Quantifying the Impact of Care Team Discontinuities on Medically Unnecessary Delays in Inpatient Flow

by

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Submitted to the Department of Electrical Engineering & Computer Science and the MIT Sloan School of Management in partial fulfillment of the requirements for the degrees of

Master of Science in Electrical Engineering & Computer Science
and
Master of Business Administration

in conjunction with the Leaders for Global Operations Program at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

June 2016

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Abstract

This thesis quantifies the impact of clinical care team discontinuities on inpatient length-of-stay (LOS) and admission wait time within Massachusetts General Hospital's Department of Medicine (DOM). The DOM is the hospital's largest clinical department by inpatient volume and supports a highly diverse patient population. Like many Academic Medical Centers, the DOM is confronted with increasing inpatient volume (>5% annual growth) and is showing symptoms of being capacity constrained, including rising patient wait times for admission from the Emergency Department. With the goal of informing specific interventions to increase patient throughput, this study evaluates the impact of end-of-rotation Attending physician handoffs (HOFs) on LOS and admission wait time on four, resident-staffed, general care floors with similar patient populations, clinical team configurations, and shift patterns.

When combined with independently-distributed patient demand and the randomized assignment of patients to floors, the hospital's residency schedule creates natural randomized experiments through which the impact of HOFs can be isolated. It is found that patients admitted to a floor two days before a HOF spend an average of 0.8 days longer in the hospital than otherwise similar patients, while patients admitted one day before a HOF spend 0.8 fewer days in the hospital (Wilcoxon-Mann-Whitney RS, two-sided, $\alpha = 0.05$). Further, average admission wait time increases by 15%-34% during the last two days of an Attending's rotation (t-test of means, pooled variance, two-sided, $\alpha = 0.05$). Finally, a series of regression models that utilize only the information available when a patient is first admitted demonstrate that proximity to a future HOF at point of admission is a significant and robust predictor of LOS across major diagnostic categories (Monte Carlo Cross-Validation, $\alpha = 0.05$).

The dynamics this study uncovers can be used to attenuate the negative impacts of HOFs on patient LOS by informing the design of clinician rotation schedules, care team structures, and new patient assignment practices.

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Acknowledgments

This thesis would not have been possible without the generous support and advice of a great many people. Thank you to my exceptional academic advisors Professor Retsef Levi of the Sloan School of Management and Professor Patrick Jaillet of the Department of Electrical Engineering & Computer Science; the team from Massachusetts General Hospital's Department of Medicine, including Rhodes Berube, Marjory Bravard, M.D., Victor Chiappa, M.D., Edward Morris, and Annie Elfar; the MGH champions of this project (and the broader MIT-MGH Collaboration), including Walter O'Donnell, M.D., Peter Dunn, M.D., Bethany Daily, and Cecilia Zenteno.

Finally, thank you to my loving (and forgiving) family, including my fiancée, Eleanor Joseph, mother, Carole Forgan, and father, Thomas Johnston.

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Chapter 1

Introduction

This chapter provides an overview of the hospital and department within which this study was performed, the motivation and hypothesis that guided the effort, the study's key findings, and the general organization of the remainder of this document.

1.1 Background

1.1.1 Massachusetts General Hospital

Massachusetts General Hospital (MGH) is consistently ranked as one of the top hospitals in the United States and remains the largest and oldest hospital in New England [31]. As part of the Harvard Medical School (HMS), it serves as a teaching hospital for the surrounding community as well as a tertiary referral center for patients from around the world [14]. In addition to serving approximately 50K inpatient and 1.5M outpatient visits annually, MGH also conducts the largest hospital-based research program in the world through its 20+ on-site clinical departments and research centers [31].

1.1.2 MIT-MGH Collaboration

The MIT-MGH Collaboration is a long-standing research partnership between MGH and the Sloan School of Management at Massachusetts Institute of Technology (MIT). The Collaboration focuses on improving the operational effectiveness of the hospital through the application of Operations Research and continuous improvement methodologies. These efforts are driven by a team composed of MIT faculty, MGH leadership, post-doctoral fellows within the Operations Management Group at the MIT Sloan School of Management, and students within the MIT Leaders for Global Operations (LGO) program [15].

While the Collaboration initially focused on driving improvements within the hospital's perioperative environment, including inpatient flow optimization [20][39][5][38][45], intensive care unit (ICU) bed allocation [9], and surgical inventory management [44][4], it has since expanded its scope to include other organizations and functions, such as primary care prescription management [43], just-in-time bed assignment in the Neurosciences ICU [29], and infusion clinic appointment scheduling [41]. The effort presented in this document, completed within the framework of an IRB-approved study[1], marks the collaboration's first project within MGH's Department of Medicine and, by concentrating heavily on system mapping and modeling, sets the stage for future initiatives in this area.

1.1.3 Department of Medicine

With over 22K admissions in 2014, the Department of Medicine (DOM) is MGH's largest department by inpatient volume[2]. It provides general, intensive, and emergency medical services through a network of patient care units spanning six buildings, twenty floors, and over 400 inpatient beds. This network is supported by front line clinical, technical, and support staff organized into numerous care team structures. The configurations and operating patterns of these teams have been designed in response to patient needs (e.g., acuity and oversight requirements), the hospital's physical layout, and the desire to foster an effective teaching environment as a component of MGH's Residency Program. These designs are frequently refined in response to patient demand, changing regulatory requirements (e.g., resident duty hour limits [16]), fixed capital investments, and the pursuit of improved clinical outcomes as well as operational and financial efficiencies.

By design, the DOM's inpatient population is decidedly heterogeneous, often arriving to the hospital with indistinct, multi-system ailments and psychosocial complexities. This heterogeneity and the diagnostic uncertainty associated with newly admitted patients create a complex and dynamic set of clinical needs [48]. Relative to departments that treat patients through a finite set of specialized services (e.g., Surgery), in the DOM – and in the general medicine units, in particular – it is significantly more challenging to develop procedure-specific efficiencies.

The DOM is challenged with managing and refining the overarching diagnosis-treatment-discharge process for a high-mix patient group. This requires the department to comprehensively support inpatient visits from the point of admission or earlier (as is the case with Emergency Department boarders [1]) to discharge as well as manage only the initial or final stages of care in series with other clinical departments. Predictably, this flexibility is not without a cost.

1.2 Project motivation

While successfully supporting continuously increasing patient volumes (>5% annual growth[3]), the DOM is displaying symptoms of being capacity constrained[4]. These symptoms include rising patient wait times for admission from the Emergency Department (ED), routine activation of capacity-triggered emergency management protocols, and high levels of attrition among non-resident physicians [28]. As shown in Figure 1-2, average ED wait time, defined as the number of hours a patient waits to be moved from the ED to one of the DOM's general care floors after an inpatient bed is requested, has increased by 38% between 2012 and 2015[5]. Similarly, the reliance on capacity-related emergency management protocols has nearly tripled from three per month in 2013 to eight in 2015 (see Figure 1-2). By triggering ad hoc staff meetings and abrupt resource reallocations that seek to make more beds available for new patients, these protocols pull clinicians away from their other responsibilities and impose direct and indirect costs throughout the hospital [33].

While experienced by many Academic Medical Centers (AMCs) [6], these trends are concerning and the DOM partnered with the MIT-MGH Collaboration with the long-term goal of increasing patient throughput by reducing medically unnecessary delays in patient progression through the hospital.

[1] MIT Protocol #12010014856, MGH-MIT Collaboration: DOM Inpatient Flow, Principal Investigator: Retsef Levi. MGH Protocol #2011P001124.

[2] Source: PEPL Inpatient Survey Fact. Filters: (1) admission Jan 1 - Dec 31 2014, (2) visit with patient assigned at least once to a DOM Responding physician.

[3] Three-year compound annual growth rate ($CAGR^{3yr}$), 2012-2014.

[4] Patient population as described in footnote 2.

[5] Number of hours between bed request and fulfillment for patients admitted through the Emergency Department. Source: EDIS. Filters: (1) admission Jan 1 2013 - Oct 31 2014, (2) bed requested on the Bigelow A/B/D/E Teaching Service.

Beyond the intuitive operational and financial costs of patients spending more time than necessary within the hospital's walls, there's a wide body of research dedicated to understanding its impact on patient health; specifically, the incidence of hospital-acquired conditions (HACs), including infections, injuries, and other traumas. For example, on any given day one in twenty-five inpatients within an acute care facility is suffering from at least one hospital-acquired infection (HAI) [13] and each additional day in the hospital increases the probability of an HAI by 1.37% [21].

A potentially useful analog to the medically necessary / unnecessary dichotomy is the popular concept of value added (VA) vs. non-value added activities (NVA) within a manufacturing environment [19]. From a clinical perspective, medically necessary time includes periods dedicated to diagnosis, treatment, and convalescence that are best or necessarily completed within the hospital's walls. Conversely, medically unnecessary time simply includes everything not captured in the above, including periods lost to redundant testing or information discovery, latency in communication or coordination, or otherwise not pursuing clinical activities as time-efficiently as possible, holding all else constant.

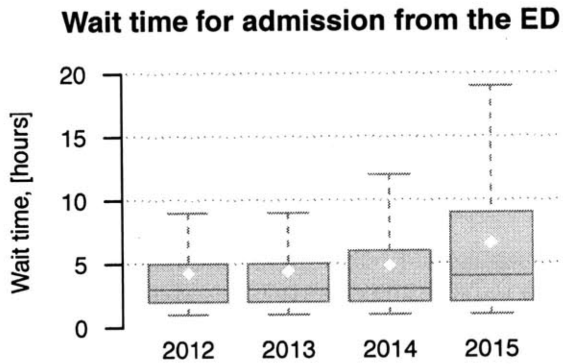

Figure 1-1: Wait time for admission from Emergency Department to Bigelow A/B/D/E[6]

While these are comfortable definitions for non-clinicians, those with experience navigating the "fog of care" will immediately conclude that seeking to cleanly decompose the universe of in-hospital activities in such a way assumes a level of process discretization and determinism that does not exist in a clinical environment. Further, clinicians, economists, and politicians alike will agree that even identifying "medically... best or necessary" is the subject of great debate.

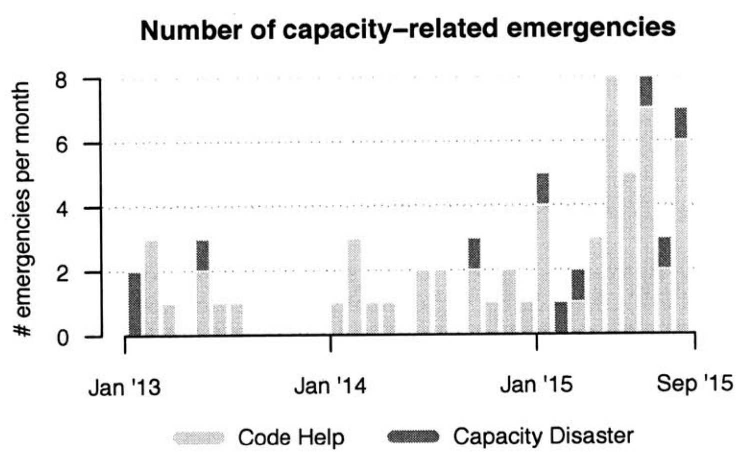

Figure 1-2: Incidence of capacity-related emergencies[7]

[6]Patient population and definition of 'ED Wait Time' as presented in Footnote 5.

These realities in mind, the objective of this study is begin quantifying medically unnecessary delays without the need to discretize clinical activities or take a position in the conversation seeking to balance cost and quality of care.

1.3 Hypothesis

During the initial diligence phases of this study, no assumptions were made concerning the many possible sources of delay. The DOM's scope and scale of operations lend themselves to a variety of areas to explore, ranging from intra- and cross-team communications to data management and operational metric design. That said, a clear theme emerged during preliminary interviews with stakeholders from across the organization: clinical care team handoffs ("handoffs"), defined as the transfer of responsibility for a patient from one clinician to another, were hypothesized to be a significant cause of unnecessarily extended length-of-stay in the hospital.

While a literature review revealed that the impact of intra-day and cross-shift handoffs within established clinical teams has been studied in several settings (see discussion in Chapter 2), that of end-of-rotation handoffs (a/k/a inter-day handoffs or sign-overs), during which the clinicians composing these teams change, has not, to the best of our knowledge, been explored within the DOM, wider MGH, or any other clinical environment. And so, focusing on end-of-rotation care team handoffs (HOFs), the hypothesis at the root of this study is as follows:

HOFs impact medically unnecessary delays in patient progression through the DOM.

1.4 Summary of methodology and findings

In order to test the above hypothesis and, further, quantify the impact of HOFs on patient progression through the DOM, this study focuses on four of MGH's resident-staffed (i.e., Teaching Service), general care floors (Bigelow A/B/D/E) that have similar patient populations, bed counts, care team structures, and shift patterns. The patient population (N=16,156) includes all patients who were admitted to and discharged from one of these floors and were cared for exclusively by that floor's resident team between Jan 2012 and Jul 2015. The outcome of interest is floor length-of-stay (LOS), measured as the number of nights a patient spent on the floor between inpatient admission and discharge.

As part of MGH's Teaching Service, the two most senior physicians on these floors' clinical teams (i.e., the Teaching Attendings) rotate off the floor every two or four weeks on the same day-of-week (Wednesday). Combined with patient demand that is demonstrably independent of the hospital's residency schedule, this periodic HOF pattern and the randomized assignment of patients to floors create *natural randomized experiments* [7] that this study uses to isolate the impact of HOFs on LOS. The results are compelling. While patients who are admitted at least three days before a HOF are not impacted by this transfer of responsibility in a statistically significant manner, those who are admitted within two days spend significantly different amounts of time in the hospital than patients who are admitted on the same day-of-week but at least a week away from the next HOF.

Patients who were admitted on a Monday and then handed-off to a new Attending the following Wednesday spent an average of 0.8 days longer in the hospital than those who didn't experience a HOF for at least a week (Wilcoxon-Mann-Whitney RS, two-sided, $\alpha = 0.05$). Further, patients who were admitted on a Tuesday and then immediately handed-off to a new Attending the next day spent an average of 0.8 fewer days in the hospital than those who didn't experience a HOF for at least a week (Wilcoxon-Mann-Whitney

[7] Source: manual data collection by MGH Admitting. Filters: (1) admission Jan 2013 - Sep 2014, (2) "Code Help" and "Capacity Disaster" activations only.

RS, two-sided, $\alpha = 0.05$). While these results appear to be at odds, they indicate two distinct effects: (1) the discovery- and diagnosis-focused activities at the start of a patient's stay are highly sensitive to a HOF during this period, and (2) Attendings are able to complete these diagnosis-focused activities more efficiently at the start of their two-week rotation, provided they do most of this work themselves.

These results are supported by a series of regression models developed to predict LOS using only the information available when a patient is first admitted, including Major Diagnostic Category (MDC), day-of-week and time-of-day of admission, gender, age, and proximity to a future HOF. While patients within different diagnostic categories demonstrate distinct sensitivities to HOFs, proximity to a HOF is consistently shown to be a significant and robust predictor of LOS for patients within each MDC (model selection via AIC_c, Monte Carlo Cross-Validation, $\alpha = 0.05$).

Informed by these results, there are several changes that could be considered while seeking to reduce extended ED boarding time and delays in patient progression. First, HOFs could be staggered such that the two Attendings on each floor do not leave on the same day. Second, assuming HOFs are staggered and one of the Attending's rotations is nearly over, the outgoing Attending could assume responsibility for existing patients who are in more stable condition while new patients are assigned to the Attending who will remain on the floor for at least another week. Finally, should the second recommendation be too inflexible, the predictive models could be used to guide which patients should be assigned to the outgoing Attending such that aggregate expected LOS is minimized.

1.5 Thesis organization

This document is written with both the clinician and non-clinician reader in mind. As a result, it begins with a review of existing literature related to the impact of care team handoffs (Chapter 2) followed by a thorough physical and functional system mapping (Chapter 3). With this foundation established, exploratory analyses are presented as a means to build intuition concerning the various structural and operational dimensions that may impact delays in patient progression (Chapter 4). Medically unnecessary delays are then quantified at both a patient and department-level by taking advantage of *natural randomized experiments* within the DOM (Chapter 5). These descriptive analyses are then complemented by patient-level predictive models (Chapter 6), and these combined results inform proposals for both future work and immediately actionable strategies for mitigating the observed costs of care team handoffs (Chapter 7).

Chapter 2

Literature Review

This chapter offers a brief review of the existing literature related to assessing the clinical and operational cost(s) of the handoffs (HOFs), managing these costs through process and team design, and analytical methods used to evaluate delays in patient progression.

2.1 Impact of care team handoffs

When defining a HOF as the transition of clinical responsibility for a patient from one clinician to another, HOFs have been the subject of numerous studies seeking to assess their operational and clinical impact as well as develop prescriptions to alleviate the resultant costs (Section 2.2).

Petersen et al. [36] studied the relationship between resident team coverage schedules and the occurrence of preventable adverse events (PAEs), e.g., patient injury or unnecessary testing. They discovered that, if a PAE occurred, it was 3.5 times more likely that the physician caring for the patient at the time was from a resident team other than the patient's primary team (Odds Ratio = 3.5, $p = 0.01$). Stated differently, given that a PAE occurred, the responsible physician was likely to be relatively unfamiliar with the patient, i.e., a HOF had recently occurred. In addition to focusing on length-of-stay as an outcome instead of PAEs, we explore the inverse of the conditional relationship demonstrated by Petersen et al. Namely, given a HOF, what is the impact on patient length-of-stay.

Lofgren et al. [40] investigated the impact of clinical handoffs on the number of laboratory tests ordered for individual patients in the Department of Medicine within the Minneapolis Veterans Affairs Medical Center. Similar to our study, they took advantage of a natural experiment in which some patients were transferred to a new physician the day after admission while others were not. It was discovered that patients who were transferred had significantly more laboratory tests run during their visit (44 vs. 32 tests on average, $p = 0.01$), even when adjusting for length-of-stay.

Laine et al. [25] studied the impact on patient care of a New York State regulation that restricted house staff working hours. By comparing general medicine patient populations before and after the work hour restrictions, they discovered an increase in the proportion of patients experiencing at least one in-hospital medical complication (35% after vs. 22% before, $p = 0.002$) as well as the proportion of patients with at least one delayed diagnostic medical test (17% after vs. 2% before, $p = 0.001$), with the delays identified via retrospective analysis. Notably, Laine et al. did not seek to explicitly link the differences they observed to the incidence of care team HOFs, as will be the case in this study.

Harding et al. [2] evaluated the impact of the 2011 ACGME duty-hour restrictions on care continuity, length-of-stay, and thirty-day readmission rates[1]. Comparing pre-restriction and post-restriction patient visits to the Bigelow Service and Step-Down Unit (SDU) within MGH's DOM, they identified an average 20% increase in the number of clinical care providers responsible for a patient during visits to the resident-staffed floors (i.e., the patient is transitioned between residents with increased frequency). While they did not find an impact on thirty-day readmission rates, they did identify a strong relationship between total number of providers and overall length-of-stay within the hospital (Spearman $\rho = 0.80$, $p < 0.001$). That said, this relationship is to be expected as patients who must spend longer in the hospital due to clinical need are likely to encounter more providers simply as a function of time.

With a motivation similar to that of this study, Kuhn et al. [10] recently (Dec 2015) sought to quantify the impact of resident service handoffs on length of hospital and intensive care unit stay for patients cared for by the University of Alabama at Birmingham's neurosurgical service. Defining a service handoff as any point when a resident transitioned responsibility for a patient to another resident for longer than 1 weekend, they found length of hospital stay (5.32 vs 3.53 days, t-test of means, $p < 0.001$) and length of ICU stay (4.38 vs 2.96 days, t-test of means, $p < 0.001$) were both longer for patients who experienced at least one service handoff. Notably, Kuhn et al. focus on intra-day clinical HOFs within the intern (most junior) members of a clinical care team and do not discuss end-of-rotation HOFs within the more senior team members who provide clinical and operational leadership, such as the Teaching Attendings that are the focus of this study.

2.2 Care team and process design

In light of the costs of care team discontinuities, both quantified (as above) and intuited, there have been numerous efforts to design care teams, shift schedules, and handoff procedures to be more robust when confronted with the myriad opportunities for miscommunication, latency, and simple clinical error.

After a survey of existing practices and key points of failure, Vidyarthi et al. [47] and Arora et al. [3], offer a set of recommendations concerning the quality and medium of exchange of clinical information during physician sign-offs (a/k/a handoffs, the transfer of responsibility for a patient from one physician to another at the end of a shift). These recommendations include establishing a formal checklist detailing the sign-off process, using structured and well-validated templates for information exchange, and formally tracking and debriefing on mistakes stemming from failed sign-offs.

Lane-Fall et al. [26] also administered a survey to 661 ICU clinicians working in seeking to understand the handoff practices for Teaching Attendings (senior physicians overseeing a team of residents). Beyond characterizing the heterogeneity within these practices (in-perspon conversation: 92.9%, telephone calls: 83.9%, emails: 69.0%, computer-generated forms: 64.6%, and text messages: 23.6%), they discovered that only 13.3% of respondents practiced a standardized process and, interestingly, only 11.5% of respondents thought that Attending handoff processes were necessary given the continuity of care offered by residents. It's worth keeping this last point in mind as the reader continues through Chapters 5 and 6.

Farhan et al. [12] went one step further and performed a prospective study in the emergency department of a large, urban teaching hospital. This involved piloting a new handoff procedure, "The ABC of Handover," which involved similar mnemonic mechanisms as were put forward by Arora et al. The pilot resulted in a 66% reduction in shifts where the recipient resident team reported "material information" was not communicated during the handover handoff procedure.

Starmer et al. [46] performed a similar prospective intervention study in which resident teams were provided with a "handoff bundle," consisting of standardized communication and handoff training, a verbal mnemonic, and a new team handoff structure. In addition to operational benefits similar to those realized by Farhan et al., they were able to realize a measurable reduction in medical errors (33.8 to 18.3 per 100 admissions,

[1]Before 2011, all residents were able to work up to 30 hours consecutively. After the rule changes, interns (PGY-1) can work no more than 16 hours consecutively, other residents (PGY-2+) can work no more than 28 hours consecutively, and all residents can work no more than 80 hours per week. See [17].

$p < 0.001$), fewer PAEs (3.3 to 1.5 per 100 admissions, $p = 0.04$), and an increased percentage of physician time spent at a patient's bedside (8.3% to 10.6%, $p = 0.03$).

In response to the 2011 duty-hour restrictions and operating with the understanding that, all else held constant, clinician handoffs should be minimized, Kazemian et al. [24] developed an integer programming (IP) model for resident shift schedules that minimizes handoffs while adhering to the ACGME duty-hour standards[2]. Using the Mayo Clinic Medical Intensive Care Unit (MICU) as a case study, they found they could reduce handoffs within the resident team by 23% while still meeting all the required and desired scheduling constraints by migrating from twelve-hour shifts (6am-6pm, 6pm-6am) to sixteen-hour shifts (6am-10pm, 10pm-2pm, 2pm-6am). Further, they could reduce handoffs by 48% if they were to meet only the required constraints, which allow for twenty-four shifts.

2.3 Predicting patient length-of-stay

Predicting the amount of time an inpatient will spend within the hospital (or a specific department or care unit therein) has long been a topic of academic and industry interest. As briefly discussed in Chapter 1, however, there is typically very little information available to clinicians when a patient first enters the hospital. Further complicating this effort, hospital medicine is a complex process and, as an outcome, length-of-stay is impacted by everything from individual patient demographics and aggregate demand to hospital operating patterns and dynamic relationships with 3$^{\text{rd}}$ parties, e.g. long-term acute care facilities. This section contains an overview of the analytical practices used in light of these challenges. Notably, while clinical HOFs have been the focus of several observational studies (see Section 2.1), they have not, to the best of our knowledge, been considered explicitly when predicting outcomes such as length-of-stay.

Utilizing ANOVA, Liu et al. [27] sought to explain variation in overall length-of-stay in the hospital using Diagnosis Related Group (DRG)[3], referral source, type of health insurance, and other patient demographic data as independent factors. They found that only 37.6% of length-of-stay variation was significantly explained by the model, with DRG (i.e., the patient's diagnosis) alone accounting for 30% of variation. As a small point of criticism, it is worth noting that, as used in this model, DRG is retrospectively assigned to patients after they have been discharged from the hospital. As a result, the DRG factor is itself an outcome of the clinical process(es) such a model would seek to predict. This in mind, the models developed in Chapter 6 of this study use only the demographic, operational, and clinical information available when a patient is first admitted as independent factors. For example, we include the patient diagnosis hypothesized at point of admission rather than DRG.

