians specialized in pediatrics. On the other hand, Gross et al. (2017) assesses additional outcomes that were unavailable in the data set used for this analysis, specifically functional status at discharge (FSD).

At first glance, the results in this analysis seem to indicate that PTCs reduce mortality risk compared to ATCs or MTCs. However, after adjusting odds ratios for covariates including injury severity, this association disappears. Patients seen at PTCs are less severely injured than those seen at ATCs and MTCs as measured by ISS, AIS head severity, and GCS. Accordingly, patients treated at ATCs and MTCs were more likely to experience a stay in the ICU, although there was no difference in their ICU (or overall) length of stay or any other secondary outcome. These results seem broadly generalizable within the US as the data represent a national sample over a recent five-year period.

The implications of these findings depend on the extent to which equivalence of mortality outcomes implies equivalence of overall care between ATCs, MTCs, and PTCs. These findings provide confirmation that adolescent patients with severe, isolated TBI will have equivalent mortality regardless of the type of Level I trauma center at which they receive care. In this respect, the verification of Level I trauma centers and regionalized trauma care is working well. However, there may be more nuanced ways in which the care differs between trauma center types that cannot be fully explored with the current data set.

For instance, previous work has demonstrated that adolescents treated at ATCs had more imaging and invasive procedures performed than those treated at PTCs.(Walther et al. 2016) Additionally, recent work using the same data set as this study has demonstrated that patients at ATCs with TBI are more likely to have a tracheostomy and more likely to have a tracheostomy early in the hospital stay, which is associated with shortened ICU and overall length of stay. It is unclear whether delaying tracheostomy—though it increases certain in-hospital metrics—can reduce the number of tracheostomies needed and whether this is better or worse overall in regard to long-term complications, length of recovery and rehabilitation, cost of care (during and after hospitalization), and quality of life. The same lack of clarity exists in the discrepancy in the amount of imaging and invasive procedures between ATCs and PTCs. Future studies that evaluate such outcomes could clarify optimal practice patterns that could be employed across trauma center types without impacting mortality.(Butler et al. 2021)

A second key outcome of this analysis was the finding that adolescent patients arriving at ATCs and MTCs were more severely injured than those seen at PTCs. Other studies comparing outcomes for pediatric patients treated at PTCs and ATCs have found similar results: initial unadjusted estimates indicate reduced mortality for PTC patients, but adjusting for severity erases the difference.(Matsushima et al. 2013; Osler et al. 2001; Walther et al. 2014) No previous study has discussed this puzzling difference in severity among patients seen at PTCs vs. ATCs and MTCs. Since all Level I trauma centers should be capable of caring for the most severely injured patients, one would expect that those that accept 15-17 year old patients would have similar levels of patient severity regardless of whether the center is a PTC, ATC or MTC. There are several possible explanations.

A previous analysis of the TQP database found that, for trauma patients up to 18 years of age, older patients have higher injury severity scores than younger patients.(Sathya et al. 2015) In our population of trauma patients 15 - 17 years of age, we found that the older patients were more likely to be cared for at ATCs and MTCs, but ISS and AIS head severity did not vary across the small age range in this patient sample. This would seem to rule out age as a contributing factor to the difference in severity among center types.

ATCs and MTCs are more numerous and, in total, cover a larger geographic area and population than PTCs regarding patients brought to them from the scene of an injury.(US Government Accountability Office n.d.) Therefore, patients—of all severity levels—are more likely to be seen at an ATC or MTC than a PTC.(Petrosyan et al. 2009) Increased volume of patients alone would not indicate increased severity unless ATCs and MTCs were located in areas in which TBIs were more severe among adolescent patients. ATCs and MTCs are more common in rural areas than PTCs. Rural ATCs and MTCs that typically do not care for 15 – 17 year old patients with severe TBI may still receive these patients from the scene for initial resuscitation if a PTC is geographically more distant. There is some evidence that pediatric patients who suffer TBIs in rural or non-metropolitan areas are at greater risk of mortality.(Leonhard et al. 2015; Reid et al. 2001) Pursuing this line of reasoning is an interesting future direction for studies that address the geographic distribution of trauma centers and its effect on TBI patient outcomes.

It is possible that patients with severe TBI are preferentially taken to ATCs and MTCs by Emergency Medical Services (EMS). Most states have requirements that EMS take trauma patients to the closest trauma center that can provide care for that patient unless the patient is in extremis. Since most ATCs and MTCs are able to provide care for patients 15-17 years and there are more ATCs and MTCs than PTCs, EMS may be less likely to drive/fly further to reach a PTC. Additionally, if the distance to an ATC or MTC is not much farther than a PTC, EMS may elect to funnel severely injured 15-17 year old trauma patients to an ATC or MTC where they take a majority of their adult trauma patients. If EMS engages in this type of sorting, then these results suggest they are doing so unnecessarily and reducing this practice could lead to faster care for patients with no impact on mortality.

Finally, these differences could be due to ATCs and MTCs preferentially transferring severely injured 15 – 17 year old patients to PTCs. If true, these patients would be excluded from the sample in this analysis due to their status as transfer patients, thus lowering the average severity at PTCs. However, all Level I trauma centers are expected to be capable of treating these types of patients, so this should be uncommon. Furthermore, sub-analysis of transfer patients found that patients transferred to PTCs were no more severely injured than those who arrived from the scene (results not shown).

Understanding whether practice patterns across center types influence care quality beyond mortality and the source(s) of severity differences between PTCs and ATCs/MTCs warrants additional research. Future work could take the form of a multicenter study that may have a smaller sample size but would allow greater access to facility-level and patient details that are not available in a large database. Such information could include available services at each hospital (e.g. child life specialists), regional variation in care (e.g. adolescent patients in one region may be primarily cared for at ATC while in another region they are cared for at PTC), determination if adolescents at MTC are cared for by adult or pediatric specialists, details on patients' social determinants of health (e.g. family income and employment, housing, primary language, and education), and additional outcomes such as cost of care and patient satisfaction. These future analyses will help contextualize the results of this study and better inform trauma systems, policymakers, and clinicians on the steps that can be taken to make care more equitable across center types.

This study faces several limitations that are typical of analyses of retrospective observational data. Researchers only observed the adult and pediatric accreditations by ACS and states, no information on geographic location or a facility identifier were present. The lack of facility-level details makes it impossible to determine what services each trauma center was capable of providing. Furthermore, mechanisms underpinning the difference in injury severity could not be fully investigated. Finally, the study is unable to estimate the effects of treatment at PTCs versus ATCs and MTCs on additional outcomes of interest such as cost of care.

In conclusion, this analysis of a national sample of adolescent trauma patients with isolated severe TBI indicates that patients seen at ATCs and MTCs have similar mortality to those seen at PTCs after adjusting for differences in injury severity. Patients seen at ATCs and MTCs were more severely injured than those seen at PTCs, an observation future research should address.

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CONCLUSIONS

1 Interdisciplinary Rounds

The contribution of interdisciplinary rounding schemes, like SIBR, to the toolbox of care coordination policies can be substantial when implemented thoughtfully. Evidence from the previous chapters shows that SIBR can reduce resource utilization and maintain quality in the general inpatient population. However, two types of patients with more complex treatment needs especially benefitted: patients transferred to SNFs and oncology patients. The complexity of these patients needs may be what drives the increased benefit they receive from SIBR. They reap the greatest benefit from care coordination because they have complex care plans. Noting these populations, future implementations of interdisciplinary rounding schemes could focus first on the most complex patients to bring the greatest impact on the value of care.