Working within an urban hospital in the U.K., Carter et al. [11] sought to predict overall length-of-stay in the hospital for patients undergoing a primary total knee replacement. Utilizing a Negative Binomial Model and similar patient demographic data as Liu et al. [27], they found age, gender, discharge destination (home vs. non-home), and day-of-week of admission (Sunday) to be significant predictors of length-of-stay (all, $p < 0.001$). For example, patients who are discharged to their home spent 0.4 fewer days in the hospital than patients who were sent to another facility, likely due to additional logistical complexity (as will be discussed in Chapter 5). Further, patients who were admitted on a Sunday spent 0.5 more days in the hospital than other patients, ostensibly because of reduced staffing on Sundays. While the model proved to be quite predictive, predicting 75% of stays within +/- 3 days (91.4% for stays 4-6 days), it is worth noting that it focuses on a relatively routine procedure performed on a well-understood patient population. Others have had similar success for other procedures [50][22][51] but, while these results are noteworthy, the heterogeneity and initial uncertainty of clinical need within the DOM's patient population make it impossible to prospectively isolate patient populations that will undergo the same procedure. As a result, the regression models developed in this study are challenged with predicting length-of-stay outcomes for patients with sometimes dramatically different diagnoses and treatment paths. As will be shown in Chapter 5, however, this difficulty is overcome,

[2]See footnote 1.

[3]Diagnosis Related Group (DRG) is a classification scheme used to group patients who receive "like" care together for the purposes of repayment. Example DRGs include: "089 Concussion" and "001 Heart transplant or implant of heart assist system." See [18].

at least in part, by isolating patient populations based upon the broad diagnostic categories assigned when patients are first admitted.

Finally, Hachesu et al. [37] built on a series of analyses [42][49] that utilized data mining techniques to classify patients into categories of length-of-stay, e.g., {0-5 days, 6-9 days, 10+ days}. Utilizing patient demographic information (e.g., age, ethnicity) and detailed clinical data (e.g., diastolic blood pressure, fasting blood sugar) collected at point of admission, they tested three types of models, (1) Artificial Neural Networks (ANN), (2) Decision Trees, and (3) Support Vector Machines (SVM), with respect to their ability to classify patients admitted to the hospital with already-diagnosed coronary artery disease (CAD). With a population of 2,064 patients (80%/20% training/validation), the SVM model had the greatest accuracy in classifying patient length-of-stay in the validation set (93.6%), followed by the Decision Tree model (83.5%), and then the ANN model (56.9%). Notably, clinical data specifically related to CAD (e.g., past history with the disease and physical stress test results) were significant ($p < 0.001$) in all the models. As the reader will see in Chapter 6, and was discussed earlier in this section, this degree of specificity is difficult to achieve in more heterogeneous environments, such as the DOM.

Chapter 3

System Mapping

With both the clinician and non-clinician reader in mind, this chapter seeks to develop a shared vernacular and intuition for the DOM's physical and functional design. It does this by first discussing the functional stages of care an inpatient progresses through while in the DOM and the various team structures in which clinicians operate in order to support patients with differing types and degrees of clinical need. Clinicians on these teams assign, share, and transfer responsibilities for patients in prescribed ways that are a function of the composition of the team and the shift patterns it practices. Finally, patients are assigned to specific floors in the DOM by matching the patient's clinical need with the floor and clinical team best suited to care for that need.

3.1 Functional stages of care

For any inpatient episode, there are three fundamental stages of care that start when the patient is first admitted:

1. **Diagnosis:** The patient's medical need is discovered via inquiry, observation, and tests.
2. **Treatment:** This medical need is addressed via a set of therapies, e.g. medication and rest.
3. **Discharge:** Post-hospital care is arranged and the patient is physically and legally discharged.

While this definition is somewhat reductive, it offers insight into the mix of clinical activities that are performed as a function of how "new" or "known" the patient is to the hospital. That said, it is notoriously difficult to delineate between stages of care both in the moment and retrospectively. Beyond technical limitations in data capture and reporting, diagnosis and treatment may occur recursively, and all three stages could be concurrent at certain points within the patient's stay (see Figure 3-1). For example, diagnosis and treatment may occur in parallel, particularly at the beginning of a stay, and treatment and discharge have the potential to conclude at the same time.

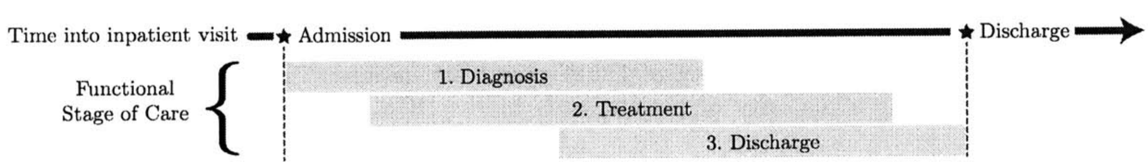

Figure 3-1: Functional stages of care

3.2 Structure of clinical care teams

As is common practice in many Academic Medical Centers (AMCs), inpatients within MGH's DOM are cared for by clinicians operating in teams called clinical care teams ("care teams"). While the clinicians composing care teams vary across AMCs [8], the DOM's include physicians and registered nurses (RNs) who collaborate while providing clinical care to one or more patients. Care teams have evolved into a range of configurations in response to patient demand, the need to support a Resident Teaching Program, and the physical constraints of the hospital. While the treatment of individual patients may involve resources external to the DOM, such as specialist consults, stable team structures vary in four primary dimensions:

1. **Teaching vs. Hospitalist Service**

   By belonging to the Teaching Service, teams necessarily include resident physicians as well as senior physicians who serve as supervisors and teachers. If the team does not include residents, it belongs to the DOM's Hospitalist Service and includes post-residency Hospitalist physicians (equivalent to Attendings) and RNs. Participation in the Teaching Service carries implications for both the team's composition and its shift schedule, the latter of which will be discussed in Section 3.6.

2. **Regionalized vs. Non-Regionalized**

   Regionalized teams are assigned to a single floor on which all of the team's patients are located. Non-regionalized teams may care for patients distributed across a variable number of floors and buildings, including areas traditionally reserved for other departments, e.g., Surgery. While not strictly deterministic, regionalization has implications for the type of patients for which a team is responsible. Specifically, the Admitting Department seeks to assign more acute (i.e., more ill) patients to regionalized teams (i.e., responsible for patients on only one floor) with the assumption that this close proximity is aligned with the patients' need for more continuous care and surveillance. Further, while all teams belonging to the DOM's Teaching Service are strictly regionalized, the converse is not always true.

3. **Involvement of the McGovern Service**

   When a patient's Primary Care Physician (PCP) leads the clinical care team in treating the patient while in the hospital, the PCP belongs to the McGovern Service and supplements the original team structure. A McGovern Attending is available only if the patient's PCP practices within MGH or the wider Partners HealthCare network. If involved, a McGovern Attending takes a variable role in leading patient-specific care decisions and does not have responsibility for or actively participate in clinical decision-making related to the team's other patients.

4. **Composition**

   Teams vary in size and composition, such as clinician seniority and roles (see Section 3.3).

3.3 Care team size and composition

While Appendix L presents the full variety of DOM care team designs, Table 3.1 illustrates the three configurations that support a majority of patient beds in the DOM: (1) Bigelow, (2) Ellison, and (3) Hospitalist.

Table 3.1: Primary clinical care team configurations

	Team Member						
Team	Senior	PGY-2	PGY-1	Student	NP	Hospitalist	Total
Bigelow*	2	1-2	5	0-3	0-1	0	9-12
Ellison*	2	2	4	0-3	0	0	8-11
Hospitalist**	0	0	0	0	0	2-3	2-3

Postgraduate year (PGY); Nurse Practitioner (NP)
*Bigelow and Ellison teams are regionalized to a single floor
**Hospitalist teams are non-regionalized and may support multiple floors

As will be further discussed over the next several sections, these teams define and share responsibilities for patients in slightly different ways. The Bigelow and Ellison teams are both regionalized and part of the Teaching Service. On these teams a group of interns (PGY-1) and possibly an NP share responsibility for providing direct care to patients on a specific floor while under the supervision of Teaching Attending (post-residency) and Junior (PGY-2) physicians.

The Hospitalist teams, on the other hand, can be regionalized or non-regionalized and are not part of the Teaching Service. On these teams, patients can be distributed across multiple floors and, as a result, direct responsibility for individual patients is generally not shared across the team.

3.4 Focusing on floors with similar patients and team structures

As the goal of this study is to quantify the impact of end-of-rotation Attending HOFs on delays in patient progression, it is necessary to focus on a subset of the DOM's numerous care units that have similar team configurations, shift patterns, bed counts, and patient populations. This subset includes four, resident-staffed, general care floors (see Table 3.2) that were initially selected because their structural and operating similarities enabled data aggregation across a larger population of patient visits relative to other options. As will become clear in subsequent sections, however, it was later discovered that the shift patterns practiced on these floors lend themselves particularly well to testing the hypothesis at the root of this study (see Section 1.3).

Table 3.2: Floors included in study focus

Team	**Building**	**Floor**	**Level of care**	**# beds***
Bigelow A	White	8	General	24
Bigelow B	White	9	General	20
Bigelow D	White	11	General	20
Bigelow E	Bigelow	11	General	24

*number of beds dedicated to general medicine

3.4.1 Clinical care team configurations

These four floors implement two variations on the standard Bigelow Service configuration (see Table 3.3). While both variations have the same number of team members, the Bigelow A/E configuration has two Junior Residents (JARs) and the Bigelow B/D configuration has one JAR and one Nurse Practitioner (NP).

Table 3.3: Bigelow team configurations

Team Member	Seniority	Function	Bigelow Team A	B	D	E
Teaching Attending	Senior Physician	Oversight	2	2	2	2
Junior Resident (JAR)	PGY-2	Oversight	2	1	1	2
Intern	PGY-1	Direct care	5	5	5	5
Nurse Practitioner (NP)	Variable	Direct care	0	1	1	1
		Total	9	9	9	9

As will be more completely discussed later in this chapter, the NP assumes responsibility for more stable patients near the end of their stay and contributes to coordinating the discharge of patients across the floor.

3.5 Responsibilities within clinical care teams

Formal responsibilities within a care team are assigned to individual clinicians and come in two flavors: (1) patient-level, and (2) team-level. Patient-level responsibilities include the clinical and legal obligations an individual clinician has for a specific patient. Team-level responsibilities, on the other hand, include the duties an individual clinician assumes to support the performance of the team as a whole, such as completing paperwork and coordinating logistics with other departments on behalf of the entire team.

3.5.1 Patient-level responsibilities

There are two types of patient-level responsibilities: (1) Responding and (2) Attending (see Table 3.4).

Table 3.4: Patient-level responsibilities

Responsibility	Assigned to	Description of responsibility
1. Responding	PGY-1, NP, Hospitalist	Responsible for coordinating and delivering minute-to-minute care for the patient.
2. Attending	Senior Physician, Chief Resident, Hospitalist	Legally responsible for the patient and supervises the Responding Clinician.

As the Responding Clinician is responsible for direct care delivery and must maintain close physical proximity to the patient, the Responding Responsibility is regularly transferred between clinicians as a function of regular shift schedules (e.g., day/night, week/weekend, on/off-shift) and intra-day load balancing within the team.

The Attending Responsibility does not require the same proximity, however, and its assignment is generally more stable. An individual clinician may remain a patient's Attending so long as that clinician is accessible should a need arise. Handoffs are generally motivated by an Attending leaving the floor for the weekend (the two Attendings alternate covering weekends) or leaving the team at the end of a multi-week rotation (discussed in Section 3.6).

While the Responding and Attending Responsibilities are assigned to two different clinicians on the Teaching Service, they are generally assigned to the same clinician on the Hospitalist Service.

3.5.2 Team-level responsibilities

Formal team-level responsibilities (see Table 3.5) are those that are not patient-specific, such as providing clinical oversight for the team as a whole, or involve tasks that can be performed more efficiently by a single clinician rather than by each clinician individually, such as the completion of repetitive paperwork and coordinating logistics with other departments.

Table 3.5: Team-level responsibilities

Responsibility	Assigned to	Description of responsibility
1. Teaching Attending	Senior Physicians or Chief Residents	Facilitate a supervised learning environment for the resident team.
2. Clinical	PGY-2 / Junior Resident (JAR)	Provide direct clinical guidance to Interns.
3. Disposition	PGY-2 / Junior Resident (JAR)	Drive discharge activities for the entire floor.
4. On-Call	PGY-1 / Intern	Provide direct clinical care to patients.
5. Swing	PGY-1 / Intern	Complete information discovery, paperwork.
6. Plan	PGY-1 / Intern	Develop treatment proposals for new patients.

Resident teams utilize team-level responsibilities to varying degrees depending upon the specific team structure implemented on a floor. For example, teams with only one Junior resident (PGY-2) will not formally assign the Disposition Responsibility and will instead distribute the associated duties across the NP and interns as a group. While Hospitalist clinicians operate in teams, formal team-level responsibilities are not commonplace.

With the exception of the Clinical and Disposition team responsibilities, an individual clinician may be assigned both patient- and team-level responsibilities concurrently (see Table 3.6). For example, a clinician who is assigned the Responding responsibility for several individual patients, driving direct care activities such as patient interviews and clinical tests, may also be assigned the Plan team-level responsibility, developing a summary and proposed course of treatment for the day's new patients. Further, a clinician who is serving as one of the team's Teaching Attendings, supervising the residents on the floor, will also be assigned the Attending responsibility for roughly half of the floor's patients.

Table 3.6: Patient and team-level responsibilities that may be assigned concurrently

		Team Responsibilities					
		1. Teaching	2. Clinical	3. Disposition	4. On-Call	5. Swing	6. Plan
Patient	1. Responding				X	X	X
	2. Attending	X					

Appendix L provides an overview of the full diversity of configurations currently practiced in the DOM.

3.6 Rotation schedule and types of handoffs

As mentioned in Section 3.2, participation in the Teaching Service carries implications for the team's shift schedule, requiring that physicians rotate on and off the team on days specified by the Resident Block Schedule ("Block Schedule"). The Block Schedule divides each year into thirteen four-week blocks and twenty-six two-week sub-blocks, each starting on a Wednesday. With few exceptions, physicians assigned to teams on the Teaching Service begin two or four-week rotations at the start of a sub-block. Individual members rotate on and off the team with a frequency that is particular to their role. As will be discussed in greater depth in Section 4.6, Attendings generally have two-week rotations that begin at the start of each sub-block and JARs and Interns have four-week rotations that begin with the start of each block. Table 3.7 and Figure 3-2 summarize these patterns.

Table 3.7: Rotation patterns vs. role

Team Member	**Seniority**	**Rotation length***	**Rotation starts**
Teaching Attending	Senior Physician	2 or 4 weeks	1st or 3rd Wednesday
Junior Resident (JAR)	PGY-2	4 weeks	1st Wednesday
Intern	PGY-1	4 weeks	1st Thursday
Nurse Practitioner (NP)	Variable	3-4 days	Mixed

* *Typical* rotation lengths. See Chapter 4 for full discussion.

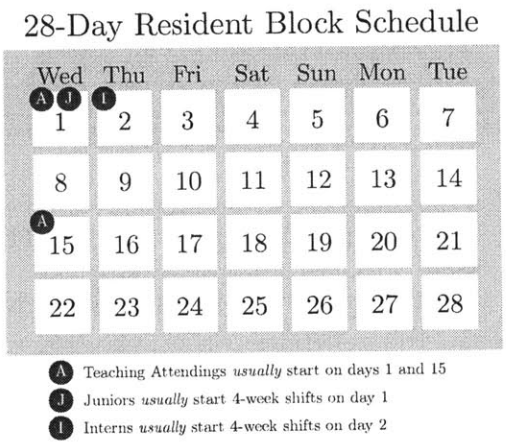

Figure 3-2: Resident block schedule

Notably, while NPs are part of several clinical care teams on the Teaching Service, their rotations are scheduled independently of the Block Schedule. Similarly, clinicians on the Hospitalist Service have rotations lasting between three and five days and do not have a requirement that individual team members start on the same day.

While the Block Schedule dictates when clinicians rotate on and off teams, there are additional layers of shift patterns (e.g., intra-day and weekly) within each rotation that dictate when clinicians are physically in the hospital as well as when the transfer of patient and team-responsibilities occurs. As summarized in Table 3.8, patient and team responsibilities are assigned and reassigned (handed-off) in response to a variety of factors, including daily and weekly shift patterns, intra-day availability, and functional training diversity during an on-floor rotation.

Table 3.8: Types and causes of handoffs

Responsibility		Cause of handoff				
Level	Name	Rotation	Training*	Week/end	Day/Night	Intra-day
Patient	Responding	X		X	X	X
Patient	Attending	X		X	X	X
Team	Teaching	X				
Team	Clinical	X	X			
Team	Disposition	X	X			
Team	On-Call	X	X	X	X	X
Team	Swing	X	X	X	X	X
Team	Plan	X	X	X	X	X

*Training during an extended rotation

Worth noting is that patient-level responsibilities are reassigned quite frequently (mostly intra-day) and team-level responsibilities are relatively stable, most particularly for the Teaching Attending responsibility, which is reassigned only when Teaching Attendings, the most senior clinicians, rotate off the floor.

As discussed in Chapters 1 and 2, there is an existing body of research into the impact of intra-day and weekend handoffs and, as a result, this study focuses on the impact of block rotation-caused handoffs within the teams' Teaching Attendings.

3.7 Inpatient flow

As Figure 3-3 illustrates, inpatients are introduced to the DOM network from multiple sources, including (1) the Emergency Department, (2) directly from home, e.g., direct admission by a Primary Care Provider, (3) another department within MGH, (4) a different hospital (transfer), and (5) another external facility, e.g., an assisted living facility (transfer).

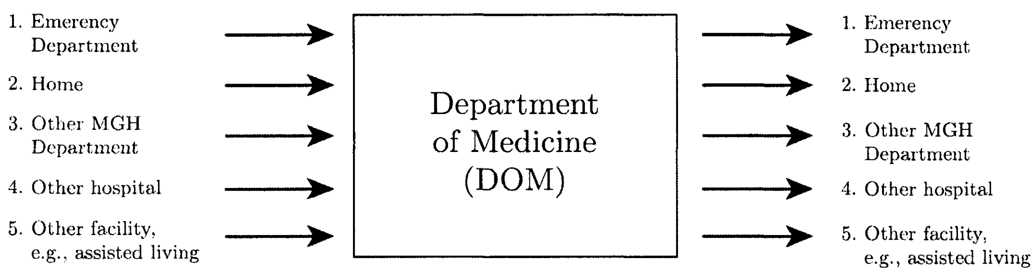

Figure 3-3: Admission sources and discharge destinations of DOM patients

Roughly 80% of DOM patients are admitted from and discharged directly to either their home or a non-hospital facility, e.g., assisted living. The majority of the remaining patients stay in the DOM as part of a longer stay in the hospital involving one or more other MGH departments[1].

While the physician who admits the patient specifies the destination department, the hospital's Admitting Department ("Admitting") determines the specific building, floor, and bed to which the patient is initially assigned. As mentioned in Section 3.2, this rolling assignment process assigns "similar" patients - those with the same degree of clinical need - to floors with similar care team models, physical configurations, and equipment (see Appendix H for a full discussion). Chapter 4 explores the degree of this similarity across the four floors that are the focus of this study and concludes that, as this process would suggest, the patient populations cared for on these floors are statistically the same.

Once within the DOM, patients may be transferred between the over 20 care units in response to the patient's evolving clinical need and/or resource availability. Further, a patient may leave the DOM to receive specialized care in another department and return at a later point during their stay. A full discussion of this dynamic is included in Appendix G.

3.8 Process for new patients

While Teaching Attendings are broadly available to the resident team throughout their rotation, they play a particularly significant role in helping the team develop an initial diagnosis and treatment plan for new patients when they are first admitted to the floor (and, as needed, at critical inflection points during the patient's stay). This is part of a standard process the clinical teams complete for each new patient, which includes:

[1]Source: PEPL Inpatient Survey Fact, EPSi. Filters: (1) Admission Jan 2013 - Sep 2014, (2) Admission sources: {ACT, ADM, BOP, E03R, EMD, EMER, PAC}, (3) Discharge destinations: all non-MGH dispositions.

Step 1. Interns review all available information, order diagnostic tests, and develop a proposed course of treatment to be reviewed by Attendings.

Step 2. Attendings review the proposed course of treatment with the intern group.

Step 3. Interns execute on the treatment plan under the supervision of the JARs (and repeat Steps 1-2, as needed).

To ensure immediate needs are identified and addressed, Step 1 is completed as soon as a new patient is brought to the floor ("on-floored" or "admitted to the floor"). Unless there is an urgent need to involve the Attending, Step 2 (the "Attending Review") may occur either the same day or the following morning (see Figure 3-4), particularly if the patient is on-floored after 12pm, is will be discussed in Section 4.4.

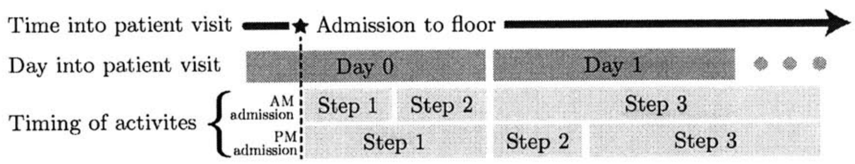

Figure 3-4: Process after a new patient is admitted to the floor

As is standard practice within Academic Medical Centers [3], the Attending review is usually performed during group meetings called *rounds* with the entire clinical team that, at MGH, are scheduled for 8am each morning. A central part of the residency learning experience, the review serves as a catalyst for clinical activities related to new patients, i.e., a treatment path is designed during the review and enacted immediately following its conclusion. Chapter 4 includes a more complete discussion of this dynamic.

Chapter 4

Exploratory Analysis

This chapter outlines the early findings that informed the final analyses conducted to quantify the impact of HOFs on delays in patient progression. It begins by offering an overview of the patient populations served by the four Bigelow teams selected for this study (and discussed in Chapter 3), continues by introducing a handful of key operational metrics that are central to the latter chapters, and concludes by illustrating the quality and quantity of handoffs experienced by patients on these floors.

4.1 Patient population

As the Bigelow team configurations were changed shortly before the start of 2012, the study window includes patients who were admitted and discharged between January 1, 2012 and July 31, 2015. Over this period, Bigelow A/B/D/E supported 18.7K unique patient hospitalizations, the annual volume of which consistently increased year-over-year, as shown in Table 4.1[1]. It is valuable to note that unique hospitalization volume includes any patient who spent at least one night in the DOM, irrespective of whether this stay was part of a longer stay at MGH. Further, if a patient was admitted multiple times, each stay within the DOM is counted separately.

Table 4.1: Unique visits to Bigelow A/B/D/E[2]

2012	2013	2014	2015*	Total
5,088	5,352	5,482	2,819	18,741

*Unannualized; through July 31, 2015

While all clinical and operational processes indicate that these floors care for similar patient populations, several statistical tests were performed to ensure comparability and ensure patients were indeed randomly assigned across floors, including:

1. Age distributions via Wilcoxon Rank-Sum Test (α= 0.05)
2. Admission sources / discharge destinations via z-test of sample proportions (α= 0.05)
3. Major Diagnostic Category (MDC) codes via z-test of sample proportions (α= 0.05)
4. Daily admission/discharge volumes (normalized by bed count) via Wilcoxon Rank-Sum Test (α= 0.05)
5. Length-of-stay in the hospital, as discussed in Section 4.1.1

[1]Source: PEPL Inpatient Survey Fact. Filters: (1) Admission and discharge within [2012-01-01 00:00:00, 2015-07-31 23:59:59], (2) Assigned to a Bigelow A/B/D/E team at least once.
[2]Population as described in footnote 1.

It was not possible to reject the null hypothesis - that the floor populations are statistically comparable in terms of quantity and quality of admitted patients - using any of the above tests. Looking beyond point of admission, however, it is challenging to compare patient populations once they have travelled along their unique care paths and diffused throughout the hospital. The next section presents the analysis of a measure - patient length-of-stay - that offers a somewhat aggregated but still valuable lens into what happens to patients during their stay.

4.1.1 Length-of-stay on Bigelow A/B/D/E

A key operational metric within the DOM is patient length-of-stay (LOS), which is a discrete measure defined as the number of midnights an inpatient spends in the hospital between admission and discharge. As shown in Figure 4-1, the overall distribution is long-tailed, with 84% of visits lasting no more than a week.

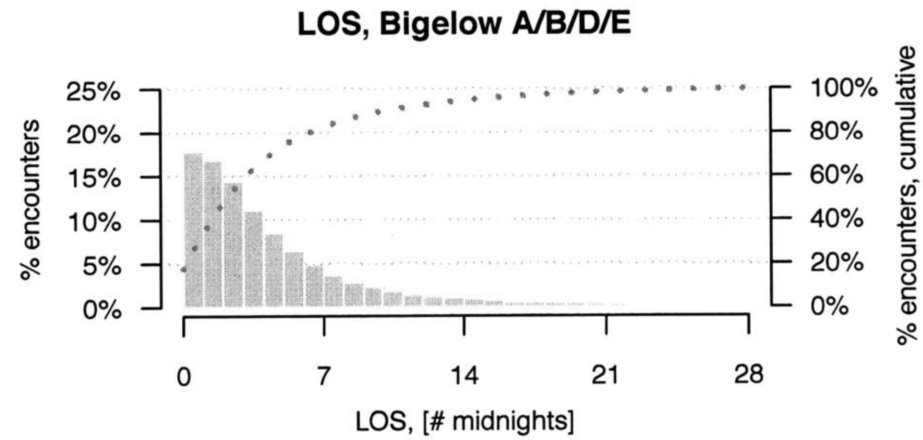

Figure 4-1: LOS for Bigelow A/B/D/E Patients[3]

While LOS is an outcome, it can be used as a coarse indicator for many of the population characteristics that would be valuable but otherwise difficult to compare, e.g., psychosocial complexity and the myriad clinical measures of health that shape how a patient progresses through the hospital.

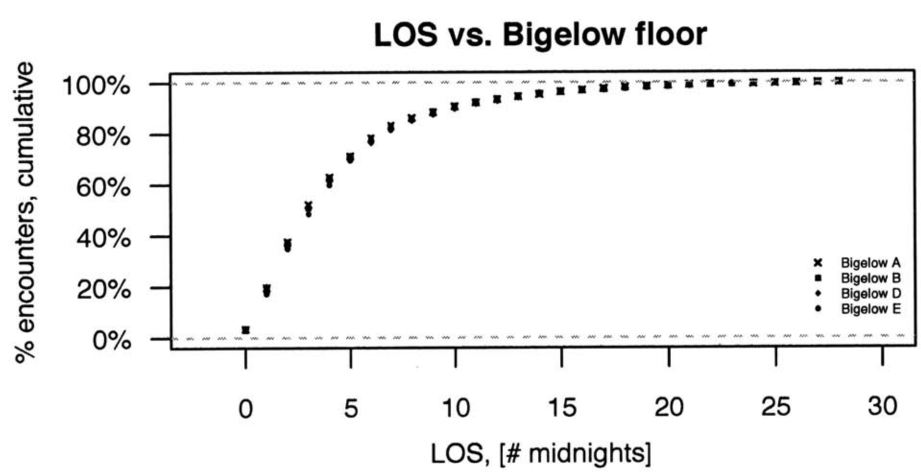

Figure 4-2: LOS vs. floor, Bigelow A/B/D/E[4]

[3]Source: PEPL Inpatient Survey Fact. Filters: (1) Admission and discharge within [2012-01-01 00:00:00, 2015-07-31 23:59:59], (2) Assigned to a Bigelow A/B/D/E resident team at least once.

As Figure 4-2 demonstrates, the LOS distributions realized by the four floors are remarkably similar upon visual inspection and statistically equivalent via two-sided Wilcoxon-Mann-Whitney RS ($\alpha = 0.05$). Considered alongside the demographics- and volume-focused tests, this result is taken as sufficient to conclude that the four floors have statistically similar patient populations and can safely be aggregated for the purposes of this study.

4.2 Timing of patient admission and discharge

Admissions to the hospital are affected by numerous external factors, including day-of-week, time-of-day, season, weather, and proximity to a major holiday. As such, there is a body of work dedicated to forecasting demand patterns for patients arriving to the hospital from the community[5]. For the purposes of this study, however, it is sufficient to understand that there are meaningful weekly and daily demand dynamics that impact both when new patients are introduced to the hospital and the timing with which they are moved about while within the hospital's walls.

4.2.1 Admission to hospital

As discussed in Section 3.7, patients are introduced to the DOM from a variety of sources, such as from another department within MGH or from the Emergency Department. Irrespective of source, each patient must first be admitted to the hospital before that patient is later moved to a particular floor within the DOM. In exploring when patients are first admitted to the hospital (see Figure 4-3), there is a clear difference between weekdays and weekends. While admission times remain concentrated between 11am - 4pm regardless of day-of-week, new patient admissions are 30% lower on Saturdays and Sundays than during the rest of the week (t-test of means, pooled variance, two-sided, $\alpha = 0.05$).

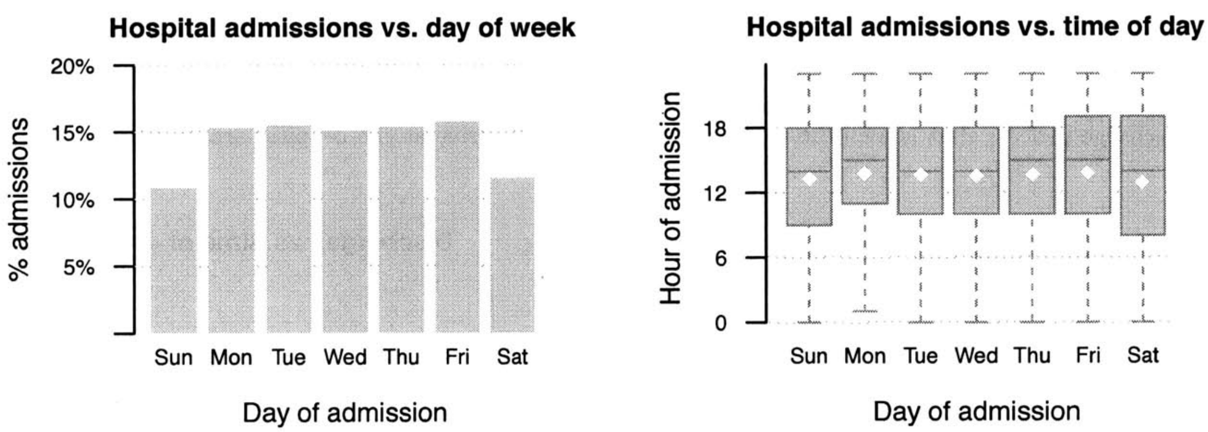

Figure 4-3: Day and time of admission to hospital, Bigelow A/B/D/E[6]

[4]Source: PEPL Inpatient Survey Fact. Filters: (1) Admission and discharge within [2012-01-01 00:00:00, 2015-07-31 23:59:59], (2) Assigned to a Bigelow A/B/D/E team at least once., (3) Removed all visits during which patients stayed on multiple Bigelow floors.

[5]See "Time of Day and Day of Week Trends in EMS Data" [23]

[6]Source: PEPL Inpatient Survey Fact. Filters: (1) Admission and discharge within [2012-01-01 00:00:00, 2015-07-31 23:59:59], (2) Assigned to a Bigelow A/B/D/E team at least once.

4.2.2 Admission to floor

Understanding that admission to the hospital precedes physically moving a patient to a specific floor within the DOM, most patients are moved to a DOM floor (a/k/a "admitted to the floor") during or immediately following the core 11am - 4pm hospital admission window. That said, there are also patients who are relocated from elsewhere within the hospital, such as from an Intensive Care Unit (ICU) after the patient has recuperated sufficiently. Generally, these are the patients who are admitted to the floor earlier in the day with the effect of shifting the timing distribution lower in Figure 4-4.

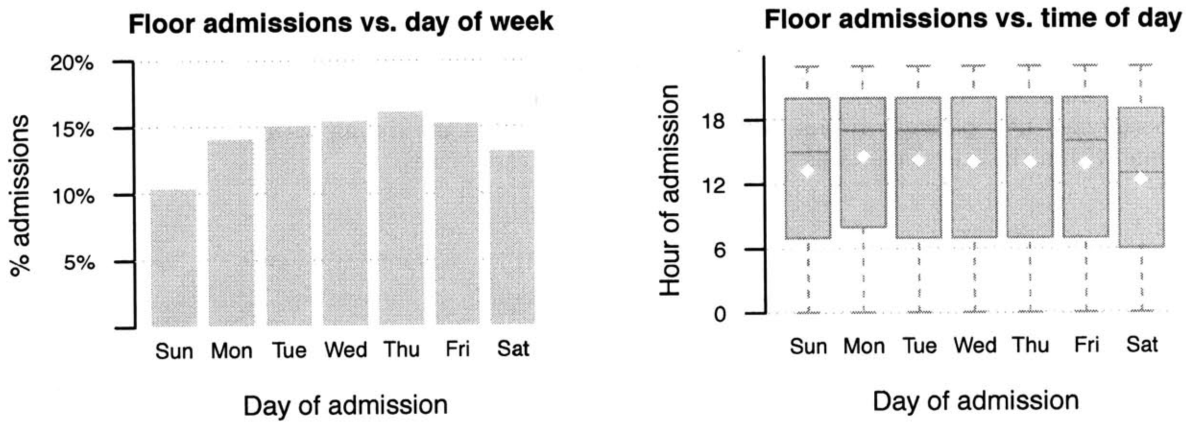

Figure 4-4: Day and time of admission to floor, Bigelow A/B/D/E[7]

4.2.3 Discharge from floor and hospital

As general care floors often serve as the final stop in a patient's care path (see Section 3.7), patients are regularly moved from the floor and discharged from the hospital at the same time. As seen in Figure 4-5, the distributions of discharge times are clustered around 2pm. This concentration is the result of the multi-hour, serial discharge process that is facilitated by day-shift staff who arrive at the hospital around 8am.

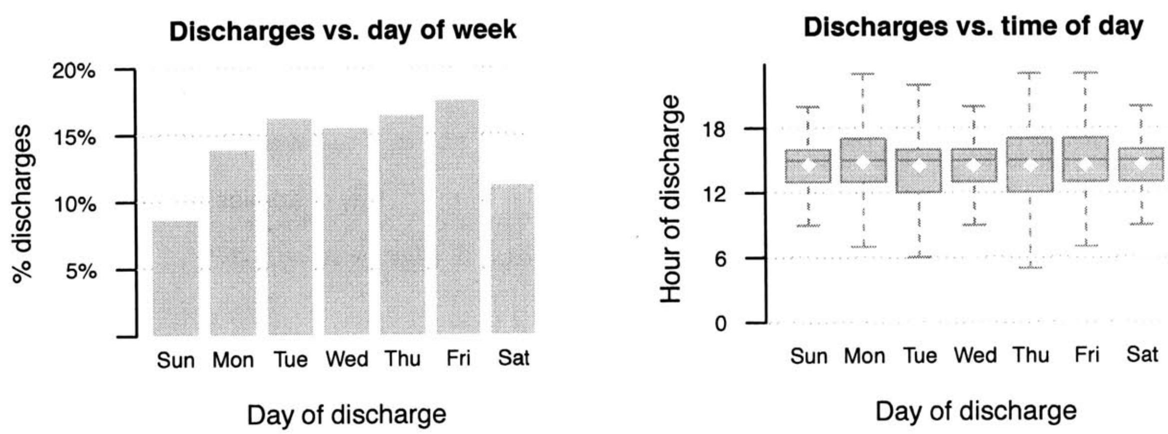

Figure 4-5: Day and time of discharge from floor and hospital, Bigelow A/B/D/E[8]

[7]Source: PEPL Inpatient Survey Fact. Filters: (1) Admission and discharge within [2012-01-01 00:00:00, 2015-07-31 23:59:59], (2) Assigned to a Bigelow A/B/D/E team at least once, (3) Time of admission to floor derived as in Appendix C.

As patients must first be discharged and their beds cleaned before new patients can be admitted to the floor, shifting discharge times to earlier in the day has been the goal of several of the DOM's recent process improvement initiatives that seek to address the rising admission wait times first presented in Chapter 1.

4.3 Admission and discharge rates

As an additional test of the comparability of the four floors, the number of admissions and discharges were compared for each day-of-week. This was done by dividing each floor's daily admission and discharge volumes by the number of beds for which the resident team is responsible on that floor[9], deriving daily rates as shown in Figure 4-6. While admission and discharge rates differed from one another on some days of the week (discussed below), these rates were statistically similar across floors when controlling for day-of-week[10].

Comparing weekday and weekend distributions, on average, both the admission and discharge rates are 2%-3% lower on weekend days than on weekdays[11]. Comparing weekday and weekend distributions separately, Mondays have fewer admissions than other weekdays and both Mondays and Wednesdays have fewer discharges[12]. While it is outside the scope of this study to seek to identify the specific reason(s) for these differences, it is reasonable to hypothesize that reduced weekend staffing levels and the weekend Attending handoff (see Section 3.5.1) contribute to the Monday effects and the Resident Block Schedule (see Section 3.2) is contributing to the Wednesday discharge differential. The next chapter will discuss the latter in more detail.

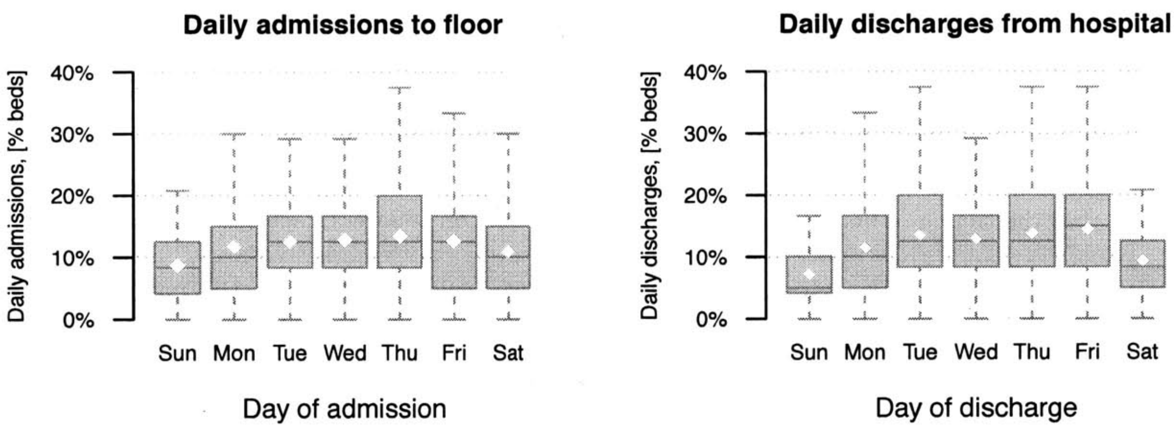

Figure 4-6: Daily admission and discharge rates, Bigelow A/B/D/E[13]

Comparing admissions to discharges, on average, more patients are admitted to the floor during the weekend than are discharged (1.7% more on Saturdays and 1.4% more on Sundays) and fewer patients are admitted on Tuesdays and Fridays than are discharged (1% fewer on Tuesdays and 1.9% fewer on Fridays)[14]. A possible explanation for the weekend differential is that the hospital staff traditionally responsible for coordinating discharge for patients with complex needs (Case Managers) are not available during the weekend. As the Tuesday and Friday discharge rates are on-par with other weekdays, the Tuesday and Friday differentials are potentially driven by behavioral economics - namely, staff seeking to avoid additional workload at the end

[8]Source: PEPL Inpatient Survey Fact, EPSi. Filters: (1) Admission and discharge within [2012-01-01 00:00:00, 2015-07-31 23:59:59], (2) Assigned to a Bigelow A/B/D/E team at least once.

[9]Admission (discharge) rate: # admissions (discharges) / 24 for Bigelow A/E, # admissions (discharges) / 20 for Bigelow B/D.

[10]Wilcoxon-Mann-Whitney RS, two-sided, $\alpha = 0.05$ and t-test of means, pooled variance, two-sided, $\alpha = 0.05$. Only statistical difference: Bigelow B and D have 1.9% more admissions on Thursdays than Bigelow E (only).

[11]Compared individual weekend days and weekdays via t-tests of means (pooled variance, two-sided, $\alpha = 0.05$) and Wilcoxon RS, two-sided, ($\alpha = 0.05$).

[12]Via Wilcoxon-Mann-Whitney Rank-Sum Test, $\alpha = 0.05$.

[13]See footnotes 8 and 9.

of the week or at the end of a block shift, as will be explored in greater depth in Chapter 5.

4.4 Timing of first review by Attending

Referencing the new patient process outlined in Section 3.8, the initial Attending Review will occur either the same day a patient is admitted to the floor or the following morning. As this review is used to develop and coordinate the patient's treatment path, it is valuable to understand when it occurs and whether this varies across floors or day-of-week. Timestamped and coded billing information was used to determine when this review occurred for each patient (see Appendix C for a full discussion). As Table 4.2 demonstrates, the probability that a patient is reviewed the next day increases monotonically with hour of patient admission to the floor. While this effect is consistent across floors, there are differences when comparing across days-of-week. Specifically, patients who are admitted after 12pm on Tuesdays and during the weekend are more likely to be reviewed the next morning than on other days (binomial test, two-sided, $\alpha = 0.05$)[15].

Table 4.2: Probability of next day review vs. day and time of admission to floor[16]

		Day-of-week of admission to floor						
		Sun	**Mon**	**Tue**	**Wed**	**Thu**	**Fri**	**Sat**
Admit hour	**00-05**	4%	5%	5%	3%	5%	6%	3%
	06-11	8%	5%	5%	6%	7%	6%	4%
	12-17	59%	47%	57%	43%	46%	44%	59%
	18-23	90%	84%	86%	83%	84%	83%	84%

While Chapter 5 contains a more complete analysis of this effect and a discussion of possible drivers, it is worth noting that the timing of first review is, anecdotally, a function of several factors:

1. **Patient condition:** If the patient's clinical need is particularly acute (i.e., the patient requires immediate attention from a senior physician), the Attending is more likely to review the patient the same day as admission, all else held constant. Conversely, if the patient's need is less acute, the Attending may be more inclined to delay review until the next morning.
2. **Individual Attending practices:** While the morning review process discussed in Section 3.8 is part of a formal schedule, the Attending has significant discretion concerning how they spend the rest of the day. As a result, when new patients are first reviewed is also a function of Attending preference.
3. **Level of familiarity with resident team:** Timing of first review may also be a product of how comfortable the Attending feels with the resident team. If the Attending has worked successfully with the residents for a period of time and is comfortable with them handling the patient until the next morning, this will result in the patient being reviewed the next day. The converse also holds.

4.5 Attending level of experience

While clinical experience level - measured by time spent practicing hospital medicine - is considered uniform across residents within each year of the Residency Program, this is not also the case for the two Teaching

[14] Via t-test of means, pooled variance, two-sided, $\alpha = 0.05$.
[15] Via binomial test ($\alpha = 0.05$) that compared "next day review rate" by day-of-week and six-hour block of time as specified in Table 4.2. Patient population as in Footnotes 7 and 8.
[16] Appendix C details how timing of initial Attending Review is derived.

Attending physicians who supervise the resident teams on each floor. While many physicians spend several months a year as a Teaching Attending or Hospitalist in the DOM, there are others who spend only two weeks a year practicing hospital medicine. Exploring the rationale behind this system is outside the scope of this study, but it was of interest to explore the impact of Teaching Attending experience level on patient LOS.

While it is not possible to use formal data sets to derive a complete understanding of a physician's level of experience with hospital medicine, DOM administrators developed a {High, Medium, Low} categorization based upon tacit knowledge of each physician [30]. Attendings within each experience level are assigned similarly across floors[17] and, as Figure 4-7 shows, patients initially assigned to a relatively inexperienced Attending physician spent an average of 0.3 days longer in the hospital[18,19]. This is a significant difference that is likely explained by these physicians' relative unfamiliarity with the floors' operations and/or limited practice leading a team of residents.

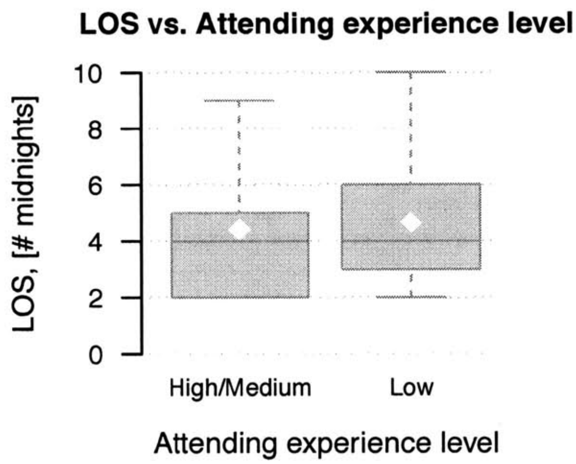

Figure 4-7: LOS vs. Attending experience level, Bigelow A/E[20]

4.6 Handoffs

Having established that the resident members of the teams thoroughly share patient and team responsibilities within each four-week rotation, this final section of exploratory analysis focuses on the incidence of Junior (JAR) and Teaching Attending handoffs. As discussed in Section 3.6, both JARs and Teaching Attendings have rotations that are synchronized with the Resident Block Schedule. As summarized in Table 4.3, Teaching Attendings generally have two (74% of the time) or four-week (12%) rotations aligned with the first and second half of a resident block. Rotation lengths are statistically similar across floors with the exception of Bigelow E, which has had roughly 5% more four-week rotations than the other floors[21].

[17]Z-test of sample proportions, $\alpha = 0.05$. Cross-floor comparison of percentage of weeks a floor is staffed by an Attending at each experience level.

[18]Limited to Bigelow A/E due to constraints in data access.
Initial Attending assignment derived as shown in Appendix C.
Source: POE_v_Order_Entry. Filters: (1) Patient admission and discharge within [2012-01-01 00:00:00, 2015-07-31 23:59:59], (2) Patients admitted to and discharged directly from Bigelow A/E, (3) Patients cared for by non-Private Attending, (4) Patients spent at least 50% of stay on Bigelow A/E.

[19]Via Wilcoxon RS test (α=0.05).

[20]See footnote 18.

[21]Compared the proportion of Attending-weeks that belong to a 1, 2, 3, 4, 5, or 6-week rotation via z-test of proportions, α=0.05.

Table 4.3: Teaching Attending rotation lengths, Bigelow A/B/D/E[22]

	Length of rotation, [# weeks] 1	2	3	4	5	6	Total
# rotations	84	498	8	83	0	1	674
# weeks	84	996	24	332	0	6	1,442
% rotations	12%	74%	1%	12%	0%	0%	100%
% weeks	6%	69%	2%	23%	0%	0%	100%

As each floor has two Teaching Attendings whose rotation lengths may differ, each week may end with one of three different types of Attending HOF: a (1) "Full HOF," in which both Attendings rotate off the floor, a (2) "Partial HOF," in which only one of the Attendings rotate off the floor, or (3) "No HOF," in which both of the Attendings continue into the next week. The same alternatives apply for JARs, and Table 4.4 summarizes how the different handoff types coincide across the two roles.

Table 4.4: % weeks ending with a JAR / Attending handoff on the floor[23]

JAR handoffs	Attending handoffs: Full	Partial	No	Total
Full	24%	1%	0%	25%
Partial*	5%	3%	1%	9%
No	10%	10%	45%	66%
Total	40%	14%	46%	100%

*Possible only on Bigelow A/E.

As shown above, if a week ends in an Attending HOF, it is likely that both Attendings will leave the floor at the same time (75% of weeks that end with either a Full or Partial HOF). Further, JARs typically have four-week rotations aligned with the interns' schedule (91% of the time) and only 1% of weeks have a JAR HOF without a coincidental Teaching Attending HOF on the same floor.

[22]Sources: AmIOn_JAR_Assignments. Filters: (1) Floors: Bigelow A/B/D/E, (2) Dates: [2012-01-01, 2015-07-31]. Teaching Attendings derived as described in Appendix C

[23]Population as described in footnote 22.
Full handoff: both leave floor; Partial: one leaves; No: neither leaves.

Chapter 5

Quantifying the Impact of Handoffs

The Resident Block Schedule ("Block Schedule") implies that Teaching Attending handoffs (HOFs) occur on prescribed days within each twenty-eight-day period. While patient demand varies with day-of-week and time-of-day, quality and quantity of demand from patients admitted directly from the community is independent of the resident schedule. Further, as was confirmed in Chapter 4, patients are randomly assigned across the four floors included in this study.

Combining independent patient demand, the random assignment of patients to floors, and the HOF patterns generated by the Block Schedule creates *natural randomized experiments* that allow the impacts of HOFs on patient flow to be isolated. This Chapter contains several analyses that take advantage of these *natural randomized experiments* to quantify the impact of HOFs on:

1. The amount of time patients wait to be admitted from the ED to the DOM's general care floors.
2. The number of admissions to and discharges from each floor.
3. The probability that new patient reviews will be postponed until the morning after admission.
4. The amount of time patients spend in the hospital, measured by floor length-of-stay.

The patient population ($N = 16,156$) includes all patients who were admitted to and discharged from one of the four floors at the focus of this study and were cared for exclusively by that floor's resident team between Jan 2012 and Jul 2015. To ensure that the results are not influenced by periods when the hospital practices non-standard operations, patients were excluded if they were admitted during the first or last week of the residency year or within three days of a hospital holiday. When a specific analysis requires additional exclusions, the rationale and derivation of these filters is discussed in-context with that analysis.