Another result that may interest policymakers who wish to implement interdisciplinary rounding schemes is the improved effect of SIBR on units with residents over units staffed only with physicians who have completed their training. This pattern may indicate that physicians introduced to SIBR early in their career are more likely to adopt and implement the model than those who were trained under a different scheme. If SIBR were presented to medical students, interns, and residents as the standard of care, some of the barriers to implementation—namely acceptance of the model by physicians—could be alleviated. Understanding when the optimal timing for introduction of SIBR to its practitioners requires further study and is a worthy subject for future work.

Despite the success of SIBR in reducing patients' length of stay and the use of central lines, it did not create spillover benefits for ICU patients. The results of the second investigation of SIBR, looking at its impact on upstream transfers to the ICU, found no effect on the external nor internal margins of ICU utilization. While there may be other second-order benefits of SIBR, care coordination of this kind was unable to influence the likelihood of transfer to the ICU or the LOS of patients who were transferred to the ICU from lower-acuity units. Future work with stronger identification may yet reveal benefits in this area, but the forces that govern upstream transfers (lack of ICU capacity, incomplete information on patients' status at admission, and rapid decompensation in condition) may simply be outside of the scope of interdisciplinary rounds.

2 Trauma Systems

Trauma systems rely on coordinated care across facilities, between trauma centers and pre-hospital caregivers, and within trauma teams. Preparation is critical to successful coordination as traumatic injuries occur without notice and require rapid responses to save patients. For traumatic brain injuries—a common and deadly injury—knowing where a patient should be taken, before an injury even occurs, can shave off critical minutes and give patients the best chances at recovery. Specialization of facilities within the trauma system is key for some patients. Young pediatric patients with TBI should be taken to the nearest pediatric trauma center for the best odds of recovery—though if the nearest adult trauma center is much closer then it is likely a better option—however, I show in the previous chapter that adolescent TBI patients can be successfully treated at either PTCs or ATCs.

Although adolescent patients with TBI have the same odds of mortality at PTCs and ATCs, patients treated at ATCs tend to be more severely injured. It is unclear why this is the case, but one possibility is that pre-hospital providers like EMS are sorting more injured patients to ATCs and away from PTCs. If so, they are doing this unnecessarily based on my results: those patients would have equivalent mortality risk if they were taken to a PTC. This highlights an ongoing need for coordination between trauma centers and EMS. Educating pre-hospital caregivers about which patients should be preferentially taken to a specialized facility—and which can be successfully treated anywhere—would improve the efficiency of the trauma system and benefit patients.

3 Future Work

The results of the studies presented in previous chapters provide several avenues for future research. Investigating the effectiveness of interdisciplinary rounds could be performed as a prospective multicenter study that more fully captures the structure of interdisciplinary teams and provides more generalizable results than a study at a single facility. Additionally, a study comparing effectiveness of SIBR when introduced to physicians at different stages in their career and training would provide evidence for the optimal timing for SIBR training. Finally, future investigations of SIBR spillover effects could take use an instrumental variables approach that looks at upstream ICU transfers only at times when the ICU has excess capacity.

Future research on trauma systems, specifically on differences in care between ATCs and PTCs for TBI patients could be implemented as a prospective multicenter study allowing more details about the facility to be captured such as physician specialties and experience, child life services, rehabilitation programs, and long-term follow-up of patients. Alternatively, this work could be carried out using a TBI registry such as the one housed at the Regenstrief Institute in Indianapolis. Whether this study takes the form of a prospective study or retrospective analysis, the key question at stake is whether equivalence in mortality for adolescent TBI patients at PTCs and ATCs implies equivalence of care in a broader sense.

APPENDICES

Appendix A: Supplemental Tables & Figures

Table A1. Descriptive statistics for individual treated units.