5.1 Resident Block Schedule

As was first discussed in Section 3.6, the Block Schedule divides the year into thirteen, twenty-eight-day blocks, each of which begins on a Wednesday and ends on a Tuesday. Figure 5-1 illustrates a sample block, with $b \in \{1, ..., 28\}$ indexing the days. Residents begin their rotations on the first Thursday and Teaching Attendings may begin their rotations on the first and third Wednesdays of the block.

28-Day Resident Schedule Block

week	Week 1							Week 2							Week 3							Week 4						
dow	Wed	Thu	Fri	Sat	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Sun	Mon	Tue
b	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28

Figure 5-1: Indexing within a 28-day resident schedule block

5.2 Impact of handoffs on admission wait time from the ED

This analysis evaluates whether HOFs impact the amount of time a patient waits to be moved from the ED to the DOM general care floors after a physician has concluded that they need to be admitted. Per Section 3.7, the ED is the largest source of admissions to the DOM, accounting for roughly 80% of new patients. As discussed at the start of this chapter, while patient demand varies with day-of-week and time-of-day, quality and quantity of demand from patients admitted directly from the community, as is the case with the ED, is independent of the resident schedule. For example, the same statistical mix of patients will arrive at the ED on a Wednesday afternoon that happens to be the first day of a new block ($b = 1$) as on a Wednesday that is a week into a block ($b = 8$).

As a result, comparing the wait time experienced by patients admitted during that first Wednesday to those admitted during the following Wednesday takes advantage of a *natural randomized experiment* that isolates the impact of position within a block with all other factors randomly distributed.

5.2.1 Data, definitions, and population

The patient population ($N = 16,156$) includes all patients admitted from the ED to one of the general care floors belonging to the Bigelow Service, which typically have new Attendings and Residents rotate onto the floor on the first and third Wednesdays and the first Thursday of a block, respectively. To ensure the results are not influenced by periods when the hospital practices non-standard operations, patients were excluded if they were admitted during the first or last week of the residency year or within three days of a hospital holiday. A full set of filters and population statistics are included in Appendix D.2.1.

The metric of interest, ED admission wait time, is defined as the amount of time it takes for a patient to be moved from the ED to one of the Bigelow Service floors after the Admitting Physician has requested a bed.

5.2.2 Hypothesis

The hypothesis motivating this analysis is that mean wait time for admission from the ED is impacted by the day within a resident schedule block during which a patient is admitted, controlling for day-of-week. For example, it is hypothesized that patients who are admitted on the first Wednesday of a block spend a different amount of time waiting, on average, than patients who are admitted on the second Wednesday of a block.

Given that patient demand is independent of the hospital's operations, any difference in wait time can attributed to the residency schedule and ensuant HOFs. A formal hypothesis statement is contained in Appendix D.2.2.

5.2.3 Results

As is visible within Figure 5-2 and Table 5.1, day within a resident schedule block, b, does not impact ED wait time for patients admitted on Wednesdays, Fridays, Saturdays, and Tuesdays. It was possible, however, to reject the null hypothesis for several pairs of Thursdays, Sundays, and Mondays (t-test of means, pooled variance, two-sided, $\alpha = 0.05$). Further, as shown in Table 5.2, these combinations have statistically different 75% quantiles (Wilcoxon-Mann-Whitney RS, two-sided, $\alpha = 0.05$).

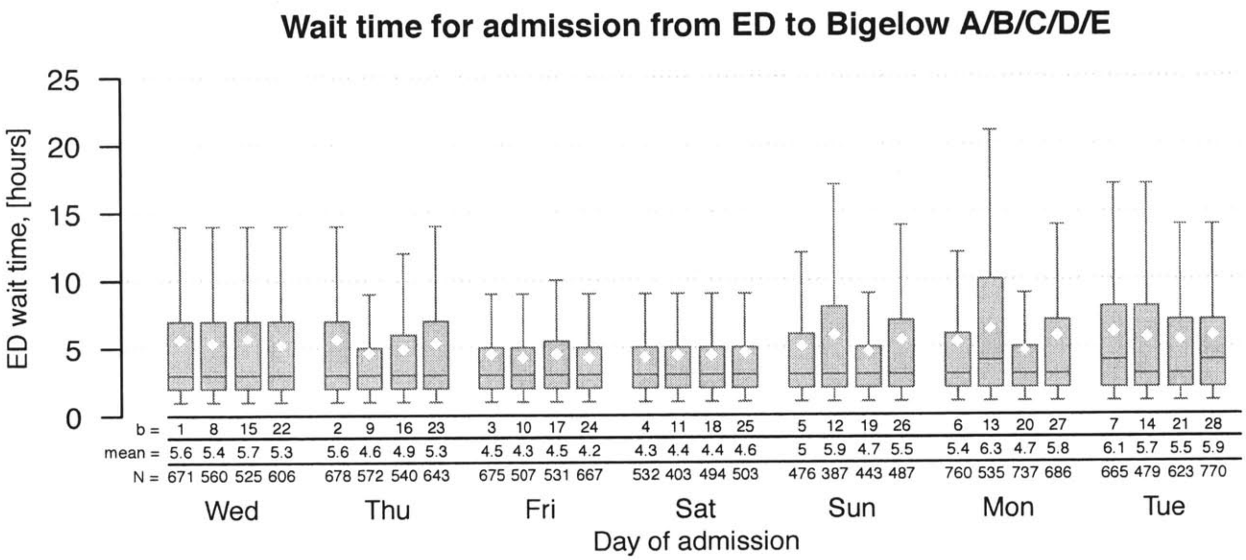

Figure 5-2: Wait time for admission from Emergency Department to Bigelow A/B/C/D/E

Patients who were admitted on the first Thursday of a schedule block - the potentially chaotic day when new residents start on all the floors - wait 15% - 22% longer to be admitted to a floor than those admitted during the second or third Thursdays of a block. Further, patients admitted on the second and fourth Sunday or Monday of a block wait 16% - 34% longer than patients admitted on other Sundays and Mondays. These days precede Attending HOFs and mark the final several days Attendings are on the floor. Since a new patient creates a significant workload for the receiving clinical team, behavioral economics may offer an explanation for the differences on Sundays and Mondays. Namely, there may be a disincentive to respond quickly to a bed request from the ED when accepting a new patient implies an increased workload at the end of a rotation.

A possible explanation for why the clear Sunday/Monday pattern is not also seen on Tuesdays is that patients admitted on the final day of an Attending's rotation may not actually cause additional workload for the outgoing Attending. As was discussed in Section 3.8, the initial review of a new patient, particularly one admitted in the afternoon, may be postponed until the next morning. In this scenario, the additional workload associated with a new patient is borne by the new Attending and the disincentive for the outgoing Attending is removed. Section 5.4 will explore this dynamic further, including how it too is impacted by HOFs.

Table 5.1: Comparison of mean wait time for admission from ED to Bigelow A/B/C/D/E

dow	b_1	b_2	N_1	N_2	$mean_1$	$mean_2$	p-value
Thu	2	9	678	572	5.6	4.6	<0.001
Thu	2	16	678	540	5.6	4.9	0.010
Sun	12	5	387	476	5.9	5	0.003
Sun	12	19	387	443	5.9	4.7	0.002
Sun	26	5	487	476	5.5	5	0.032
Sun	26	19	487	443	5.5	4.7	0.015
Mon	13	6	535	760	6.3	5.4	0.002
Mon	13	20	535	737	6.3	4.7	<0.001
Mon	27	6	686	760	5.8	5.4	0.041
Mon	27	20	686	737	5.8	4.7	<0.001

Via-test of means, pooled variance, two-sided, $\alpha = 0.05$

Table 5.2: Comparison of wait time quantiles, Bigelow A/B/C/D/E

dow	b_1	b_2	Quantile	Q_{b_1}	Q_{b_2}	p-value
Thu	2	9	75%	7.0	5.0	<0.001
Thu	2	16	75%	7.0	6.0	0.026
Sun	12	5	75%	8.0	6.0	0.004
Sun	12	19	75%	8.0	5.0	<0.001
Sun	26	5	75%	7.0	6.0	0.041
Sun	26	19	75%	7.0	5.0	0.007
Sun	13	6	75%	10.0	6.0	0.001
Sun	13	20	75%	10.0	5.0	<0.001
Sun	27	6	75%	7.0	6.0	0.033
Sun	27	20	75%	7.0	5.0	0.018

Via Wilcoxon-Mann-Whitney, two-sided, $\alpha = 0.05$

5.3 Impact of handoffs on floor admission and discharge rates

Having shown that HOFs delay the flow of patients from the ED to general care floors at a department-level, this next analysis tests whether HOFs impact the number of admissions to and discharges from individual floors. As discussed in Section 4.2, daily admission and discharge rates can be derived for each floor by dividing the number of admissions and discharges during each day by the number of beds on each floor for which the resident team is responsible, e.g., 15% of beds on the floor received a new patient. Per Section 4.6, it is possible to categorize each floor-week by whether it begins or ends with a HOF. With each floor-week categorized as in Figure 5-3 below, it is then possible to compare aggregated admission and discharge rates for each day-of-week and isolate the impact of proximity to a HOF with all other factors being statistically similar.

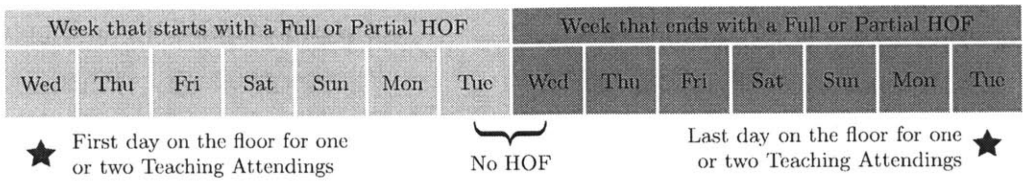

Figure 5-3: Weeks that either start or end with a Teaching Attending handoff

5.3.1 Data, definitions, and population

The daily admission and discharge rates are calculated from a population of patient visits ($N = 9,743$) during which the patient was admitted to a single general care floor from any source and discharged directly from the floor to any destination outside the hospital (see Section 3.7). Patients cared for by a McGovern Attending (see Section 3.2) were excluded, as they maintain the same Attending regardless of HOFs in the clinical team. These patients were identified via timestamped and coded billing information, as discussed in Appendix C. A full set of filters and population statistics are included in Appendix D.3.1.

For this analysis, a HOF is defined as when at least one of a floor's two Teaching Attendings end their rotation. This includes both "Partial" HOFs, when only one Attending leaves, and "Full" HOFs, when both Attendings leave. As with the identification of patients cared for by a McGovern Attending, Teaching Attending assignments were derived from timestamped and coded billing information (see Appendix C).

5.3.2 Hypothesis

The hypothesis motivating this analysis is that mean admission (discharge) rates are impacted by whether the admission (discharge) occurs during a week that begins or ends with a HOF. For example, the rate of admissions on Mondays immediately before a HOF is different than on Mondays that do not precede a HOF. A formal hypothesis statement is contained in Appendix D.3.2.

5.3.3 Results

While the results presented below assume HOFs include both "Full" and "Partial" HOFs, the key findings are robust to limiting this definition to include only "Full" HOFs. Further, there is no statistical difference in rates when comparing "Full" and "Partial" HOF weeks (t-test of means, pooled variance, two-sided, $\alpha = 0.05$). Further, because Bigelow A/E and Bigelow B/D have slightly different care team configurations (see Section 3.4), with B/D including one Nurse Practitioner in the place of a Junior Resident, this and the following analyses are run for the two pairs of floors separately.

Focusing first on admission rates, it is possible to reject the null hypothesis only for Sunday admissions for Bigelow A/E (t-test of means, pooled variance, two-sided, $\alpha = 0.05$). Per Figure 5-4, the average daily admission rate is 1.2% lower on Sundays that proceed a HOF. As in the ED wait time analysis, a possible explanation for this difference is a tendency to avoid new admissions (and the increased workload they create) shortly before the end of a rotation.

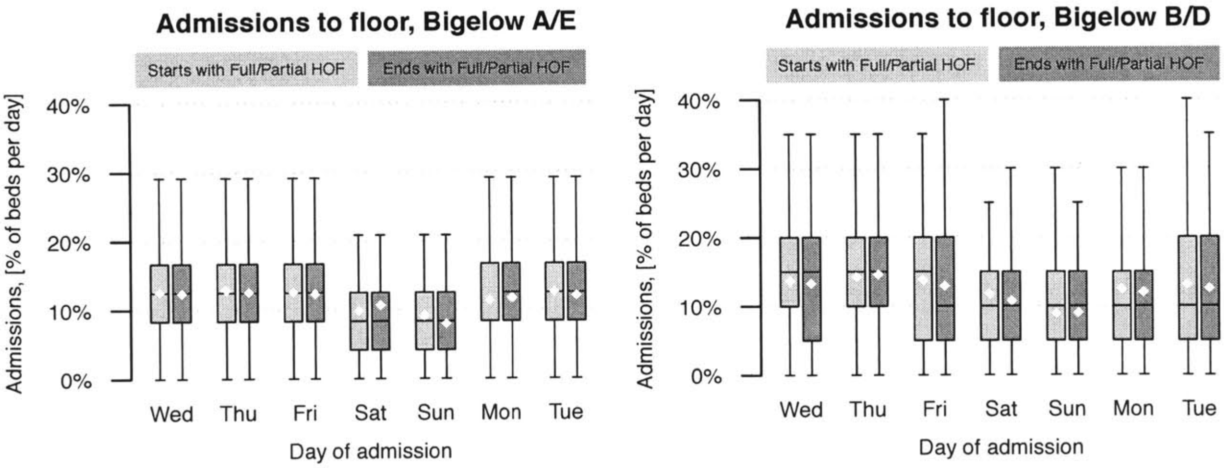

Figure 5-4: Daily admission rate vs. proximity to next Teaching Attending handoff

Admission to floor, Bigelow A/E

	Wed		Thu		Fri		Sat		Sun		Mon		Tue	
(S)tart/(E)nd	S	E	S	E	S	E	S	E	S	E	S	E	S	E
N	135	173	135	173	154	156	154	156	151	159	149	161	135	173
mean, [%]	12.6	12.3	12.9	12.6	12.6	12.3	9.9	10.6	9.1	7.9	11.4	11.6	12.6	12.0
p-value	0.782		0.718		0.655		0.359		0.036*		0.762		0.782	

Admission to floor, Bigelow B/D

	Wed		Thu		Fri		Sat		Sun		Mon		Tue	
(S)tart/(E)nd	S	E	S	E	S	E	S	E	S	E	S	E	S	E
N	113	194	113	171	138	171	138	171	137	172	139	170	135	173
mean, [%]	13.7	13.3	14.2	14.6	13.7	13.0	11.7	10.8	8.9	9.0	12.5	12.0	13.1	12.5
p-value	0.705		0.731		0.416		0.238		0.957		0.591		0.782	

Via t-test of means, pooled variance, two-sided, $\alpha = 0.05$

Focusing now on discharges, it is possible to reject the null hypothesis for Mondays on Bigelow B/D (t-test of means, pooled variance, two-sided, $\alpha = 0.05$). Per Figure 5-5, there are 1.5% fewer discharges during the Mondays immediately before a HOF than during other Mondays. As with the admissions rate results, this may be explained by an incentive to postpone discharges (and the resulting new admissions) until after the end of a rotation.

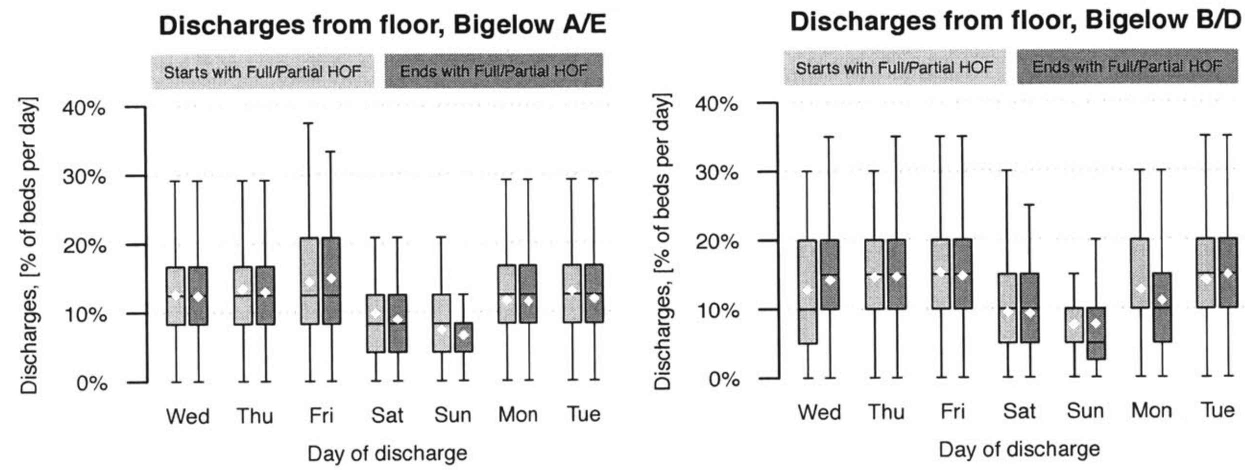

Figure 5-5: Daily discharge rate vs. proximity to next Teaching Attending handoff

Discharge from floor, Bigelow A/E

	Wed		Thu		Fri		Sat		Sun		Mon		Tue	
(S)tart/(E)nd	S	E	S	E	S	E	S	E	S	E	S	E	S	E
N	135	173	135	173	154	156	154	156	151	159	149	161	147	163
mean, [%]	12.7	12.5	13.3	13.0	14.4	14.9	9.8	9.0	7.3	6.6	11.5	11.5	13.0	11.8
p-value	0.387		0.339		0.297		0.124		0.126		0.490		0.085	

Discharge from floor, Bigelow B/D

	Wed		Thu		Fri		Sat		Sun		Mon		Tue	
(S)tart/(E)nd	S	E	S	E	S	E	S	E	S	E	S	E	S	E
N	113	194	113	194	138	171	138	171	138	172	139	170	138	171
mean, [%]	12.8	14.2	14.6	14.7	15.3	14.8	9.5	9.3	7.7	7.8	12.7	11.2	14.1	14.9
p-value	0.081		0.455		0.320		0.418		0.448		0.047*		0.227	

Via t-test of means, pooled variance, two-sided, $\alpha = 0.05$

5.4 Impact of handoffs on next day review rate

Having shown that HOFs materially slow the flow of patients from the ED to the floors but have only a moderate impact on daily admission and discharge rates, this analysis tests whether proximity to a HOF impacts whether patients are first reviewed the same day they are introduced to the floor or the following morning. Given the results already discussed in this chapter, it is reasonable to expect that the proportion of new patients who are first reviewed the next day - particularly those on-floored after noon - will increase towards the end of an Attending's shift on the floor. Utilizing the same floor-week classification as in Section 5.3, it is possible to compare next-day review rates for each day-of-week and isolate the impact of proximity to an Attending handoff with all other factors randomly distributed.

5.4.1 Data, definitions, and population

The patient population ($N = 4,650$) is a subset of that used in Section 5.3.1 and, given the focus above, includes only those visits during which the patient was admitted to the floor after 12pm. A full set of filters and population statistics are included in Appendix D.4.1.

As in the previous analysis, a HOF is defined as when at least one of a floor's two Teaching Attendings end their rotation.

5.4.2 Hypothesis

The hypothesis motivating this analysis is that the proportion of patients who are first reviewed by an Attending the day after being on-floored increases as a HOF approaches. For example, given that a patient is admitted after noon on a Tuesday, Attendings are more likely to let that patient wait until the next morning when it is the last day of their rotation than on Tuesdays that do not precede a HOF. A formal hypothesis statement is contained in Appendix D.4.2.

5.4.3 Results

As shown in Table 5.3, the null hypothesis can be rejected for Fridays on Bigelow B/D and for Tuesdays on both Bigelow A/E and Bigelow B/D (Fischer Exact Probability Test, one-sided, $\alpha = 0.05$). That patients admitted after noon on the final day of an Attending's rotation are more likely to be reviewed the following morning (by a new Attending) aligns with intuition and the results presented up to this point. As we'll see in the next section, this behavior has a significant impact on the amount of time patients ultimately spend in the hospital.

Table 5.3: Next day review rate

Next day review rate, Bigelow A/E

	Wed		Thu		Fri		Sat		Sun		Mon		Tue	
(S)tart/(E)nd	S	E	S	E	S	E	S	E	S	E	S	E	S	E
N, total	175	198	213	219	208	221	133	146	130	105	175	178	196	215
N, next day	111	135	152	154	133	153	108	117	98	89	120	128	133	181
% next day	63.4	68.2	71.4	70.3	63.9	69.2	81.2	80.1	75.4	84.8	68.6	71.9	67.9	84.2
p-value	0.196		0.635		0.145		0.646		0.0528		0.285		<0.001*	

Next day review rate, Bigelow B/D

	Wed		Thu		Fri		Sat		Sun		Mon		Tue	
(S)tart/(E)nd	S	E	S	E	S	E	S	E	S	E	S	E	S	E
N, total	132	185	157	227	150	195	132	128	97	119	124	172	147	173
N, next day	98	136	112	172	102	156	96	92	81	94	94	128	104	147
% next day	74.2	73.5	71.3	75.8	68.0	80.0	72.7	71.9	83.5	79.0	75.8	74.4	70.7	85.0
p-value	0.196		0.635		0.008*		0.616		0.845		0.657		0.002*	

Via Fisher Exact Probability (Binomial) Test, one-sided, $\alpha = 0.05$

5.5 Impact of handoffs on length-of-stay

This analysis tests whether proximity to a HOF impacts the amount of time a patient spends on the floor, as measured by floor length-of-stay (LOS), defined as the number of nights the patient spends on the floor between admission and discharge. Given the results already presented in this chapter, it is reasonable to expect that close proximity to a HOF will impact LOS, particularly for patients admitted to the floor during the Monday or Tuesday before the end of an Attending's rotation.

As Teaching Attendings assume the Attending responsibility for individual patients (Section 3.5.1) and typically do not transfer this responsibility to another physician until the end of their multi-week rotation, this analysis is performed at the individual Attending and patient-level. As visualized in Figure 5-6, individual patients are categorized not only by the day-of-week during which they are introduced to the floor, but also how much longer the specific Attending to whom they are initially assigned is on the floor.

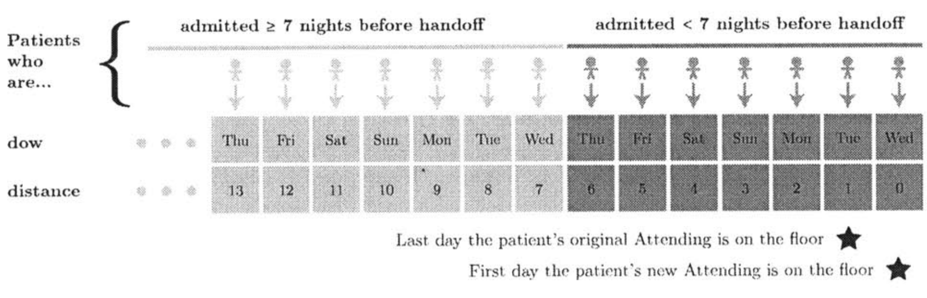

Figure 5-6: Patient categorization by day-of-week of admission and distance from Attending handoff

As in the previous analyses, it is possible to isolate the impact of distance, measured by number of nights, from the initial Attending HOF with all other factors randomly distributed.

5.5.1 Data, definitions, and population

The patient population ($N = 4,171$) includes only those visits during which the patient was admitted to a single general care floor directly from the ED or other pre-location area (see Appendix D) and discharged directly from the floor to the patient's home. The admission requirement is motivated by the desire to keep patient demand independent of the hospital's residency schedule, which may influence how patients are transferred between departments. The discharge requirement is motivated by the discovery that sending a patient to a non-home destination, e.g., a skilled nursing facility, may cause significant delays in patient progression. On Bigelow B/D, patients for whom a Nurse Practitioner (NP) became the Responding clinician before the Attending HOF were excluded from the analysis, as described in Appendix C. While still formally assigned to the Bigelow B/D team, these patients are, in practice, entirely cared for by the NP and could unnecessarily bias the results. Finally, as before, patients cared for by a McGovern Attending are excluded. A full set of filters and population statistics are included in Appendix D.5.1.

5.5.2 Hypothesis

The hypothesis motivating this analysis is that the distribution of LOS for patients who are admitted to the floor within a week of when their Attending leaves is different than that for patients who are admitted more than a week before their Attending leaves, controlling for day-of-week and when the patient is first reviewed.

For example, the LOS distribution for patients who were admitted to the floor the Monday before their Attending's rotation ended is different than that for patients who were admitted on a Monday at least a week before when their Attending's rotation ended. A formal hypothesis statement is contained in Appendix D.5.2.

5.5.3 Results

Focusing first on the 56% of patients who are admitted to the floor and reviewed by an Attending the same day (Figure 5-8), the null hypothesis can be rejected for Mondays on both Bigelow A/E and Bigelow B/D (Wilcoxon-Mann-Whitney, two-sided, $\alpha = 0.05$). Specifically, patients who are admitted on a Monday and reviewed that day by an Attending whose rotation ends the following evening spend an average of one day longer in the hospital than patients who do not experience an Attending HOF for at least another week (Figure 5-7).

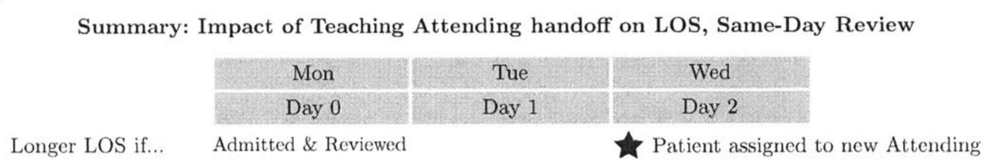

Figure 5-7: Summary: Impact of Teaching Attending handoff on LOS, Same-Day Review

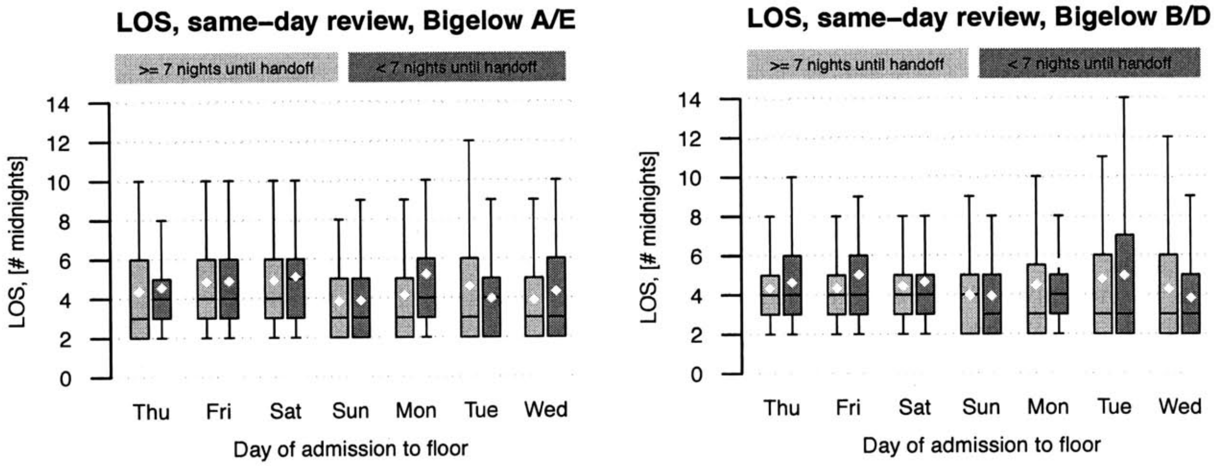

Figure 5-8: LOS vs. proximity to Attending handoff, same-day review

LOS, same-day review, Bigelow A/E

	Thu		Fri		Sat		Sun		Mon		Tue		Wed	
Distance to HOF	≥ 7	< 7	≥ 7	< 7	≥ 7	< 7	≥ 7	< 7	≥ 7	< 7	≥ 7	< 7	≥ 7	< 7
N	101	98	126	103	111	81	73	46	104	74	106	63	108	76
mean	4.3	4.5	4.8	4.9	4.9	5.1	3.9	3.8	4.2	5.2	4.6	4.0	3.9	4.3
75%	6.0	5.0	6.0	6.0	6.0	6.0	5.0	5.0	5.0	6.0	6.0	5.0	5.0	6.0
50%	3.0	4.0	4.0	4.0	4.0	5.0	3.0	3.0	3.0	4.0	3.0	4.0	3.0	3.0
25%	2.0	3.0	3.0	3.0	3.0	3.0	2.0	2.0	2.0	3.0	2.0	2.0	2.0	2.0
p-value	0.166		0.262		0.139		0.328		0.005*		0.192		0.235	

Via Mann-Whitney-Wilcoxon Rank-Sum (RS) Test, two-sided, $\alpha = 0.05$

LOS, same-day review, Bigelow B/D

	Thu		Fri		Sat		Sun		Mon		Tue		Wed	
Distance to HOF	≥ 7	< 7	≥ 7	< 7	≥ 7	< 7	≥ 7	< 7	≥ 7	< 7	≥ 7	< 7	≥ 7	< 7
N	75	70	98	80	102	69	64	38	76	41	74	41	82	58
mean	4.4	4.6	4.3	5.0	4.4	4.7	4	3.9	4.5	5.6	4.8	5.0	4.3	3.8
75%	5.0	6.0	5.0	6.0	5.0	5.0	5.0	5.0	5.5	5.0	6.0	7.0	6.0	6.0
50%	4.0	4.0	4.0	4.0	4.0	4.0	4.0	3.0	3.0	4.0	3.0	3.0	3.0	3.0
25%	3.0	3.0	3.0	3.0	3.0	3.0	2.0	2.0	2.0	3.0	2.0	2.0	2.0	2.0
p-value	0.169		0.207		0.450		0.356		0.006*		0.387		0.230	

A possible explanation of this difference is based on the high intensity of clinical activity within the first several days of a patient's visit. As illustrated in Figure 5-9, over 50% of all clinical orders are created within the first two days for patients who spend two to six nights on the floor, which includes 88% of patients in this study. This aligns with intuition given the functional stages of care discussed in Section 3.1. There is a flurry of activity and focused clinical decision-making during the first few days of a patient's stay, but this intensity then tapers off as the treatment path for the patient is refined and/or the patient's need becomes less acute.

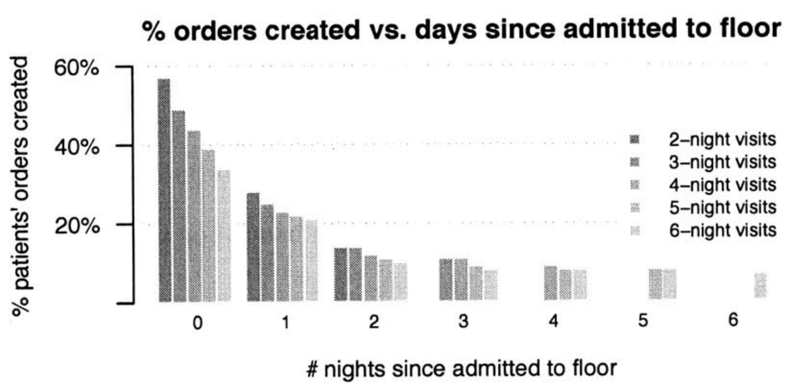

Figure 5-9: Clinical order volume vs. day into visit, Bigelow A[1]

[1]Limited to Bigelow A due to constraints in data access.
Day into patient visit defined as number of midnights since patient admission to the floor and filters implemented per Appendix C.
Source: POE_v_Order_Entry. Filters: (1) Orders created for patients while on White 8 and assigned to the Bigelow A team, (2) Patient admission and discharge within [2012-01-01 00:00:00, 2015-07-31 23:59:59], (3) Patients admitted to and discharged directly from White 8, (4) Patients cared for by non-Private Attending, (5) Patients spent at least 50% of stay assigned to Bigelow A team.

Switching the clinician who supervises the care of the patient during this critical, discovery-focused period is, intuitively, likely to introduce delays such as redundant information collection or testing by the new Attending. Further, as the patient has already been formally presented and reviewed by the clinical team under the supervision of the initial Attending, the new Attending may never achieve the same level of familiarity with the patient. As described in Section 3.8, while Attendings are highly involved in the development of the initial treatment plan for new patients, their involvement with those who have already been on the floor for a few days may be limited. Namely, after a patient's clinical need has been defined and a suitable treatment plan developed, that patient is generally cared for by the residents on the team (i.e., the Interns and JARs), unless there is a major change in the patient's status.

Focusing now on the 44% of patients who are admitted to the floor and reviewed by an Attending the next morning, the null hypothesis can be rejected for both Monday and Tuesday on Bigelow A/E (Wilcoxon-Mann-Whitney RS, two-sided, $\alpha = 0.05$). As shown in Figure 5-11, patients who are admitted on a Monday and first reviewed the following Tuesday by an Attending who is going off shift that evening, spend an average of 0.6 days longer in the hospital than similar patients who do not experience a HOF for at least another week. The intuition here is the same as that for the same-day day review results.

Patients who are admitted on a Tuesday and first reviewed by a new Attending the following Wednesday, however, spend 0.9 fewer days in the hospital than similar patients who do not experience a HOF. Potential explanations for this difference include the possibility that a new Attending may be able to focus more completely on the first patients they review (i.e., clinical bandwidth is spread more thinly as they balance several days worth of patients in the diagnosis stage of care), the outgoing Attending consciously postponed the review of less acute patients, the residents on the clinical team may be more responsive to a new Attending, and/or the new Attending may offer more freedom to the resident team as the rotation progresses.

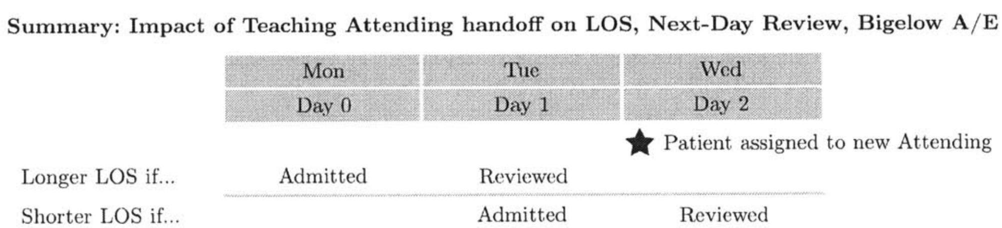

Figure 5-10: Results summary, LOS vs. proximity to Attending handoff, next-day review, Bigelow A/E

While Bigelow B/D very nearly demonstrates the same behavior on Tuesdays ($p = 0.051$), it is not possible to reject the null hypothesis for any day-of-week. A possible explanation is that the Bigelow B/D teams include Nurse Practitioners (NPs) whose rotations are completely independent of the Resident Block Schedule (see Section 3.6). While NPs are directly responsible for only a subset of patients on the floor at any given time (and these patients are excluded from this analysis), they are present for initial patient reviews and daily rounds for all patients. As a result, this role may offer a degree of continuity on the floor that dampens the impact of Teaching Attending HOFs for all patients.

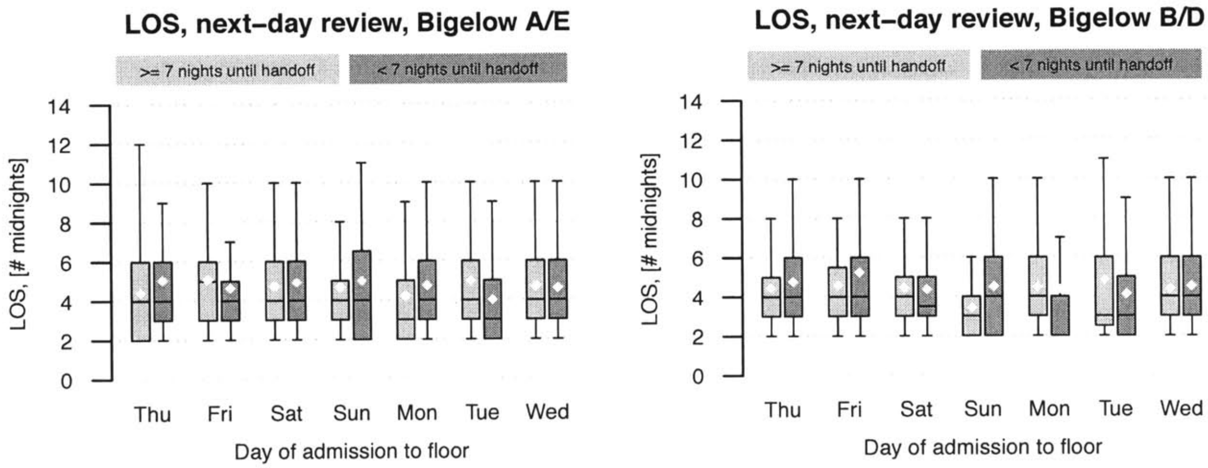

Figure 5-11: LOS vs. proximity to Attending handoff, next-day review

LOS, next-day review, Bigelow A/E

	Thu		Fri		Sat		Sun		Mon		Tue		Wed	
Distance to HOF	≥ 7	< 7	≥ 7	< 7	≥ 7	< 7	≥ 7	< 7	≥ 7	< 7	≥ 7	< 7	≥ 7	< 7
N	99	94	100	88	68	70	84	48	81	60	100	104	96	64
mean	4.4	5.0	5.1	4.6	4.7	4.9	4.7	5.0	4.2	4.8	4.9	4.0	4.7	4.6
75%	6.0	6.0	6.0	5.0	6.0	6.0	5.0	6.5	5.0	6.0	6.0	5.0	6.0	6.0
50%	4.0	4.0	5.0	4.0	4.0	4.0	4.0	4.0	3.0	4.0	4.0	3.0	4.0	4.0
25%	2.0	3.0	3.0	3.0	3.0	3.0	3.0	2.0	2.0	3.0	3.0	2.0	3.0	3.0
p-value	0.089		0.064		0.432		0.303		0.014*		0.003*		0.370	

LOS, next-day review, Bigelow B/D

	Thu		Fri		Sat		Sun		Mon		Tue		Wed	
Distance to HOF	≥ 7	< 7	≥ 7	< 7	≥ 7	< 7	≥ 7	< 7	≥ 7	< 7	≥ 7	< 7	≥ 7	< 7
N	93	90	79	74	77	30	60	38	90	41	95	63	71	61
mean	4.4	4.8	4.6	5.2	4.4	4.4	3.4	4.5	4.5	4.4	4.8	4.1	4.4	4.5
75%	5.0	6.0	5.5	6.0	5.0	5.0	4.0	6.0	6.0	4.0	6.0	5.0	6.0	6.0
50%	4.0	4.0	4.0	4.0	4.0	3.5	3.0	4.0	4.0	4.0	3.0	3.0	4.0	4.0
25%	3.0	3.0	3.0	3.0	3.0	3.0	2.0	2.0	3.0	2.0	2.5	2.0	3.0	3.0
p-value	0.361		0.101		0.341		0.094		0.346		0.051		0.426	

Via Mann-Whitney-Wilcoxon Rank-Sum (RS) Test, two-sided, $\alpha = 0.05$

This dampening effect is further highlighted by pooling the same-day and next-day review populations, as shown in Figure 5-12. Irrespective of when a patient is first reviewed, it is possible to reject the null hypothesis on both Monday and Tuesday for Bigelow A/E and it is impossible to do so for any day-of-week for Bigelow B/D.

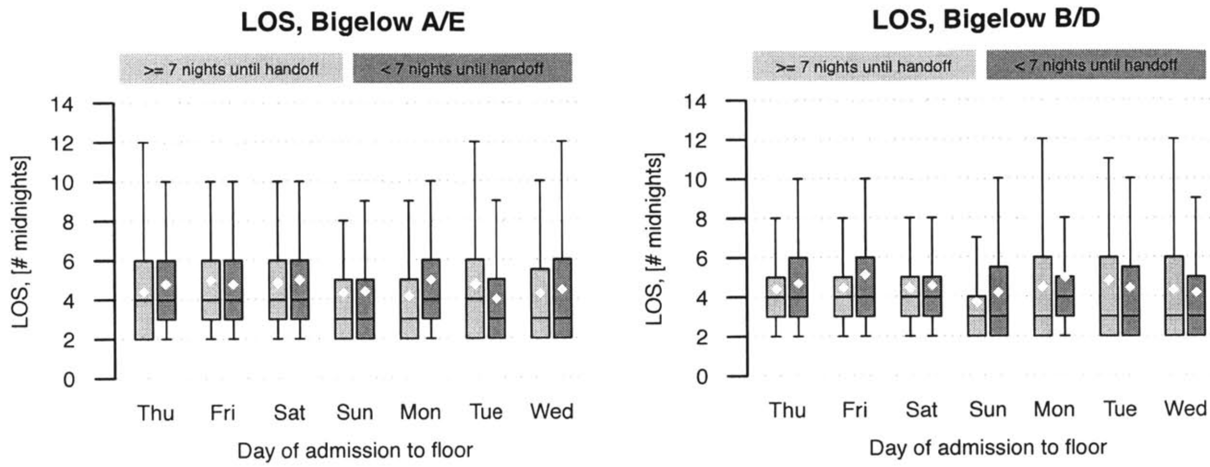

Figure 5-12: LOS vs. proximity to Attending handoff

LOS, next-day review, Bigelow A/E

	Thu		Fri		Sat		Sun		Mon		Tue		Wed	
Distance to HOF	≥ 7	< 7	≥ 7	< 7	≥ 7	< 7	≥ 7	< 7	≥ 7	< 7	≥ 7	< 7	≥ 7	< 7
N	200	192	226	191	179	151	157	94	185	134	206	167	204	140
mean	4.4	4.8	4.9	4.8	4.8	5.0	4.3	4.4	4.2	5.0	4.8	4.0	4.3	4.5
75%	6.0	6.0	6.0	6.0	6.0	6.0	5.0	5.0	5.0	6.0	6.0	5.0	5.5	6.0
50%	4.0	4.0	4.0	4.0	4.0	4.0	3.0	3.0	3.0	4.0	4.0	3.0	3.0	3.0
25%	2.0	3.0	3.0	3.0	3.0	3.0	2.0	2.0	2.0	3.0	2.0	2.0	2.0	2.0
p-value	0.055		0.310		0.247		0.470		0.001*		0.007*		0.401	

LOS, next-day review, Bigelow B/D

	Thu		Fri		Sat		Sun		Mon		Tue		Wed	
Distance to HOF	≥ 7	< 7	≥ 7	< 7	≥ 7	< 7	≥ 7	< 7	≥ 7	< 7	≥ 7	< 7	≥ 7	< 7
N	168	160	177	154	179	99	124	76	166	82	169	104	153	119
mean	4.4	4.7	4.5	5.1	4.4	4.6	3.7	4.2	4.5	5.0	4.8	4.5	4.3	4.2
75%	5.0	6.0	5.0	6.0	5.0	5.0	4.0	5.5	6.0	5.0	6.0	5.5	6.0	5.0
50%	4.0	4.0	4.0	4.0	4.0	4.0	3.0	3.0	3.0	4.0	3.0	3.0	3.0	3.0
25%	3.0	3.0	3.0	3.0	3.0	3.0	2.0	2.0	2.0	3.0	2.0	2.0	2.0	2.0
p-value	0.182		0.064		0.368		0.222		0.105		0.144		0.345	

Via Mann-Whitney-Wilcoxon Rank-Sum (RS) Test, two-sided, $\alpha = 0.05$

5.6 Summary of results

Table 5.4 summarizes the main results and hypothesized explanations discussed earlier in this chapter. Conclusively, proximity to a Teaching Attending HOF has a material impact on how long patients spend in the hospital. This is particularly true for those who experience a HOF shortly into their stay, when the intensity of clinical care is highest and both their diagnosis and treatment plan are likely to be most unclear and dynamic. The next chapter builds on the results of these descriptive analyses by presenting a series of predictive models that demonstrate how, provided with only the very limited information available when a patient is first admitted to a floor, distance from a future HOF is a significant predictor of LOS.

Table 5.4: Summary of key results, quantifying the impact of handoffs

Metric	Result	Hypothesized explanation
ED Wait Time	• **15% - 22% longer** on 1^{st} Thursday of block	New resident teams begin their rotations on this day and this may introduce temporary process inefficiencies.
	• **16% - 26% longer** on 2^{nd} and 4^{th} Sunday of block • **16% - 34% longer** on 2^{nd} and 4^{th} Monday of block	There may be an incentive to avoid new patients and their associated workload towards the end of a Teaching Attending's rotation.
Admission Rate	• **1.2% lower** on Sundays before a HOF (Bigelow A/E)	
Discharge Rate	• **1.5% lower** on Mondays before a HOF (Bigelow B/D)	
Next Day Review Rate	• **16% higher** the day before a HOF (Bigelow A/E) • **14% higher** the day before a HOF (Bigelow B/D)	
Length-of-stay	• **0.8 days longer** for patients admitted the Monday (2 days) before a HOF* (Bigelow A/E)	Diagnosis-focused activities at the start of a patient's stay may be highly sensitive to a HOF* during this period. Further, the new Attending may not achieve the same level of familiarity with a patient who was first reviewed by an earlier Attending.
	• **1.0 day longer** for patients admitted the Monday (2 days) before a HOF* and reviewed the same day (Bigelow A/E/B/D)	
	• **0.6 days longer** for patients admitted the Monday (2 days) before a HOF* and reviewed the next day (Bigelow A/E)	
	• **0.8 days shorter** for patients admitted the Tuesday (1 day) before a HOF* (Bigelow A/E)	A new Attending may be able to focus more completely on the first patients they review at the start of their rotation. Further, the outgoing Attending may consciously postpone the review of less acute patients. Finally, the residents on the clinical team may be more responsive to a new Attending.
	• **0.9 days shorter** for patients admitted the Tuesday (1 day) before a HOF* and reviewed the next day (Bigelow A/E)	

HOF includes when either one or both of the floor's Teaching Attendings rotate off the floor.
HOF* is when the patient's initial Attending rotates off the floor, irrespective of what the floor's other Attending does.
ED Wait Time: # hours between bed request and fulfillment for patients admitted from the Emergency Department to a Bigelow Service floor.
Admission Rate: % of general medicine beds on a floor receiving a new patient on a given day
Discharge Rate: % of general medicine beds on a floor from which a patient is discharged on a given day
Next Day Review Rate: % of patients admitted to a floor after noon who are initially reviewed by an Attending the next morning.
Length-of-stay: # midnights between patient admission to the floor and discharge from the hospital.

Chapter 6

Predicting the impact of handoffs

This chapter builds upon the results presented in Chapters 4 and 5 by presenting a series of regression models that demonstrate the reliable significance of proximity to a Teaching Attending handoff (HOF) in predicting floor length-of-stay (LOS).

While prior work has approached predicting LOS using patient demographics and detailed clinical data (e.g., blood test results) as independent factors (see Chapter 2), many of these data are not available when a patient is first admitted and may, in fact, be influenced by the kind of dynamics this study seeks to explore. For example, a HOF early in a patient's visit may impact the care a patient receives and, thus, the results of the blood tests used to predict overall LOS. As a result, this effort seeks to predict LOS using only the information available to clinical teams when a patient is first admitted, including basic demographics, diagnosis hypothesized at time of admission, time and day of admission, and the number of days until the patient's initial Attending ends their rotation.

As discussed in Chapter 2 (see Carter et al. [11] and Hachesu et al. [37]), the patient's underlying illness often explains a majority of LOS variance and operational factors are generally excluded when models are selected using techniques that favor more parsimonious designs with fewer predictors. This is particularly the case when different illnesses may be variably sensitive to HOFs, as was alluded to by Hachesu at al.

This in mind, models are developed for several individual categories of illness, called Major Diagnostic Categories (MDCs), to allow the impact of HOFs to carry through as well as to explore the range of HOF sensitivities demonstrated by different disease categories.

6.1 Data

The patient population ($N = 4,171$) is the same as in Section 5.5, and includes only those visits during which the patient was admitted to a single general care floor directly from the ED or other pre-location area (see Appendix D) and discharged directly from the floor to the patient's home. The admission requirement is motivated by the desire to keep patient demand independent of the hospital's residency schedule, which may influence how patients are transferred between departments. Further, the discharge requirement is motivated by the discovery that sending a patient to a non-home destination, e.g., a skilled nursing facility, may cause significant delays in patient progression that are outside the control of the clinical team. As before, patients for whom a Nurse Practitioner (NP) became the Responding clinician before the Attending HOF and patients cared for by a McGovern Attending were excluded from the analysis (see Appendix C for methodology).