	MedProg	**Med1**	**Neuro**	**Med2**	**Onc**	**Ort1**	**Ort2**
N	1,432	3,907	2,640	3,584	2,501	2,607	2,220
Weekly Discharges	15.4 (9.0)	39.1 (6.0)	26.4 (10.0)	35.8 (8.1)	25.0 (10.4)	26.1 (6.2)	22.2 (5.8)
LOS	4.93 (4.41)	5.06 (4.47)	4.77 (4.57)	4.94 (4.32)	5.91 (6.40)	3.45 (2.66)	4.76 (3.66)
30-day Readmission	0.12 (0.33)	0.12 (0.33)	0.13 (0.33)	0.13 (0.34)	0.21 (0.41)	0.08 (0.27)	0.08 (0.27)
Mortality	0.03 (0.16)	0.01 (0.11)	0.01 (0.08)	0.01 (0.11)	0.03 (0.16)	0.00 (0.03)	0.00 (0.04)
Discharged to SNF	0.24 (0.43)	0.24 (0.42)	0.21 (0.41)	0.24 (0.43)	0.12 (0.33)	0.28 (0.45)	0.36 (0.48)
CMI	1.50 (1.01)	1.42 (0.83)	1.46 (1.07)	1.43 (0.90)	1.51 (0.96)	2.76 (1.47)	2.14 (1.31)
MD Panel Size	7.72 (3.63)	7.83 (3.43)	4.65 (3.09)	7.70 (3.44)	5.98 (3.88)	3.36 (2.05)	4.58 (2.54)
Age	64.4 (19.2)	65.5 (18.5)	63.6 (18.6)	64.6 (18.5)	58.4 (18.3)	63.3 (16.0)	60.5 (20.9)
Female	0.54 (0.50)	0.56 (0.50)	0.54 (0.50)	0.54 (0.50)	0.58 (0.49)	0.56 (0.50)	0.50 (0.50)
White	0.73 (0.44)	0.73 (0.45)	0.82 (0.39)	0.72 (0.45)	0.72 (0.45)	0.90 (0.30)	0.90 (0.30)
Medicare	0.48 (0.50)	0.47 (0.50)	0.41 (0.49)	0.48 (0.50)	0.39 (0.49)	0.43 (0.49)	0.36 (0.48)

Table A2. Descriptive statistics for control units grouped by specialty.

	Cardiology	**OB/GYN**	**ICU**	**Oncology**
N	4,507	760	765	1,904
Weekly Discharges	15.2 (13.6)	4.1 (2.8)	6.0 (5.0)	9.6 (7.9)
LOS	4.97 (4.65)	3.13 (4.07)	7.96 (7.44)	4.20 (4.20)
30-day Readmission	0.12 (0.32)	0.18 (0.39)	0.06 (0.23)	0.09 (0.29)
Mortality	0.03 (0.17)	0	0.34 (0.47)	0.00 (0.05)
Discharged to SNF	0.12 (0.32)	0.00 (0.05)	0.07 (0.26)	0.08 (0.27)
CMI	2.01 (1.73)	0.83 (0.35)	3.89 (3.84)	1.78 (1.57)
MD Panel Size	4.26 (3.73)	3.93 (2.72)	4.08 (3.07)	4.99 (4.00)
Age	65.9 (15.2)	32.1 (9.1)	60.1 (18.0)	58.6 (16.3)
Female	0.42 (0.49)	1	0.49 (0.50)	0.65 (0.48)
White	0.84 (0.37)	0.67 (0.47)	0.85 (0.36)	0.82 (0.38)
Medicare	0.48 (0.50)	0.03 (0.16)	0.46 (0.50)	0.31 (0.46)

Table A2. Descriptive statistics for control units grouped by specialty. Continued.

	Surgery	**Inpt Rehab**	**Med/Psych**
N	1,617	643	398
Weekly Discharges	19.5 (14.7)	6.4 (2.4)	7.5 (5.0)
LOS	4.89 (4.70)	12.40 (4.88)	4.60 (6.11)
30-day Readmission	0.12 (0.33)	0.14 (0.35)	0.06 (0.23)
Mortality	0.00 (0.07)	0.00 (0.07)	0.01 (0.07)
Discharged to SNF	0.10 (0.30)	0.16 (0.37)	0.11 (0.31)
CMI	1.63 (1.04)	1.15 (0.38)	1.09 (0.59)
MD Panel Size	5.56 (3.61)	12.45 (1.97)	8.68 (3.76)
Age	60.0 (17.8)	64.5 (15.6)	48.6 (16.7)
Female	0.55 (0.50)	0.46 (0.50)	0.44 (0.50)
White	0.82 (0.38)	0.81 (0.39)	0.84 (0.37)
Medicare	0.35 (0.48)	0.51 (0.50)	0.23 (0.42)

Figure A1. Histogram of patients' LOS.