6.2 Model development

As discussed in Chapter 2, predicting LOS is the subject of a great deal of study but remains notoriously difficult, particularly for the DOM and other departments with similar levels of patient heterogeneity. Colloquially, the combination of limited information at the point of admission and the sheer diversity of patient needs that may be served make it difficult to predict what kind of treatment is required, let alone how long it will take for the patient to be well enough to leave the hospital. These caveats in mind, the regression models presented in this chapter seek to predict LOS using only the information available at the point of patient admission, including:

- When the patient was admitted, including day-of-week and time-of-day
- Whether the patient was admitted one, two, or three days before a HOF
- Patient demographic information, including age and gender
- Patient psychosocial factors, such as addiction or psychological disorders
- The experience level of the patient's initial attending (see Section 4.5)
- The patient's Major Diagnostic Category hypothesized at admission (discussed below)

**The complete list of independent factors is included in Appendix E.1*

As the LOS distribution is long-tailed (Section 4.1.1), the dependent variable was chosen to be the log transform of LOS, specifically $\log_{10} LOS$, in order to allow the residuals of a linear model to be more symmetrically distributed and, thus, easier to interpret. To capture some of the more subtle effects identified in Chapter 5, e.g., that patients admitted after noon the day before a HOF are 18% more likely to be reviewed by an Attending the next morning, the full set of independent factors includes those listed above as well as their centered second-degree interactions.

Despite constraining predictors to the set of information available when the patient is first admitted, feature selection was still necessary to avoid over-fitting. Of the two primary alternatives for feature selection, Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC_c), BIC is generally considered the more conservative. This is because, unlike AIC_c, BIC tends not to select interactions and the penalty it assigns to additional factors scales with the log of the sample size. Referencing the previous work discussed in Chapter 2, including Carter et al. [11] and Hachesu et al. [37], the most highly significant factors in predicting LOS are often targeted clinical data, e.g., lab results, while operational factors are generally less so. As the available feature set is almost entirely non-clinical and the sample size is large, BIC would likely to be too conservative for the purposes of this study. Thus, for each of the models discussed below, AIC_c was used for model selection.

After selection, the model was then trained on a subset (80%) of the patient population with the remaining 20% reserved for validation. To test the stability of the model's coefficients as well as its overall predictive power, training and validation were performed 1,000 times on randomly selected, complementary subsets (Monte Carlo Cross-Validation, $\alpha = 0.05$). For the training set, the resultant R^2 and key coefficient and p-value distributions are presented. For the validation set, the distribution of Root-Mean-Square Error (RMSE) values is used to evaluate the the stability of each model's predictive power.

6.3 Length-of-stay vs. Major Diagnostic Category

Before presenting the model results, a brief overview of Major Diagnostic Categories (MDCs) is necessary. A patient's MDC represents the single major organ system that the admitting physician believed to be at the root of the patient's illness when the patient was first admitted to the hospital and sent to one of the four floors in this study. As summarized in Table 6.1, there are twenty-four MDCs within the patient population, with the top five accounting for 62% of patients. This method of categorizing patients into high-level, mutually exclusive diagnosis areas is a function of the difficulty of achieving diagnostic precision early in a patient's visit as well as the desire to align initial categorizations with hospital departmental and/or clinical specialty boundaries. As a result, and as will come into play later in this chapter, there are differing levels of specificity within the set of MDCs. For example, "Diseases and Disorders of the Skin, Subcutaneous Tissue, and Breast" applies to a more narrow set of underlying ailments than, say, "Diseases and Disorders of the Circulatory System" [32].

Table 6.1: Summary of Major Diagnostic Categories

	N		LOS						
MDC	**#**	**%**	**Avg.**	**95%**	**75%**	**50%**	**25%**	**5%**	**Description**
All	4,171	100%	4.6	10.0	6.0	4.0	3.0	2.0	All MDCs
5	697	17%	4.9	11.0	6.0	4.0	3.0	2.0	Diseases and Disorders of the Circulatory System
4	591	14%	4.5	11.0	6.0	4.0	3.0	2.0	Diseases and Disorders of the Respiratory System
6	555	13%	4.3	10.0	5.0	4.0	3.0	2.0	Diseases and Disorders of the Digestive System
20	373	9%	4.0	8.4	5.0	3.0	2.0	2.0	Alcohol/Drug Use or Induced Mental Disorders
7	366	9%	4.8	10.0	6.0	4.0	3.0	2.0	Diseases and Disorders of the Hepatobiliary System And Pancreas
11	285	7%	4.6	11.0	6.0	4.0	3.0	2.0	Diseases and Disorders of the Kidney And Urinary Tract
18	245	6%	5.4	10.8	6.0	4.0	3.0	2.0	Infectious and Parasitic DDs (Systemic or unspecified sites)
10	227	5%	4.2	10.0	6.0	4.0	3.0	2.0	Diseases and Disorders of the Endocrine, Nutritional And Metabolic System
1	147	4%	4.4	8.0	5.0	3.0	2.0	2.0	Diseases and Disorders of the Nervous System
9	146	4%	4.2	11.8	5.0	3.0	2.3	2.0	Diseases and Disorders of the Skin, Subcutaneous Tissue And Breast
8	135	3%	5.5	11.3	6.0	4.0	3.0	2.0	Diseases and Disorders of the Musculoskeletal System And Connective Tissue
21	118	3%	4.0	11.0	5.0	3.5	2.0	2.0	Injuries, Poison And Toxic Effect of Drugs
16	97	2%	4.2	11.0	6.0	4.0	2.0	2.0	Diseases and Disorders of the Blood and Blood Forming Organs
other	189	5%	4.8	10.6	6.0	4.0	3.0	2.0	All other MDCs

6.4 Results and Sensitivities

This section presents a series of predictive models developed first for the entire set of MDCs and then for several MDCs individually. As each model is unique and includes numerous independent factors, the coefficient and p-value distributions discussed below are limited to the focus of this study: proximity to a HOF and its second-degree interactions. The relevant factors are $\{distance\_0, distance\_1, distance\_2\}$, indicating whether the patient was admitted the day their initial Attending's rotation began (a Wednesday), the last day of a rotation (a Tuesday), or the second-to-last day of a rotation (a Monday), respectively. Stated differently, the results of model validation were presented only for the significant ($p \leq 0.05$) HOF-related factors. Full details concerning each model's parameters, e.g. coefficients, standard error, and significance, are included in Appendix F.

6.4.1 Model #1, all patients without MDC as a predictor

As shown in Table 6.2, excluding MDC as an independent factor while including the entire patient population results in a model with relatively low predictive value but with significant factors that align with the results discovered earlier in this study (full model in Appendix F). All else held constant, admission to the floor the Monday before a HOF increases LOS by 1.1 days (calculated: $10^{0.056}$), while admission to the floor the Tuesday before a HOF decreases LOS by 1.1 days. As shown in Table 6.3, the significance and impact of $distance\_1$ and $distance\_2$ are both robust to the selection of training and validation sets.

Table 6.2: Summary of fit, all patients

N	R^2	$Adj.R^2$	$RMSE$
4,171	0.035	0.028	0.213

Table 6.3: Model validation, all patients

		R^2	RMSE	distance_1 Coef.	distance_1 P-value	distance_2 Coef.	distance_2 P-value
	Avg.	0.035	0.232	-0.056	0.006	0.056	0.005
quantile	95%	0.038	0.244	-0.045	0.019	0.066	0.017
	75%	0.037	0.236	-0.051	0.008	0.061	0.006
	50%	0.035	0.232	0.056	0.004	0.056	0.003
	25%	0.034	0.227	0.060	0.002	0.052	0.001
	5%	0.032	0.220	0.066	0.001	0.046	<0.001

N: 4,171; 3,337 (834) training (validation)

As discussed in Section 5.5, the reason why patients admitted two days before a HOF spend longer in the hospital may be because the high clinical intensity typical of these first forty-eight hours makes this period particularly sensitive to a HOF. Further, the new Attending may not develop the same level of familiarity with a patient that they do not review in great detail as part of the formal morning review process (see Section 3.8) despite the patient still being relatively early in their stay. As was also discussed in Section 5.5, the reason why patients admitted one day before a HOF spend less time in the hospital may be because many of these patients are first reviewed the next morning by a new Attending whose attention is not yet distributed across a large number of patients.

6.4.2 Model #2, all patients with MDC as a predictor

As expected, including MDC as an independent factor for the entire patient population increases the predictive value of the model (Table 6.4), but the predictor set derived via AIC_c is dominated by combinations of MDCs and their interaction terms, i.e., the type of illness largely drowns out the effects of the HOF-related factors we are interested in exploring. These results in mind, the next several sections explore similarly-derived models for individual MDC populations with the goal of allowing these effects to surface.

Table 6.4: Summary of fit, all patients with MDC as an independent factor

N	R^2	*Adj.*R^2	*RMSE*
4,171	0.075	0.059	0.201

6.4.3 Model #3, MDC 5, Diseases and Disorders of the Circulatory System

As shown in Table 6.5, limiting the patient population to the single largest MDC, "Diseases and Disorders of the Circulatory System," allows for a model with roughly double the predictive power but a slightly higher RMSE than Model #2 (full model in Appendix F). Upon inspection, the latter is driven by a relatively high concentration of long-LOS patients in this MDC compared to the population as a whole.

Table 6.5: Summary of fit, MDC 5

N	R^2	*Adj.*R^2	*RMSE*
697	0.141	0.124	0.240

Per Table 6.6, sensitivity to a HOF is quite stable and manifests most strongly for patients who are admitted after noon the Monday (two days) before a HOF. These patients are expected to spend 1.6 days ($10^{0.199}$) longer in the hospital, all else held constant. Referencing the intuition established in Chapters 4 and 5, these patients are likely to experience two types of delay: (1) their initial review may be postponed until the next morning, and (2) they will be transitioned to another Attending during that critical forty-eight-hour period at the start of their stay. Notably, while AIC_c does include $distance_1$ and $distance_2$ in the model developed for this MDC and these have the expected effects (longer LOS and shorter LOS, respectively), they are not individually significant predictors of LOS (see Appendix F).

Table 6.6: Model validation, MDC 5

		R^2	RMSE	distance_2*time_pm Coef.	distance_2*time_pm P-value
	Avg.	0.145	0.245	0.199	0.048
quantile	95%	0.160	0.273	0.261	0.130
quantile	75%	0.151	0.256	0.219	0.059
quantile	50%	0.145	0.245	0.198	0.036
quantile	25%	0.139	0.233	0.176	0.021
quantile	5%	0.131	0.218	0.141	0.008

N: 697; 558 (139) training (validation)

6.4.4 Model #4, MDC 4, Diseases and Disorders of the Respiratory System

Limiting the patient population to the next most common MDC, "Diseases and Disorders of the Respiratory System," highlights that, while some categories of illness are less predictable than others (Table 6.7, Appendix F), proximity to a HOF is reliably a significant driver of LOS. Here again, admission to the floor two days before a HOF results in patients spending 1.3 days longer in the hospital, all else held constant (Table 6.8).

Table 6.7: Summary of fit, MDC 4

N	R^2	$Adj.R^2$	$RMSE$
591	0.079	0.055	0.224

Table 6.8: Model validation, MDC 4

		R^2	RMSE	distance_2 Coef.	distance_2 P-value
	Avg.	0.080	0.225	0.124	0.019
quantile	95%	0.088	0.275	0.143	0.044
quantile	75%	0.083	0.244	0.130	0.024
quantile	50%	0.080	0.224	0.124	0.016
quantile	25%	0.077	0.206	0.117	0.012
quantile	5%	0.072	0.180	0.105	0.005

N: 591; 473 (118) training (validation)

As discussed in Section 6.3, not all MDC categories possess a similar breadth of ailments. Some, like MDC 5 and 4, are quite commonly used by admitting physicians and describe a relatively wide variety of underlying patient ailments. Others, like MDC 8 and 9 discussed below, are used less frequently and encompass a relatively narrow set of conditions.

6.4.5 Model #5, MDC 8, Diseases and Disorders of the Musculoskeletal System

As shown in Table 6.9, limiting the patient population to a relatively specific MDC, "Diseases and Disorders of the Musculoskeletal System," allows for a model with high predictive power and similarly reliable sensitivity to proximity to HOF (Table 6.10). While a discussion of the clinical drivers of this predictability are outside the scope of this study, it is valuable to observe that the distribution of LOS for this MDC is statistically similar to those of the other MDCs already discussed (Table 6.1)[1].

Table 6.9: Summary of fit, MDC 8

N	R^2	$Adj.R^2$	$RMSE$
135	0.486	0.380	0.191

Table 6.10: Model validation, MDC 8

				distance_2	
		R^2	RMSE	Coef.	P-value
	Avg.	0.505	0.243	0.212	0.043
quantile	95%	0.565	0.370	0.258	0.194
	75%	0.530	0.257	0.239	0.039
	50%	0.506	0.229	0.223	0.012
	25%	0.479	0.206	0.198	0.006
	5%	0.441	0.174	0.130	0.002

N: 135; 108 (27) training (validation)

6.4.6 Model #6, MDC 9, Diseases and Disorders of the Skin

Interestingly, while limiting the patient population to another relatively specific MDC, "Diseases and Disorders of the Skin," does support a predictive model with reliable sensitivity to HOFs (Table 6.11 and 6.12), this sensitivity is only statistically significant for patients admitted the last day of an Attending's rotation. Specifically, these patients are likely to spend 1.6 fewer days in the hospital, all else held constant.

Table 6.11: Summary of fit, MDC 9

N	R^2	$Adj.R^2$	$RMSE$
146	0.216	0.158	0.190

Table 6.12: Model validation, MDC 9

				distance_1	
		R^2	RMSE	Coef.	P-value
	Avg.	0.216	0.197	-0.192	0.044
quantile	95%	0.249	0.252	-0.282	0.092
	75%	0.230	0.217	-0.195	0.049
	50%	0.218	0.197	-0.184	0.037
	25%	0.206	0.174	-0.175	0.027
	5%	0.164	0.142	-0.157	0.002

N: 146; 117 (29) training (validation)

A possible explanation for the relatively low predictive power of this model compared to that for MDC 8, is that MDC 9 is simply a more complex diagnostic category, capturing a wider variety of different underlying ailments. Further, while these results align with the general intuition established previously, why this MDC displays this particular sensitivity so strongly (and, unlike other categories, does not seem to be particularly

[1]Wilcoxon-Mann-Whitney RS Test, two-sided, $\alpha = 0.05$.

affected by admission two days before a HOF) remains an open question and, perhaps, an area for future investigation.

In summary, it is valuable to understand that different MDCs have distinct sensitivities to HOFs. LOS for some patients may be greatly increased by a HOF two days after admission, as is the case with MDC 8, while others may experience little to no deleterious effect from a HOF, as is the case with MDC 9. A possible explanation is that the latter may require relatively little clinical decision-making after the first day or has a standard treatment procedure that is robust to the patient being transferred from one Attending to another.

As will be discussed in the next chapter, understanding these sensitivities at the point of admission creates a number of opportunities for reducing delays in patient progression and improving throughput in the DOM.

Chapter 7

Recommendations, Future Work, and Conclusions

7.1 Recommendations

There are several changes to the DOM's rotation scheduling and intra-shift patient assignment processes that could be considered when seeking to reduce delays in patient progression, including:

1. **Stagger Teaching Attending shifts:** While there are benefits to utilizing administratively simple shift schedules, in which pairs of Attendings rotate on and off the floor on the same days, this study quantified the operational costs of this simplicity for both the system and individual patients. At the floor-level, it would be advisable to avoid situations in which both Teaching Attendings rotate on the same day. As a preponderance of Attending shifts last two weeks (and with the assumption that this remains the case going forward), it is possible to simply stagger start dates by one week with limited additional administrative burden. This would have the system-level benefit of avoiding the (non-rare) scenario in which a majority of floors are staffed by entirely new senior physicians on the same day.

2. **Do not assign new patients to Attendings who are about to leave:** As new patients are generally sensitive to Attending discontinuities, it would be preferable to avoid assigning them to Attendings whose rotation is nearly over. Instead, patient load could be rebalanced with the following goals in mind: (1) shift more stable patients to the outgoing Attending in order to (2) allow the remaining Attending to assume responsibility for new patients requiring a higher degree of (uninterrupted) clinical focus.

3. **Use MDC to guide the assignment of new patients to Attendings:** Per Chapter 6, handoffs have a variable impact on LOS and at least part of this variability is driven by patient MDC. If recommendation #2 (above) is too restrictive in practice, MDC could be used to understand which new patients should be assigned to the outgoing Attending with the objective of minimizing aggregate LOS impact across the day's new patients. For example, LOS for MDC 4 patients is less sensitive to a HOF two days after admission than for MDC 8 patients (+1.3 days vs. +1.7 days). Thus, given the choice, an MDC 4 patient should be assigned to an outgoing Attending over an MDC 8, resulting in an expected net benefit of 0.4 fewer patient-days in the hospital.

4. **Increase team diversity:** The Nurse Practitioner (NP) role does seem to attenuate the LOS-impacts of Attending HOFs (Section 5.5). While this benefit may be a result of the NP's independent shift schedules, it may also be driven by their practice of assuming responsibility for more stable patients,

allowing the physician team to focus on patients that are more clinically demanding. Introducing this role (or otherwise achieving this asynchronicity and patient segmentation within the existing team structure) has the potential to reduce the impact of HOFs for teams beyond Bigelow B and D.

7.2 Future Work

During the completion of this study, we identified several areas that would benefit from further exploration, including:

1. **Hospitalist regionalization:** While utilizing different configurations than resident-staffed teams, hospitalists operate on teams of two to three that support patients distributed across a number of floors and buildings, i.e., hospitalists are non-regionalized (Section 3.2). In addition to a similar study focused on the impact of HOFs for hospitalist teams, it would be valuable to explore the impact of "degree of regionalization," i.e., how distributed the team's patients are, on operating metrics such as hospital and floor LOS. Owing to the relative simplicity of adjusting regionalization policy (as voiced by DOM staff), this study would have the added benefit of readily lending itself to short-term pilots and rapid learning.

2. **MDC-level operational sensitivities:** As discussed in Chapter 6, Major Diagnostic Categories (MDCs) display differing levels of sensitivity to Attending HOFs, as well as to the broader set of independent factors available to the models. Understanding that there may be unidentified processes or resources within the hospital that are contributing to these differences, their clinical and operational drivers warrant further focused attention, particularly for MDCs that demonstrate particularly strong and/or unique sensitivities.

3. **Data normalization:** During the completion of this study, data discovery (e.g., seeking to understand what data is stored where) and cleaning (e.g., removing obviously erroneous data points) demanded significant time and resources. While every implemented data system is path-dependent and, almost definitionally, incomplete, a rigorous review of the DOM's approach to data management, including documenting the relationships between complementary systems of record and their supporting business processes, would greatly speed and simplify the completion of future studies as well as pay dividends in the management of day-to-day operations.

7.3 Conclusions

The first to explore the effects of end-of-rotation care team discontinuities in a general medicine environment, this thesis quantified the impact of Attending HOFs on delays in patient progression through the hospital, as indicated by floor length-of-stay (LOS). It accomplished this by systematically mapping the responsibilities and dynamics within each team and isolating the impact of HOFs by taking advantage of natural randomized experiments created by the combination of independently-distributed patient demand and MGH's resident block schedule. Further, using only the limited information available when a patient is first admitted, proximity to a future HOF was demonstrated to be a significant and robust predictor of LOS across diagnostic categories. Taken as a whole, this study offers a novel means to understand and actively shape a key determinant of LOS and its associated costs. Further, as the MIT-MGH Collaboration's first project within MGH's DOM, this effort serves as a first step towards improving patient throughput using multidisciplinary care team design, rotation schedules, and HOF-sensitive patient assignments as levers.

Appendix A

Glossary

Term	Definition
Acuity	Intensity of clinical care a patient requires.
Admission	Event when a patient is admitted to the hospital and reclassified as an inpatient.
Admission to floor ("on-flooring")	Event when an inpatient is moved to a bed on a floor in the hospital.
Admit	Patient who has recently been admitted to the hospital, e.g. "Tuesday admits"" are patients admitted on Tuesday."
Attending Responsibility	Type of patient-level responsibility that includes legal responsibility for the patient and supervision of the Responding clinician.
Bigelow A/B/D/E	Four of the clinical teams in the Bigelow Service that are the focus of this study.
Bigelow Service	Several clinical teams with similar configurations that form part of the Teaching Service.
Clinical care team	Team of physicians and registered nurses who share responsibility for a collection of patients.
Clinician	A physician or registered nurse who is qualified to provide clinical (medical) care to a patient in the hospital.
Department of Medicine (DOM)	Department within MGH that is the focus of this study. See Section 1.1.3.
Discharge	Event when a patient is released from the hospital and inpatient status is removed.
Discharge disposition	Location to which a patient is released after discharge, e.g. home or a skilled nursing facility.
Encounter	Specific inpatient visit to the hospital by a patient, bounded by a single admission and a single discharge.

Handoff (HOF)	Transfer of a responsibility from one clinician to another.
Hospitalist	Non-resident physician who practices hospital medicine.
Hospitalist Service	Collection of clinical teams that are only staffed by non-resident clinicians
Inpatient	Patient who has been admitted to the hospital.
Intern	Resident who is in the first year of MGH's Residency Program.
Junior (JAR)	Resident who is in the second year of MGH's Residency Program.
Length-of-stay, hospital (LOS)	Operational metric; the number of midnights between admission to the hospital and discharge from the hospital.
Length-of-stay, floor (LOSF)	Operational metric; the number of midnights between admission to a floor and discharge from that floor.
Massachusetts General Hospital (MGH)	Hospital that is the focus of this study.
Medical Record Number (MRN)	Hospital-specific unique identifier for a patient.
Outpatient	Patient who has not been admitted to the hospital.
Patient	Individual who receives medical care at the hospital as either an outpatient or an inpatient.
Patient care path	Sequence of states an inpatient passes through while progressing through a visit to the hospital, beginning with admission and ending with discharge.
Patient-level responsibility	Responsibility for a specific patient assigned to a specific clinician, e.g. ensuring the patient is fit to leave the hospital before discharge.
Physician	Type of clinician who has completed an M.D.
Post Graduate Year (PGY)	Refers to the seniority of residents, e.g. a PGY-1 is a resident who is in the first year of the Residency Program (an intern)
Regionalization	Dimension of clinical care team design. A regionalized team is one that is responsible for a collection of patients on a single floor. A non-regionalized team is responsible for a collection of patients on multiple floors.
Registered Nurse (RN)	Type of clinician who has completed advanced nursing certifications, including the NCLEX-RN examination, but who does not have an M.D.
Resident	Physician who is participating in MGH's Residency Program.
Resident Block Schedule	Schedule that specifies when clinicians on the Teaching Service rotate on and off clinical teams.
Responding Responsibility	Type of patient-level responsibility that includes coordinating and delivering minute-to-minute care for a patient.

Sign-off	Type of handoff that occurs when a clinician rotates off a clinical team at the end of a multi-day / week shift.
Teaching Attending	Senior, non-resident physician who is staffed on a resident team in order to provide clinical mentorship to the residents.
Teaching Service	Collection of clinical teams that are staffed, at least in part, by resident physicians.
Team-level responsibility	Responsibility for a team of clinicians assigned to a specific clinician, e.g. completing all the paperwork for all the patients a team is collectively caring for.
The Attending	Clinician who has the Attending Responsibility for a patient. See Section 3.5.1.
The Responding	Clinician who has the Responding Responsibility for a patient. See something. See Section 3.5.1.

Appendix B

Hospital Data Sources

Tables B.1 and B.2 summarize the data sources used during this study.

B.1 Databases

Table B.1: Hospital databases

Database	Description
PEPL	Dates active: Jan 1, 2012 – Dec 31, 2015* Purpose: Inpatient Responding and Attending Physician assignments**
EPSi	Dates active: Jan 1, 2012 - Dec 31, 2015* Purpose: Billing details; retrospective summary of patient visits**
POE	Dates active: Jan 1, 2012 - Dec 31, 2015* Purpose: Clinical order details, e.g. timestamps, type, creator, authorizer**
Billing	Dates active: Jan 1, 2012 - Dec 31, 2015* Purpose: Time-based coding and billing for Attending physicians**
AmIOn	Dates active: Jan 1, 2012 - Dec 31, 2015* Purpose: Shift assignments for DOM teaching and hospitalist services**
EDIS	Dates active: Jan 1, 2013 - Dec 31, 2015* Purpose: Emergency Department visit details, e.g. timestamps, discharge metadata**
Block Schedule	Dates active: Jan 1, 2012 - Dec 31, 2015* Purpose: Historical and forecasted start/stop dates for Resident Block Schedule
Experience Level	Dates active: Jan 1, 2012 – Jul 31, 2015* Purpose: Categorization of physician experience level, {High, Medium, Low} Provided by the DOM's operations group

*Minimum range. All databases were in active use through entirety of study period.
**Minimum purpose; as utilized within this study.

B.2 Data Tables

Table B.2: Hospital data tables

Database	Table	Description
PEPL	Survey_Fact	Purpose: Inpatient Responding and Attending Physician assignments* Accessed via direct query on 2015-09-01. No filters.
EPSi	Inpatient_Encounter	Purpose: Inpatient billing details; retrospective summary of patient visits* Accessed via direct query on 2015-09-01. No filters. Note: accurate billing details are unavailable up to 4 weeks after discharge.
Billing	Teaching_Attending_Time	Purpose: Time-based coding and billing for Attending physicians* Accessed via transfer from DOM operations group, with filter: Attending time was billed to the Teaching Service
POE	v_Order_Entry	Purpose: Clinical order details, e.g. timestamps, type, creator, authorizer* Accessed via direct query with filters: $time^{creation}$ of order between [2012-01-01 00:00:00, 2015-7-31 00:00:00] Patient either on White 8 OR Bigelow 11
Block Schedule	Schedule	Purpose: Historical and forecasted start/stop dates for Resident Block Schedule Accessed via transfer from the DOM operations group
EDIS	EDIS_Encounter	Purpose: Emergency Department visit details, e.g. timestamps, discharge metadata* Accessed via direct query with filter: $time^{admit}$ between [2012-01-01 00:00:00, 2015-11-31 00:00:00]
Experience Level	Experience_Level	Purpose: Categorization of physician experience level, {High, Medium, Low} Accessed via transfer from the DOM's operations group

*Min purpose as utilized within this study.

Appendix C

Data Methods

This section discusses the rationale behind and derivation of the Patient-Encounter population and care team features used in this study. The definitions established in Chapter 5 are relied upon heavily. Data sources are referenced in Database/table format.

C.1 Patient admission/discharge from hospital

Data: EPSi/Inpatient_Encounter (Appendix B)

Timestamps for patient admission to and discharge from the hospital are derived from billing data (rather than operational), as these are considered more reliable by the hospital staff. This intuition was verified by observing that EPSi had fewer incomplete fields and fewer timestamps indicating the patient was discharged before being admitted. Patient-Encounters were excluded from the study population if either the $time_p^{admit}$ or $time_p^{discharge}$ timestamps were null, $time_p^{admit} = time_p^{discharge}$, or $time_p^{discharge} < time_p^{admit}$.

Absent a unique identifier for a patient visit, the concatenation of the patient's Medical Record Number (MRN) and admission timestamp was used to link across databases:

$uid_p = MRN_p || time_p^{admit}$

C.2 Patient admission to floor

Data: PEPL/Survey_Fact (Appendix B)

When a patient becomes the responsibility of a regionalized care team is a function of being both physically moved to the floor and formally assigned to the floor's team. While these events can occur independently for numerous operational and clinical reasons, both timestamps can be accessed through the PEPL database. As a result, $time_p^{floor}$ is defined as the first time a patient, p, is both assigned to a floor's care team and marked as physically present in a bed on the floor. Note: PEPL is not the system of record (SOR) for bed movements, but reliably receives these data in real-time from the SOR.

C.3 Length-of-stay (LOS)

Data: EPSi/Inpatient_Encounter, PEPL/Survey_Fact (Appendix B)

This study references both hospital length-of-stay and floor length-of-stay. Hospital length-of-stay, LOS_p^H, measures the number of midnights a patient spends in the hospital from admission to discharge. Floor length-of-stay, LOS_p^F, measures the number of midnights a patient spends in a care unit from point of admission to the floor to discharge. As this study focuses only on patients who are discharged directly from the floor, time of discharge is the same for both measures. Formally:

$$LOS_p^H = DATE(time_p^{discharge}) - DATE(time_p^{admit})$$
$$LOS_p^F = DATE(time_p^{discharge}) - DATE(time_p^{floor})$$

C.4 Identifying Teaching Attendings

As a complete Teaching Attending schedule is not available before Jan 2014, it was necessary to derive a list of which two Teaching Attendings were assigned to each floor each week. This was done by counting the number of discrete billing events each physician created on each floor and week. For each floor and week, the top two physicians by billing event count were determined to be the floor's Teaching Attendings during this period.

Data source: Billing/Teaching_Service_Attending_Time

$Define:$

$F = \{floor_1, ..., floor_f, ..., floor_{|F|}\}$ be the set of floors.
$W = \{week_1, ..., week_w, ..., week_{|W|}\}$ be the complete set of all weeks during the study period
and $week_p = [date_p^{start}, date_p^{end}]$
where $date_p^{start}$ is a Wednesday, and $date_p^{end}$ is the following Tuesday.

$B = \{billing_1, ..., billing_b, ..., billing_{|B|}\}$ be the set of billing events.
and $billing_b = \{floor_b, physician_b, patient_b, timestamp_b\}$

$P = \{physician_1, ..., physician_p, ..., physician_{|P|}\}$ be the set of unique physicians.

$Then:$

$\forall f \in F, w \in W, p \in P, b \in B:$

$$x_{f,w,p,b} = \begin{cases} 1, & \text{if } floor_b = floor_f, physician_b = physician_p, timestamp_b \in week_w \\ 0, & \text{otherwise} \end{cases}$$

$$\forall f \in F, w \in W, p \in P : z_{f,w,p} = \sum_{\forall b \in B} x_{f,w,p,b}$$

the largest two values for $z_{f,w,p}$ determine the Teaching Attendings for that floor-week

C.5 Identifying patients with Private Attendings

Data source: Billing/Teaching_Service_Attending_Time (Appendix B)

Having derived the pairs of Teaching Attendings staffed on each floor during each week (Appendix C.4), it was possible to identify patients who were cared for by Private Attendings. This was done by finding the set of patients that were never billed for a Teaching Attending's time while they were on the floor.

C.6 Identifying when the patient was first reviewed by an Attending

Data source: Billing/Teaching_Service_Attending_Time (Appendix B)

Whether a patient, p, was first reviewed the day s/he was on-floored or the following morning was determined through billing data. Specifically, the time of first review was marked by the first instance of any of billing code by one of the floor's two Teaching Attendings marked the time of first review.

C.7 Identifying patients cared for by a Nurse Practitioner

In order to exclude patients who were cared for by a Nurse Practitioner (NP) in advance of an Attending handoff, it was necessary to:

1. Identify NPs in the hospital's systems.
2. Identify which patients an NP cared for.
3. As applicable, identify when an NP first began caring for a patient.

Data: PEPL/Survey_Fact (Appendix B)

C.7.1 Identifying Nurse Practitioners

Absent reliable role types within the available data tables, a set of NP names, $\mathcal{NP}$, was developed by searching for the following character strings within the "Responding Clinician Name" field: {"RN","R.N","RN.","R.N."}. R.N. (and all its variants) is an acronym for Registered Nurse, a certification that all NPs must possess. This designation is appended after the name of NPs, just as M.D. is appended after the name of physicians.

C.7.2 Identifying which patients a Nurse Practitioner cared for

On Bigelow B/D, 95% of patients who are cared for by an NP once remain assigned to an NP for the remainder of their stay[1]. The remaining 5% are, with rare exception, repeatedly transitioned between the NP and the interns on the care team. As a result, for the purposes of this study, any patient who had a clinician $\in \mathcal{NP}$ as a Responding clinician at least once is considered "an NP patient."

[1] Determined from 8am-5pm Responding clinician assignments for all patients specified in Section 5.5. The Responding assignment is transitioned to a night-shift intern during the evenings irrespective of whether the patient has been assigned to an NP.

C.7.3 Identifying when a Nurse Practitioner began caring for a patient

The first time an NP is assigned to a patient as the Responding clinician, $time_p^{NP}$, is considered the point when responsibility for that patient is transitioned from the resident team to the NP for the remainder of the patient's stay.

Appendix D

Notation - Quantifying the impact of handoffs

D.1 Definitions

The following definitions relate to the Resident Block Schedule first introduced in Section 3.6 and are used throughout the analyses presented in Chapters 5 and 6. As Figure D-1 illustrates, each 28-day resident schedule block ("block") can be indexed by week, day-of-week, and day within the block, b.

(Def D.1-a)	p	:	patient visit, bounded by a single admission and discharge
(Def D.1-b)	$time_p^{admission}$	:	time of admission to hospital for patient visit, p
(Def D.1-c)	$time_p^{discharge}$	:	time of discharge from hospital for patient visit, p
(Def D.1-d)	d	:	calendar date starting at 12am and ending at 11:59pm
(Def D.1-e)	DOW	:	set of days of the week, $DOW \equiv \{Sun, Mon, Tue, Wed, Thu, Fri, Sat\}$
(Def D.1-f)	dow	:	day of the week, $dow \in DOW$
(Def D.1-g)	$dow(d)$	:	day of the week of d, $dow(d) \in DOW$
(Def D.1-h)	B	:	set of days within a 28-day resident schedule block, $B \equiv \{1, ..., 28\}$
(Def D.1-i)	b	:	index within a 28-day resident schedule block, $b \in B$
(Def D.1-j)	$b(d)$	:	index of d within a 28-day resident schedule block, $b(d) \in B$
(Def D.1-k)	B_{dow}	:	set of $b \in B$ that fall on $dow \in DOW$, e.g. $B_{wed} = \{1, 8, 15, 22\}$
(Def D.1-l)	B_{HOF}^A	:	indices when new Teaching Attendings typically join a floor, $B_{HOF}^A = \{1, 15\}$
(Def D.1-m)	B_{HOF}^R	:	indices when new Residents (Interns, Juniors) typically join a floor, $B_{HOF}^R = \{2\}$

28-Day Resident Schedule Block

week	Week 1							Week 2							Week 3							Week 4						
dow	Wed	Thu	Fri	Sat	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Sun	Mon	Tue
b	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28

Figure D-1: Indexing within a 28-day resident schedule block

D.2 Impact of handoffs on admission wait time from the ED

D.2.1 Data, definitions, and population

With raw data sourced from the EDIS/Summary data table and the historical Resident Block Schedule (see Appendix B and M), the following additional definitions are used in this analysis:

(Def D.2.1-a)	$admit_p^{ED}$	:	a patient, p, who is admitted as an inpatient from the ED
(Def D.2.1-b)	$admitting_p^{ED}$	:	the physician who admits $admit_p^{ED}$
(Def D.2.1-c)	bed	:	a bed in an inpatient care unit within the hospital
(Def D.2.1-d)	$time_p^{request}$	:	time when any bed is first requested for $admit_p^{ED}$ by $admitting_p^{ED}$
(Def D.2.1-e)	$time_p^{floor}$	:	time when $admit_p^{ED}$ is first moved to any bed
(Def D.2.1-f)	$wait_p^{ED}$	:	number of hours between $time_p^{request}$ and $time_p^{floor}$
(Def D.2.1-g)	W_{dow}^b	:	set of $wait_p^{ED}$ where $time_p^{request}$ is on dow and $b(time_p^{request}) = b$
(Def D.2.1-h)	$\bar{w}_{dow}^b$	:	mean of W_{dow}^b

The patient population (N = 16,156) includes all patients admitted from the ED to one of the general care floors belonging to the Bigelow Service, which typically have new Attendings and Residents rotate onto the floor on B_{HOF}^A and B_{HOF}^R, respectively. The full set of filters applied include:

(Filter D.2.1-a)	$time_p^{request}$ within [2012-01-01 00:00:00, 2015-11-30 23:59:59]
(Filter D.2.1-b)	$admit_p^{ED}$ moved to a bed on Bigelow A/B/C/D/E
(Filter D.2.1-c)	$admit_p^{ED}$ initially assigned to the resident team on Bigelow A/B/C/D/E
(Filter D.2.1-d)	Excluded $admit_p^{ED}$ admitted during hospital holidays +/- 3 days (Appendix N)
(Filter D.2.1-e)	Excluded $admit_p^{ED}$ admitted during the first & last week of the residency year (Appendix N)

D.2.2 Hypothesis

The hypothesis motivating this analysis is that mean wait time for admission from the ED is impacted by the position within a resident schedule block during which a patient is admitted, controlling for day-of-week. Formally:

$$\begin{aligned} H_o: &\quad \bar{w}_{dow}^i = \bar{w}_{dow}^{j \neq i} \qquad \forall dow \in DOW, \quad \forall i, j \in B_{dow} \\ H_a: &\quad \bar{w}_{dow}^i \neq \bar{w}_{dow}^{j \neq i} \qquad \forall dow \in DOW, \quad \forall i, j \in B_{dow} \end{aligned} \tag{D.1}$$

The test used to evaluate the null hypothesis is the two-sided t-test of means with pooled variance ($\alpha = 0.05$).

D.3 Impact of handoffs on floor admission and discharge rates

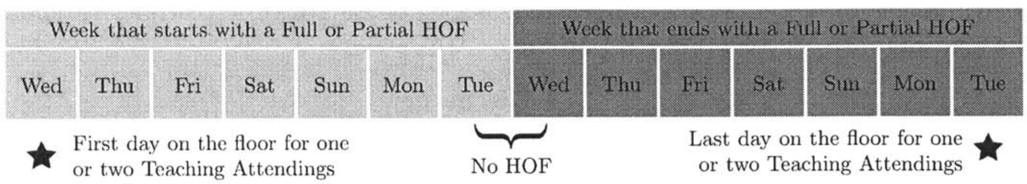

Figure D-2: Weeks that either start or end with a Teaching Attending handoff

D.3.1 Data, definitions, and population

With raw data sourced from the PEPL/Inpatient_Survey_Fact, EPSi/Inpatient_Encounter, and Billing data tables as well as the historical Resident Block Schedule (see Appendix B and M), the following additional definitions are used in this analysis:

(Def D.3.1-a)	$\mathcal{F}$	:	set of floors, f, in this study, $\mathcal{F}$ = {Bigelow A, Bigelow B, Bigelow D, Bigelow E}
(Def D.3.1-b)	$\mathcal{W}$	:	set of weeks this study
(Def D.3.1-c)	w	:	specific week, $w \in \mathcal{W}$
(Def D.3.1-d)	$type$	:	set of types of week, $type$ = {starts, ends} with a Teaching Attending handoff
(Def D.3.1-e)	$type(w^f)$	:	type of week, w, on floor, f
(Def D.3.1-f)	$\grave{r}_d^f$	:	daily admission rate for day, d, and floor, f
(Def D.3.1-g)	$\acute{r}_d^f$	:	daily discharge rate for day, d, and floor, f
(Def D.3.1-h)	$\grave{R}_{type}^{dow}$	:	set of daily admission rates, $\grave{r}_d^f$, where $dow(d) = dow$, $d \in w$, $type(w^f) = type$
(Def D.3.1-i)	$\acute{R}_{type}^{dow}$	:	set of daily discharge rates, $\acute{r}_d^f$, where $dow(d) = dow$, $d \in w$, $type(w^f) = type$
(Def D.3.1-j)	$\grave{\bar{r}}_{type}^{dow}$	:	mean of $\grave{R}_{type}^{dow}$
(Def D.3.1-k)	$\acute{\bar{r}}_{type}^{dow}$	:	mean of $\acute{R}_{type}^{dow}$

The daily rates are calculated from a population of patient visits (N = 9,743) during which the patient was admitted to a single general care floor from any source and discharged directly from the floor to any destination outside the hospital (Section 3.7). Patients cared for by a Private Attending (Section 3.2) were excluded, as they maintain the same Attending regardless of handoffs in the clinical team. The full set of filters applied include:

(Filter D.3.1-a)	d within [2012-01-01, 2015-7-31]
(Filter D.3.1-b)	p admitted directly to a *bed* on Bigelow A/B/D/E from any source
(Filter D.3.1-c)	p discharged directly from Bigelow A/B/D/E to outside the hospital
(Filter D.3.1-d)	p spent at least 50% of visit on Bigelow A/B/D/E
(Filter D.3.1-e)	p not cared for by a Private Attending (Appendix C)
(Filter D.3.1-f)	Excluded p admitted within 3 days after a hospital holiday (Appendix N)
(Filter D.3.1-g)	Excluded p admitted during the first/last week of the residency year (Appendix N)
(Filter D.3.1-h)	Excluded the 3% of floor-weeks that didn't start or end with a Teaching Attending handoff
(Filter D.3.1-i)	Excluded the 2% of floor-weeks that started and ended with a Teaching Attending handoff

D.3.2 Hypothesis

The hypothesis motivating this analysis is that mean admission (discharge) rates are impacted by whether the admission (discharge) occurs during a week that begins or ends with a Teaching Attending handoff. Formally:

$$
\begin{array}{llll}
\textbf{Admission} & & \textbf{Discharge} & \\
H_o: \; \bar{\grave{r}}^{dow}_{starts} = \bar{\grave{r}}^{dow}_{ends} & \forall dow \in DOW & H_o: \; \bar{\acute{r}}^{dow}_{starts} = \bar{\acute{r}}^{dow}_{ends} & \forall dow \in DOW \\
H_a: \; \bar{\grave{r}}^{dow}_{starts} \neq \bar{\grave{r}}^{dow}_{ends} & \forall dow \in DOW & H_a: \; \bar{\acute{r}}^{dow}_{starts} \neq \bar{\acute{r}}^{dow}_{ends} & \forall dow \in DOW
\end{array}
\tag{D.2}
$$

The test used to evaluate the null hypothesis is the two-sided t-test of means with pooled variance ($\alpha = 0.05$).

D.4 Impact of handoffs on next day review rate

D.4.1 Data, definitions, and population

With raw data sourced from the PEPL/Inpatient_Survey_Fact, EPSi/Inpatient_Encounter, and Billing data tables as well as the historical Resident Block Schedule (see Appendix B and M), the following additional definitions are used in this analysis:

(Def D.4.1-a)	q^f_d	:	# patients admitted to floor, f, after noon on day, d
(Def D.4.1-b)	$\hat{q}^f_d$	:	# patients admitted to floor, f, after noon on day, d, and first reviewed the next day
(Def D.4.1-i)	Q^{dow}_{type}	:	sum of q^f_d, where $dow(d) = dow$, $d \in w$, $type(w^f) = type$
(Def D.4.1-i)	$\hat{Q}^{dow}_{type}$	:	sum of $\hat{q}^f_d$, where $dow(d) = dow$, $d \in w$, $type(w^f) = type$

The filters and resulting patient population (N = 4,650) are the same as used in Section 5.3.1 with one addition:

(Filter D.4.1-a) $HOUR(time^{floor}_p)$ within [12, 23]

D.4.2 Hypothesis

The hypothesis motivating this analysis is that proportion of patients who are first reviewed by an Attending the day after being on-floored after noon increases as a Teaching Attending handoff approaches. Formally:

$$
\begin{array}{ll}
H_o: \; \dfrac{\hat{Q}^{dow}_{starts}}{Q^{dow}_{starts}} \geq \dfrac{\hat{Q}^{dow}_{ends}}{Q^{dow}_{ends}} & \forall dow \in DOW \\
H_a: \; \dfrac{\hat{Q}^{dow}_{starts}}{Q^{dow}_{starts}} < \dfrac{\hat{Q}^{dow}_{ends}}{Q^{dow}_{ends}} & \forall dow \in DOW
\end{array}
\tag{D.3}
$$

The test used to evaluate the null hypothesis is the one-sided Fisher Exact Probability Test ($\alpha = 0.05$).

D.5 Impact of handoffs on length-of-stay

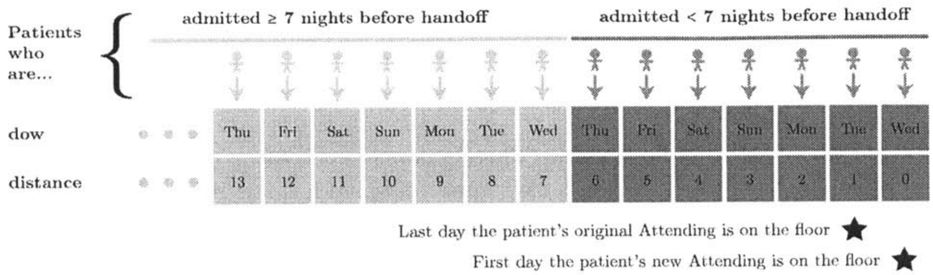

Figure D-3: Patient categorization by day-of-week of admission and distance from Attending handoff

D.5.1 Data, definitions, and population

The patient visit data used for this analysis are a subset of those used for the admission/discharge rate and next-day review rate analyses above (Sections 5.3 and 5.4, respectively), and the following additional definitions used:

(Def D.5.1-a)	$time_p^{floor}$	:	time when patient, p, is admitted to the floor
(Def D.5.1-b)	rev_p	:	day when patient, p, is first reviewed by an Attending, $rev \in \{same, next\}$
(Def D.5.1-c)	los_p	:	# midnights between $time_p^{floor}$ and $time_p^{discharge}$
(Def D.5.1-d)	a_p	:	attending to whom patient, p, is assigned when admitted to the floor
(Def D.5.1-e)	$date(a_p)$	:	date when a new attending replaces $attending_p$ on the floor
(Def D.5.1-f)	$dist(a_p)$	:	# midnights between $time_p^{floor}$ and $date(a_p)$
(Def D.5.1-g)	$dist^{near}$	:	set of distances that are $\leq$ a week of $date(a_p)$, $dist^{near} = \{0, ..., 6\}$
(Def D.5.1-h)	$dist^{far}$	:	set of distances that are $>$ a week from $date(a_p)$, $dist^{far} = \{7, ..., 27\}$
(Def D.5.1-i)	$\overset{rev\ \ dow}{LOS}_{dist^{near}}$	:	set of los_p where $dow = dow(time_p^{floor})$, $dist(a_p) \in dist^{near}$, $rev = rev_p$
(Def D.5.1-j)	$\overset{rev\ \ dow}{LOS}_{dist^{far}}$	:	set of los_p where $dow = dow(time_p^{floor})$, $dist(a_p) \in dist^{far}$, $rev = rev_p$

To ensure the los_p metric reflects only the time a patient spends on the floor that is within the Attending's control, los_p values are included for a population of patient visits (N = 4,171) during which the patient was admitted to a single general care floor directly from the ED or other pre-location area (see below) and discharged directly from the floor to the patient's home. The discharge requirement is motivated by the discovery that sending a patient to a non-home destination, e.g. a skilled nursing facility, may cause significant delays in patient progression. Finally, on Bigelow B/D, patients for whom a Nurse Practitioner (NP) became the Responding clinician before the Attending handoff were excluded from the analysis. While still formally assigned to the Bigelow B/D team, these patients are, in practice, no longer part of resident team's responsibilities.

The full set of filters applied include:

(Filter D.5.1-a)	p admitted and discharged from the hospital within [2012-01-01 00:00:00, 2015-08-31 23:59:59]
(Filter D.5.1-b)	p admitted directly to a *bed* on Bigelow A/B/D/E from the ED or a staging area[1]
(Filter D.5.1-c)	p discharged directly from Bigelow A/B/D/E to the patient's home
(Filter D.5.1-d)	p spent at least 50% of visit on Bigelow A/B/D/E
(Filter D.5.1-e)	p not cared for by a Private Attending
(Filter D.5.1-f)	p does not have a Nurse Practitioner as a Responding clinician before the day of an Attending handoff
(Filter D.5.1-g)	$dist(a_p) \in \{0, 1\}$
(Filter D.5.1-h)	$1 < los_p \leq 21$ to avoid scenarios where a patient experiences two handoffs
(Filter D.5.1-i)	Excluded p admitted within 3 days after a hospital holiday (Appendix N)
(Filter D.5.1-j)	Excluded p admitted during the first & last week of the residency year (Appendix N)

D.5.2 Hypothesis

The hypothesis motivating this analysis is that the distribution of LOS for patients who are admitted to the floor within a week of when their Attending leaves is different than that for patients who are admitted more than a week before their Attending leaves, controlling for day-of-week and when the patient is first reviewed. Formally:

$$\begin{aligned} H_o: &\quad {}^{rev}LOS^{dow}_{distance^{far}} \stackrel{d}{=} {}^{rev}LOS^{dow}_{distance^{close}} \quad \forall rev, dow \\ H_a: &\quad {}^{rev}LOS^{dow}_{distance^{far}} \stackrel{d}{\neq} {}^{rev}LOS^{dow}_{distance^{close}} \quad \forall rev, dow \end{aligned} \tag{D.4}$$

The test used to evaluate the null hypothesis is the two-sided Mann–Whitney–Wilcoxon Rank-Sum (RS) Test ($\alpha = 0.05$). A non-parametric test is used because los_p belongs to a long-tailed, non-normal distribution (Section 4.1.1).