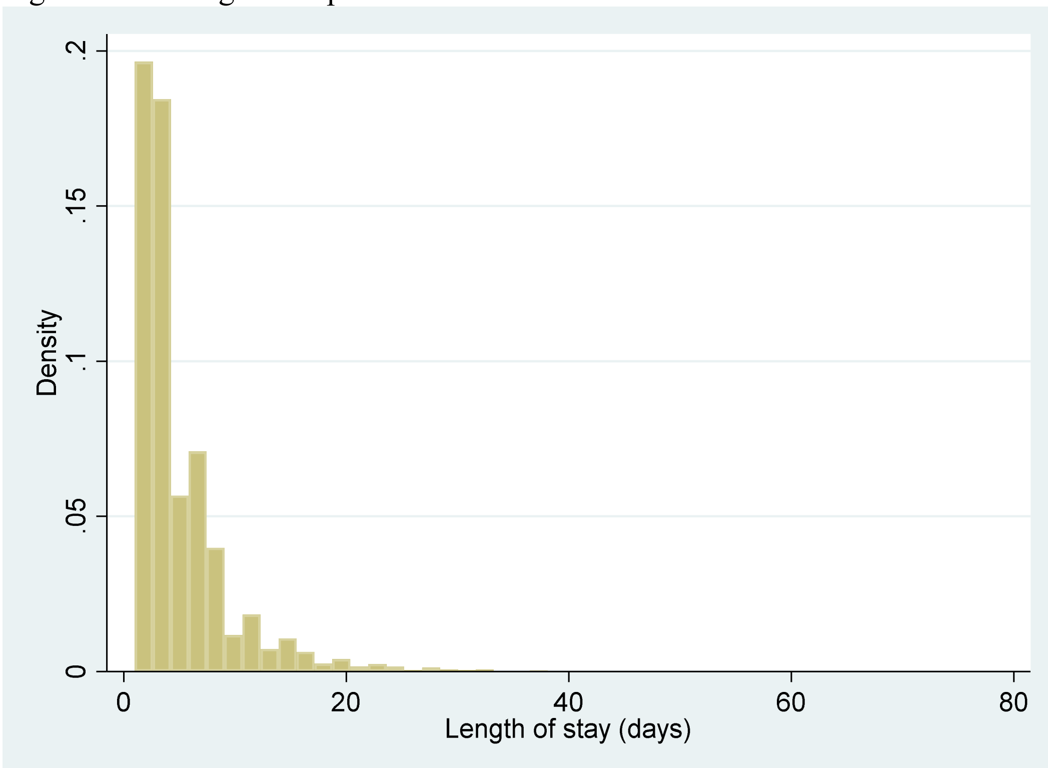
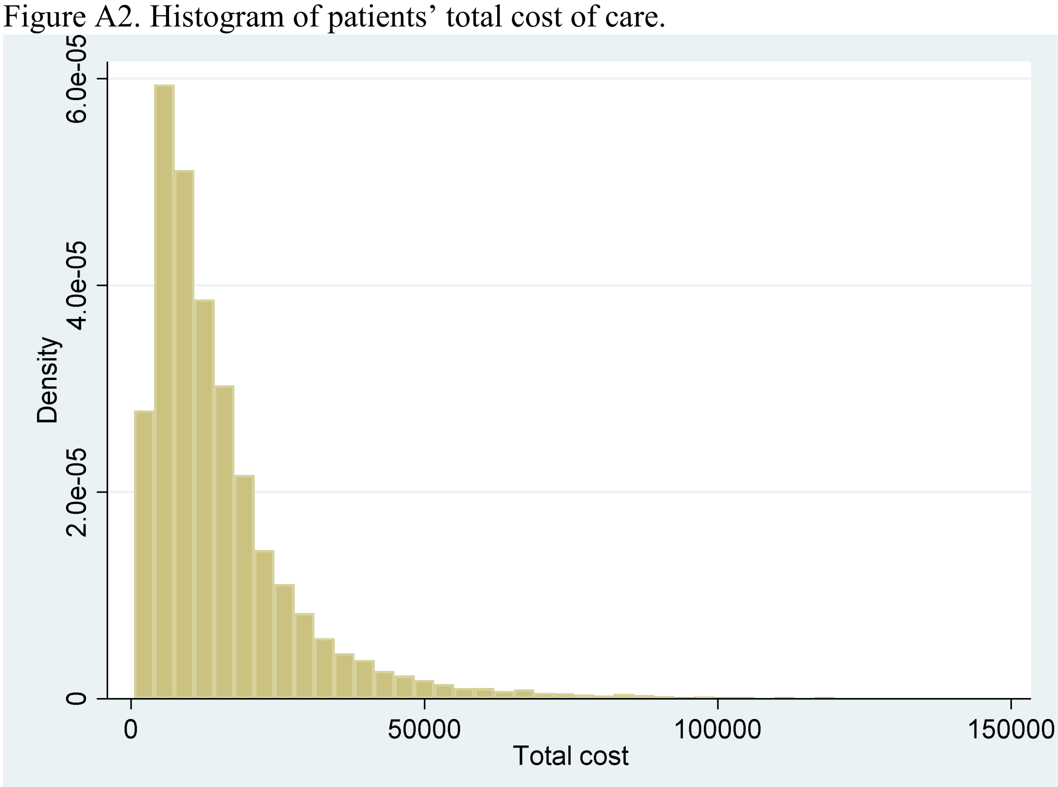