[1]Staging areas include the Addictions Consult Team (ACT), Admissions (ADM), Emergency Room Staging (E03R), BOP, and Psychology Assessment Center (PAC)

Appendix E

Factors used to predict length-of-stay

E.1 Independent factors

Table E.1: Independent factors for predicting floor length-of-stay

(Factor E.1-a)	*dow*	:	$\{0,1\}^7$	:	Day-of-week patient was admitted to the floor
(Factor E.1-b)	*time*	:	$\{0,1\}^2$	:	Time-of-day {am,pm} patient was admitted to the floor
(Factor E.1-c)	*gender*	:	$\{0,1\}^2$	:	Gender of patient, {male,female}
(Factor E.1-d)	*location*	:	$\{0,1\}^4$	:	Floor to which patient is admitted, {A,B,D,E}
(Factor E.1-e)	*distance_0*	:	$\{0,1\}^1$	:	Patient was admitted the Wednesday a new Attending is on the floor*
(Factor E.1-f)	*distance_1*	:	$\{0,1\}^1$	:	Patient was admitted the Tuesday before a HOF*
(Factor E.1-g)	*distance_2*	:	$\{0,1\}^1$	:	Patient was admitted the Monday before a HOF*
(Factor E.1-h)	*mdc*	:	$\{0,1\}^{24}$	:	Major Diagnostic Category (MDC) hypothesized when the patient was admitted [1]
(Factor E.1-i)	*experience*	:	$\{0,1\}^2$	:	Experience level of the Attending to whom the patient is initially assigned, {High/Medium, Low}
(Factor E.1-j)	*flag_precaution*	:	$\{0,1\}^1$	:	Was the patient admitted with a physical precaution, e.g. MRSA?
(Factor E.1-k)	*flag_psych*	:	$\{0,1\}^1$	:	Was the patient admitted with a psychological precaution, e.g. bipolar?
(Factor E.1-l)	*flag_restraint*	:	$\{0,1\}^1$	:	Did the patient need to be physically restrained, e.g. for violent behavior?
(Factor E.1-m)	*flag_addiction*	:	$\{0,1\}^1$	:	Was addiction a concern when the patient was admitted?

*Distance until HOF is determined on a patient-by-patient basis, as in Section 5.5

[1] In this context, MDC refers to the single bodily system that the admitting physician believes to be the primary driver of the patient's clinical need. See [34]

Appendix F

Predictive model results

This section contains the models derived using AIC_c and discussed in Chapter 6. A description of each factor is included in Table E.1. The outcome for each is the log transform of floor length-of-stay, $log_{10}LOS$.

F.1 Model, all MDCs

Table F.1: Parameter Estimates, all patients

Term	Estimate	Std. Error	p-value	
Intercept	0.569	0.010	<.0001	*
distance_1	-0.055	0.018	0.003	*
distance_2	0.056	0.018	0.002	*
dow_sun	-0.009	0.014	0.513	
dow_tue	0.031	0.015	0.034	*
dow_thu	0.028	0.012	0.023	*
dow_fri	0.051	0.012	<.0001	*
dow_sat	0.035	0.013	0.007	*
time_am	-0.011	0.008	0.157	
location_a	0.002	0.008	0.812	
location_d	-0.010	0.009	0.266	
flag_psych	0.048	0.011	<.0001	*
flag_addiction	0.095	0.064	0.138	
flag_precaution	0.173	0.078	0.026	*
distance_1*flag_precaution	0.119	0.246	0.629	
distance_2*time_am	0.054	0.035	0.124	
distance_2*flag_addiction	0.252	0.108	0.020	*
dow_sun*location_a	0.050	0.027	0.059	
dow_tue*time_am	0.043	0.022	0.054	
dow_tue*location_a	-0.031	0.023	0.171	
dow_tue*flag_psych	-0.101	0.030	0.001	*
dow_thu*time_am	0.035	0.021	0.104	
dow_thu*location_d	0.040	0.023	0.080	
dow_thu*flag_addiction	-0.335	0.104	0.001	*
dow_fri*flag_psych	-0.033	0.031	0.278	
dow_sat*time_am	0.055	0.022	0.012	*

F.2 Model, MDC 5, Diseases and Disorders of the Circulatory System

Table F.2: Parameter Estimates, MDC 5

Term	Estimate	Std. Error	p-value	
Intercept	0.620	0.026	<.0001	
distance_1	-0.015	0.048	0.754	
distance_2	0.060	0.050	0.234	
dow_sun	-0.111	0.033	0.001	*
dow_mon	-0.047	0.035	0.178	
dow_tue	-0.039	0.034	0.256	
dow_wed	-0.038	0.034	0.263	
dow_thu	-0.010	0.028	0.722	
time_pm	0.024	0.019	0.216	
location_a	0.010	0.025	0.692	
location_b	0.041	0.027	0.126	
location_d	-0.042	0.026	0.109	
flag_psych	0.129	0.040	0.002	*
flag_addiction	-0.147	0.143	0.307	
distance_1*time_pm	-0.159	0.086	0.064	
distance_1*location_b	0.157	0.106	0.139	
distance_2*time_pm	0.200	0.093	0.032	*
distance_2*location_a	-0.241	0.101	0.017	*
distance_2*location_b	0.161	0.129	0.214	
dow_sun*time_pm	0.106	0.060	0.078	
dow_sun*location_b	0.126	0.080	0.115	
dow_sun*flag_psych	-0.375	0.139	0.007	*
dow_mon*location_b	-0.139	0.073	0.057	
dow_tue*location_a	-0.140	0.058	0.016	*
dow_tue*flag_psych	-0.285	0.098	0.004	*
dow_wed*location_b	0.212	0.078	0.007	*
dow_wed*location_d	0.166	0.072	0.022	*
dow_thu*time_pm	0.085	0.053	0.110	
dow_thu*location_a	-0.128	0.060	0.034	*
dow_thu*location_d	0.079	0.063	0.206	
time_pm*location_b	0.120	0.044	0.007	*
time_pm*flag_addiction	0.500	0.304	0.101	

F.3 Model, MDC 4, Diseases and Disorders of the Respiratory System

Table F.3: Parameter Estimates, MDC 4

Term	Estimate	Std. Error	p-value	
Intercept	0.567	0.019	<.0001	*
distance_2	0.124	0.050	0.014	*
dow_mon	-0.060	0.035	0.087	
dow_tue	-0.056	0.029	0.056	
dow_fri	-0.029	0.027	0.287	
dow_sat	0.032	0.030	0.287	
time_am	0.003	0.020	0.877	
location_e	0.011	0.021	0.609	
flag_psych	0.127	0.040	0.002	*
flag_precaution	0.248	0.133	0.064	
dow_mon*time_am	0.134	0.058	0.021	*
dow_tue*location_e	0.123	0.062	0.047	*
dow_tue*flag_psych	-0.055	0.089	0.541	
dow_fri*location_e	0.109	0.053	0.041	*
time_am*location_e	-0.085	0.043	0.048	*

F.4 Model, MDC 8, Diseases and Disorders of the Musculoskeletal System

Table F.4: Parameter Estimates, MDC 8

Term	Estimate	Std. Error	p-value	
Intercept	0.581	0.042	<.0001	*
distance_1	-0.023	0.139	0.868	
distance_2	0.230	0.078	0.004	*
dow_tue	0.056	0.057	0.327	
dow_fri	0.071	0.050	0.160	
dow_sat	0.187	0.054	0.001	*
time_am	-0.039	0.036	0.279	
location_a	0.080	0.047	0.091	
location_b	-0.026	0.058	0.653	
location_d	-0.005	0.051	0.927	
flag_psych	0.134	0.076	0.082	
flag_addiction	0.394	0.157	0.014	*
distance_1*location_b	0.535	0.287	0.065	
distance_1*location_d	1.679	0.398	<.0001	*
distance_2*location_b	0.553	0.228	0.017	*
dow_tue*time_am	0.416	0.116	0.001	*
dow_tue*location_d	-0.269	0.137	0.051	
dow_fri*time_am	-0.142	0.105	0.179	
dow_fri*location_a	-0.321	0.122	0.010	*
dow_fri*location_d	-0.275	0.127	0.033	*
dow_sat*flag_psych	0.435	0.173	0.013	*
time_am*location_b	0.331	0.117	0.006	*
location_d*flag_psych	-0.566	0.218	0.011	*

F.5 Model, MDC 9, Diseases and Disorders of the Skin

Table F.5: Parameter Estimates, MDC 9

Term	Estimate	Std. Error	p-value	
Intercept	0.477	0.029	<.0001	*
distance_1	-0.183	0.085	0.034	*
dow_mon	0.129	0.045	0.005	*
dow_thu	0.081	0.043	0.061	
dow_fri	0.107	0.045	0.019	*
location_b	0.095	0.044	0.032	*
location_d	0.041	0.037	0.263	
distance_1*location_d	-0.360	0.212	0.092	
dow_mon*location_b	0.543	0.128	<.0001	*
dow_thu*location_b	0.156	0.097	0.112	

Appendix G

Framework for patient care paths

A patient who is receiving care at the hospital can be classified as either an outpatient or an inpatient. Formally, an inpatient has been admitted to the hospital by a physician with the expectation that they will spend at least one night in a hospital bed. Outpatient status is reserved for individuals whose clinical needs do not warrant extended, intense medical care (and its associated costs), including most patients undergoing routine tests, ambulatory surgery, or treatment in the Emergency Department (ED).

There are numerous clinical and regulatory drivers that may motivate a physician to admit a patient and, when this occurs, the patient is classified as an inpatient. This status change carries significant procedural, legal, and financial implications for both the patient and hospital that are beyond the scope of this study. For now, however, it is sufficient to understand that when an individual is admitted to the hospital, it is because a knowledgeable party has determined the patient's clinical needs require the type of medical care that can best be delivered within the hospital's walls. Similarly, when the specific physician responsible for the patient while in the hospital determines the patient's needs no longer warrant inpatient status, that physician formally discharges the patient from the hospital and bookends the visit. As Figure G-1 illustrates, this discharge event is both physical, i.e., the patient physically leaves the hospital, as well as financial and legal, i.e. the hospital no longer has the significant responsibilities associated with caring for the patient as an inpatient.

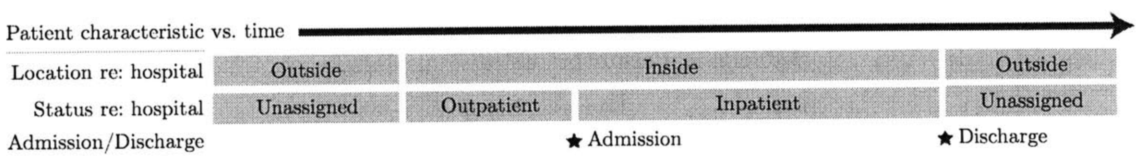

Figure G-1: Patient out/inpatient status vs. admission and discharge events

For the purposes of this study, a patient care path is loosely defined as the sequence of states an inpatient passes through while progressing through the hospital[1], beginning with patient admission and ending with patient discharge . Each of these states is described – again very loosely – by the patient's clinical need and how the hospital has configured its resources to meet this need. Put more formulaically,

[1]Not to be confused with Clinical Pathways, as in [35]

$$
\begin{aligned}
\text{Patient Care Path} &\equiv \{\text{Admission} \rightarrow \ldots \rightarrow State_s \rightarrow \ldots \rightarrow \text{Discharge}\} \\
State_s &\equiv \{\text{Patient need}, \text{Hospital configuration}\} \\
\\
\text{Patient need} &\equiv \{\text{Acuity of need}, \text{Stage of care}\} \\
\text{Hospital configuration} &\equiv \{\text{Location}, \text{Equipment}, \text{Structure of care team}\} \\
\\
\text{Acuity of need} &\in \{\text{Emergent}, \text{Intensive}, \text{General}\} \\
\text{Stage of care} &\in \{\text{Diagnosis}, \text{Treatment}, \text{Discharge}\} \\
\text{Location} &\equiv \{\text{Department}, \text{Building}, \text{Floor}, \text{Bed}\} \\
\text{Equipment} &\in \{\text{Equipment A}, \text{Equipment B}, \ldots\} \\
\text{Structure of care team} &\in \{\text{Team Model A}, \text{Team Model B}, \ldots\}
\end{aligned}
\tag{G.1}
$$

This is by no means a precise definition, but it does offer insight into the basic relationships between patient need (demand) and the hospital's response (supply). For example, Patient A, who is known to need surgery, will be assigned to the Department of Surgery and to a building, floor, and bed that have the specialized equipment and care team structures that are best matched to the patient's need. Patient B, who has an uncertain but severe medical need, may be assigned to the DOM and to a building, floor, and bed with equipment and teams geared towards diagnosis and intensive care delivery.

It is important to note that Patient A and Patient B may be the same person, only at different stages of care. Further, a patient may oscillate between levels of acuity, stages of care, locations, and care teams any number of times during a single visit to the hospital – such is the complexity of the underlying system and need it is designed to serve. Fortunately, this study is able to bound some of this complexity by limiting its focus to a handful of similar floors within the DOM.

Appendix H

Acuity of patient need

Broadly defined, acuity of need ("acuity") refers to the intensity of clinical attention a patient requires. While its exact definition varies widely in both the hospital and literature, acuity serves as an abstraction of a patient's clinical standing used to guide budgeting and staffing requirements, such as type of care team and minimum ratio of nurses-to-patients. For instance, if a patient's underlying condition is highly uncertain or otherwise requires continuous monitoring and interventions, acuity is high. If the patient is stable and will likely be discharged within the next several days, acuity is low.

While acuity is a continuous measure, the hospital uses it to assign patients to three broad categories of clinical need and associated level of care: (1) Emergency, (2) Intensive, and (3) General (Table H.1). As staffing and operating patterns vary significantly across levels of care, individual floors maintain a specific care level designation. Further, care level and the physical features of the floor (e.g. number of beds) jointly determine the set of care team models that may be utilized on the floor.

Table H.1: Care level vs. patient acuity

Level of care	Nurse-to-Patient Ratio	Description of patient need
Emergency	1:1 to 1:3	Unknown, potentially acute and unstable condition that possibly requires intensive nursing care and surveillance
Intensive	1:1 to 1:2	Acutely ill, unstable condition that requires very intensive nursing care and surveillance
General	1:3 to 1:5	Acutely ill, but stable condition that requires less intensive nursing care and surveillance

Appendix I

Inpatient Medical Care Units

Table I.1 lists the physical locations (buildings, floors) and bed counts composing the Department of Medicine's Patient Care Units.

Table I.1: Department of Medicine, Inpatient Medical Service, Patient Care Units

		Care Level, [# beds]		
Building	**Floor**	**General**	**Intensive**	**Emergency**
White	8 (Team A)	24		
White	9 (Team B)	20		
White	10 (Team C)	20		
White	11 (Team D)	20		
Bigelow	9 (RACU)		18	
Bigelow	11 (Team E)	24		
Bigelow	12 (ED Observation)			*Boarder Service*
Ellison	1 (ED)			*Boarder Service*
Ellison	8 (Cardio)		8	
Ellison	9 (CICU)		16	
Ellison	10 (SDU)		36	
Ellison	11 (Cardio)		36	
Ellison	12	36		
Ellison	16	10		
Ellison	19	10		
Phillips	20	20		
Lunder	9 (Oncology)	32		
Lunder	10	32		
Blake	7 (MICU)	8		
Blake	12		[1,18]	

Appendix J

Clinical Orders

When treating a patient, clinicians generate clinical orders ("orders") to trigger activities elsewhere within the hospital as well as asynchronously coordinate care amongst a distributed team. Examples of orders include, but are not limited to:

1. **Requesting tests,** e.g., radiological imaging and blood panels.
2. **Specifying treatments,** e.g., medication types and schedules.
3. **Involving external resources,** e.g., specialty consultants and social workers.
4. **Communicating information,** e.g., patient preferences and precautions.
5. **Initiating workflows,** e.g., patient discharge or relocation within the hospital.

As a detailed discussion of the various order types and qualities is beyond the scope of this text, orders can best be understood as an atomic unit of care: each reflecting a discrete decision or action taken by a clinician in response to patient need. As such, order creation can be viewed as an indicator of clinical care and the time-density of orders as a measure of the intensity of care.

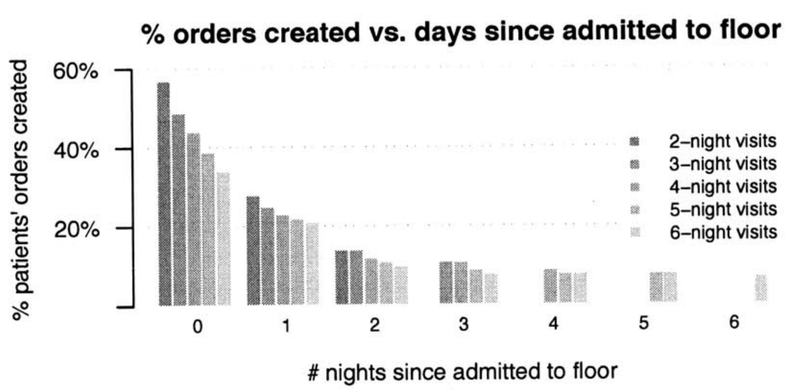

Figure J-1: Clinical order volume vs. day into visit, Bigelow A[1]

As Figure J-1 illustrates, intensity of care is highest at the beginning of a patient's visit. Over 50% of all orders are created within the first two days for patients who spend three to seven days on the floor. This aligns with intuition given the functional stages of care discussed in Section 3.2.2. There is a flurry of activity and focused clinical decision-making during the first few days of a patient visit. This intensity rapidly tapers off as the treatment path for the patient is refined and/or the patient's need becomes less acute.

Appendix K

Orders vs. Responding assignment

As discussed in Section 3.5.1, clinicians are assigned formal responsibilities for specific patients. One such responsibility is the "Responding" clinician, which implies that the assigned clinician coordinates and delivers direct care for the patient. Given that clinicians operate in teams on Bigelow A/B/D/E with up to seven clinicians capable of being a "Responding" clinician on any given day, it is valuable to understand how the assignment of this responsibility relates to actual clinical decision-making and activities, as indicated by the creation of orders. As shown in Figure K-1, there is very little relationship between the number of clinicians placing orders and those with formal responsibility for individual patients ($\rho = 0.24$). As is also apparent while observing these floors, the assignment of the "Responding" clinician responsibility is largely a formality, and the associated functional duties are distributed across the team's interns and nurse practitioners (if on Bigelow B/D). This practice allows clinicians in these less-senior roles to maintain a similar baseline knowledge of each patient and, ostensibly, limits the impact of ensuring interns fairly alternate team responsibilities and day/night-shifts during their four-week block shift.

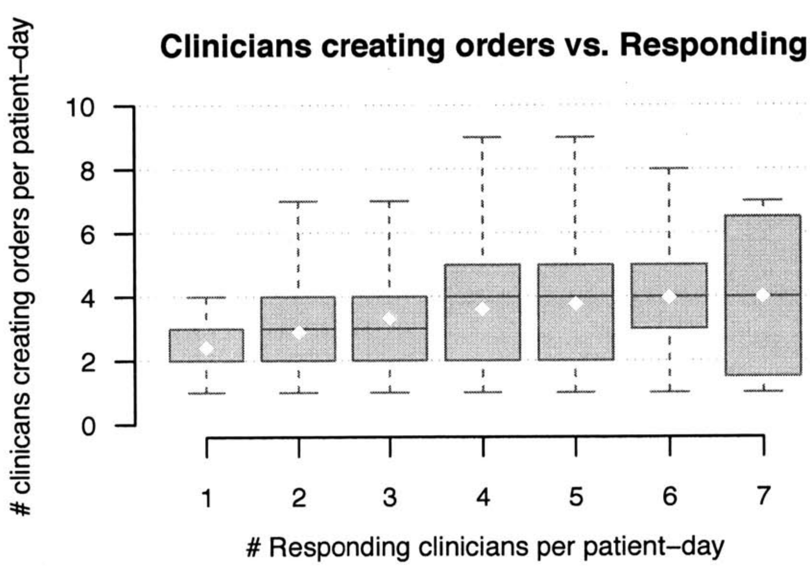

Figure K-1: Order creation vs. formal Responding responsibility, Bigelow A[1]

[1] Order set as described in Footnote 1.
Responding responsibility assignments derived from PEPL_Inpatient_Survey_Fact as discussed in Appendix C.
If present, the order "Approver" is considered the order creator.

Appendix L

Team Configurations

Table L.1 lists the team configurations practiced across the Department of Medicine inpatient care units.

Table L.1: Team configurations, Department of Medicine inpatient care units

Team	Location	# beds	Attending	Pr. Attending	PGY-3	PGY-2	PGY-1	NP	Hospitalist
Bigelow A	White 8	24	2	10		2	5		
Bigelow B	White 9	20	2	10		1	5	1	
Bigelow C*	White 10	20	1	10		1	5	1	
Bigelow D	White 11	20	2	10		1	5	1	
Bigelow E	Bigelow 11	24	2	10		2	5		
Team 1	Ellison 16	18		10	1		2		
Team W	Ellison 16	16		10	1		2		
Team 4**	Ellison 12	36		10					2
Team 4**	Bigelow floors	7		10					2
Team J**	Phillips 20	20		10					3
Team J**	Ellison 19	10		10					3
AHS**	Bigelow 9	8		10				1	1
AHS**	White 9	5		10				1	1
Team 3**	Lunder 9	14	1		1		2		
Team 3**	Lunder 10	18	2		1		2		
NP Oncology**	Lunder 9	18						1	1
NP Oncology**	Lunder 10	14						1	1
Oncology	variable	variable						2	2
RACU	Bigelow 9	10						1	2

* Bigelow C's Attending is a Chief Resident
** Several teams are distributed across multiple locations
Attending = Teaching Attending
Pr. Attending = Private Attending
PGY-3 = Senior Resident
PGY-2 = Junior Resident
PGY-1 = Intern
NP = Nurse Practitioner

Appendix M

Resident Block Schedule

Table M.1 lists the key dates of the Resident Block Schedule for the 2011-2015 resident years. A resident year always begins on June 25th and ends the following June 24th.

Table M.1: Resident Block Schedule, 2011-2015

		Start date of block / sub-block					
Block	**Sub-block**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**
8	A	*	12-Jan	10-Jan	9-Jan	7-Jan	7-Jan
8	B	*	26-Jan	24-Jan	23-Jan	21-Jan	21-Jan
9	A	*	9-Feb	7-Feb	6-Feb	4-Feb	4-Feb
9	B	*	23-Feb	21-Feb	20-Feb	18-Feb	18-Feb
10	A	*	8-Mar	7-Mar	6-Mar	4-Mar	3-Mar
10	B	*	22-Mar	21-Mar	20-Mar	18-Mar	17-Mar
11	A	*	5-Apr	4-Apr	3-Apr	1-Apr	31-Mar
11	B	*	19-Apr	18-Apr	17-Apr	15-Apr	14-Apr
12	A	*	3-May	2-May	1-May	29-Apr	28-Apr
12	B	*	17-May	16-May	15-May	13-May	12-May
13	A	*	31-May	30-May	29-May	27-May	26-May
13	B	*	14-Jun	13-Jun	12-Jun	10-Jun	9-Jun
1	A	25-Jun	25-Jun	25-Jun	25-Jun	25-Jun	*
1	B	14-Jul	12-Jul	11-Jul	9-Jul	9-Jul	*
2	A	28-Jul	26-Jul	25-Jul	23-Jul	23-Jul	*
2	B	11-Aug	9-Aug	8-Aug	6-Aug	6-Aug	*
3	A	25-Aug	23-Aug	22-Aug	20-Aug	20-Aug	*
3	B	8-Sep	6-Sep	5-Sep	3-Sep	3-Sep	*
4	A	22-Sep	20-Sep	19-Sep	17-Sep	17-Sep	*
4	B	6-Oct	4-Oct	3-Oct	1-Oct	1-Oct	*
5	A	20-Oct	18-Oct	17-Oct	15-Oct	15-Oct	*
5	B	3-Nov	1-Nov	31-Oct	29-Oct	29-Oct	*
6	A	17-Nov	15-Nov	14-Nov	12-Nov	12-Nov	*
6	B	1-Dec	29-Nov	28-Nov	26-Nov	26-Nov	*
7	A	15-Dec	13-Dec	12-Dec	10-Dec	10-Dec	*
7	B	29-Dec	27-Dec	26-Dec	24-Dec	24-Dec	*

Appendix N

Hospital Holidays

Table N.1 lists hospital holidays, as referenced in Chapters 5 and 6.

Table N.1: Hospital Holidays

Holiday	**Dates**
New Years Day	{2012-01-01, 2013-01-01, 2014-01-01, 2015-01-01}
MLK Jr. Day	{2012-01-16, 2013-01-21, 2014-01-20, 2015-01-19}
President's Day	{2012-02-20, 2013-02-18, 2014-02-17, 2015-02-16}
Memorial Day	{2012-05-28, 2013-05-27, 2014-05-26, 2015-05-25}
Independence Day	{2012-07-04, 2013-07-04, 2014-07-04, 2015-07-04}
Labor Day	{2012-09-03, 2013-09-02, 2014-09-01, 2015-09-07}
Columbus Day	{2012-10-12, 2013-10-13, 2014-10-14, 2015-10-15}
Thanksgiving Day	{2012-11-22, 2013-11-28, 2014-11-27, 2015-11-26}
Christmas Day	{2012-12-31, 2013-12-31, 2014-12-31, 2015-12-31}

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