Figure A2. Histogram of patients' total cost of care.



CURRICULUM VITAE

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Education

- IUPUI – PhD Economics 2022
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- IU Bloomington – BS Biology 2010
- IU Bloomington – BA Mathematics 2010
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Honors, Awards, & Fellowships

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- Carlin Award for Outstanding Graduate Paper in Empirical Economics (April 2019)
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Professional Experience

- Peyton Manning Children's Hospital – Research Scientist (2021 -)
- St. Vincent Hospital Indianapolis – Data Analyst (2015 – 2021)
- IU School of Medicine – Research Coordinator (2013 – 2015)
- IU School of Medicine – Research Assistant (2011 – 2013)

Conferences

- American Society of Health Economists Conference 2020 (paper accepted, could not attend)
- Mini-Health Economics Conference 2019 (WIP feedback session)
- American Society of Health Economists Conference 2019 (panel presentation)
- Midwest Economics Association Conference 2019 (panel presentation and discussant)
- East-North-South-Central Health Economics and Policy Mini-Conference 2018 (presentation)
- AAMC 11th Annual Health Workforce Studies Research Conference 2015 (presentation)
- AAMC 10th Annual Health Workforce Studies Research Conference 2014 (poster)
- AAMC 9th Annual Health Workforce Studies Research Conference 2013 (poster)
- 16th Annual Indiana Rural Health Association Conference 2013 (panel)

Publications

- Sheff, Zachary T. MPH; Engbrecht, Brett W. MD, MPH. Monthly Pediatric trauma volume remained steady in 2020 despite COVID-19, currently under review.
- Sheff, Zachary T. MPH; Engbrecht, Brett W. MD, MPH; Rodgers, Richard MD; Jacobson, Lewis E. MD; Smith, Jodi L. PhD, MD, FAAN. Mortality of Adolescents with Isolated Traumatic Brain Injury Does Not Vary with Type of

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