

Task Allocation and Training in Nonprofit Emergency Departments

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Abstract

Nonprofit teaching hospitals contribute almost half of Health Care and Social Assistance GDP and educate more than 90% of all future physicians. Despite the importance of teaching, both policy discourse aimed at improving healthcare efficiency and existing models of nonprofit hospitals do not account for it, thereby missing an important trade-off between the short-term delivery of health services and the long-term benefits of physician training. I leverage unusually detailed electronic health record and audit log data from the emergency department of a large, urban teaching hospital to characterize the static costs of training across a range of granular patient outcomes and process measures. Using panel variation in patient assignment to residents, I find that hospitals must extend length of stay for complex patients by 1% to make a resident 0.047% faster in the future. Over the four-year program, this accrues to a reduction of about 9.4% and implies faster patient throughput. Then, to understand how the hospital trades off throughput costs today with future benefits of more intense physician training, I develop and estimate a dynamic model of training and care quality. Commonly-discussed payment reforms for insurers to reduce costs may increase the shadow cost of training. This could have negative effects on the career outcomes of graduating physicians 17 times larger than the savings for the teaching hospital, but feasible remedies such as increasing the staffing of attending physicians by 5% lessens the penalty by 81%.

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I Introduction

Healthcare spending is far higher in the United States than in other developed countries, yet Americans experience worse health outcomes.¹ This is despite a large fraction of care—45% of all Health Care and Social Assistance GDP in 2019—flowing through academic teaching hospitals, widely regarded as the best hospitals in the world.² To reduce costs and improve outcomes, both private and public insurers have been turning to financial incentives such as payment reform, but these policies typically do not consider the dual role of teaching hospitals of treating patients and training the next generation of physicians. While the changes may incentivize teaching hospitals to increase care quality, they may also induce them to reduce teaching, which would have serious consequences for future patients. Understanding how private, nonprofit teaching hospitals trade off the quantity and quality of patient care with resident training is crucial in order to properly assess the impact of such policy changes.

In this paper, I study how nonprofit teaching hospitals allocate patients of varying complexity to residents (trainees) and attending physicians (teaching faculty who also work independently) in order to trade off care quantity, quality, and training. First, by leveraging detailed electronic health record and audit log data, I characterize the static costs of training: to learn, residents must practice on patients, but because they are not yet trained, they achieve worse patient outcomes than a fully-trained attending would. Then, to understand how the hospital trades off present training costs with benefits realized in the future, I develop and estimate a dynamic model of physician training and care quality. I use the model to quantify the long-run consequences for future patients caused by changes in physician training that result from changes in incentives for current patient care quality.

I focus on emergency medicine (EM) residents at the University of California, San Francisco (UCSF). The UCSF EM Residency’s day-to-day operations are typical of EM Residency programs. Most patients are seen by a single resident, the trainee, who is supervised by an attending physician, a faculty member. The remaining patients are seen by attendings working independently. Residents choose patients with assistance and guidance from attendings. Via their patient allocation decisions, attending physicians execute the hospital’s desired trade-off between training and care quality.

The granularity of my data allow me to examine resident learning in great detail. I observe resident and attending identifiers for each distinct, disaggregated action, which allow me to attribute not only patient-level outcomes and decisions but also the dozens of individual decisions and actions for each patient to specific physicians. Timestamps for each action are unmasked, which allow me to not only correctly order patients and actions during each resident’s history of work, but also to examine how time duration to important actions evolves with experience. This combination of granularity in actions, physician identifiers, and unmasked timestamps is rare even in health data, much less data from other industries.³

I begin by characterizing the ways in which residents learn by doing over the course of the four-year residency program. I find that residents become much more productive in terms of total patients seen per shift. By managing additional patients simultaneously, they go from seeing three patients per eight-hour shift when they enter the program to seeing almost eight patients per eight-hour shift prior to graduation. Residents also improve significantly for each individual patient. For instance, they become 20% faster at signing the first batch of medical orders. These speed gains only accrue to complex patients, which

¹In 2021, the United States spent 17.8% of GDP on healthcare, compared to the OECD average of 9.6%, but life expectancy was 77.0 years compared to the OECD average of 80.4 (Gunja, et al., 2023).

²Academic Hospital GDP: the author’s calculations using data from the BEA and AAMC. Global hospital rankings: [Newsweek.com](https://www.newsweek.com/global-hospital-rankings).

³Notable exceptions include Levitt, et al. (2013) and Adhvaru, et al. (2023) in the automobile manufacturing industry.

I define as those who are ex-ante predicted to require inpatient admission: patient length of stay decreases by 9.4% over four years. Despite meaningful learning, I find no evidence of statistically or economically significant improvements in the 14-day readmission rate, the key measure of ED outcome quality, or in the number of orders signed, a measure of efficiency.⁴

When examining heterogeneity in resident learning by patient type, I find that most of the improvement is driven by or only present in complex patients. Therefore, I conclude that residents learn how to treat complex patients and become faster as a result of their increased skill. Conversely, residents learn relatively little about treating simple patients. Under the assumption that residents cannot learn about complex patients by treating simple patients, this means that the hospital is able to choose the amount of training it provides by changing the allocation of complex patients to residents. Because the number of examination rooms is fixed and almost always at capacity, changes in length of stay directly affect patient throughput: the number of patients seen per day. Therefore, the hospital trades off resident training and patient throughput when determining the optimal patient assignment.

While the throughput costs of training are paid today, the benefits accrue in the future. Consequently, a model of the hospital's objective function must incorporate dynamics. I develop a discrete-time, infinite-horizon model where the hospital allocates complex patients to residents of different cohorts and attendings working alone to maximize the discounted sum of resident training, subject to a budget constraint written in terms of patient throughput. This builds upon models of non-profit hospital behavior by [Newhouse \(1970\)](#), [Lakdawalla and Philipson \(1998\)](#), and others. My contributions are to add a teaching objective and the necessary dynamics to the hospital's utility function and to estimate the parameters empirically. The estimates allow me to simulate how training behavior might respond to counterfactual changes in the hospital's payoffs to higher productivity in the present.

I find that an objective function where the hospital maximizes training with respect to a lower bound of patient length of stay can rationalize the observed patient assignment shares during the academic year. That is, the hospital allocates complex patients to maximize the skill of graduating residents, subject to the constraint that average patient length of stay is constant in each quarter of the academic year. I apply the model estimates to two counterfactual exercises and consider the impact of decreased training on physician career outcomes and patient utility. Decreased training means that physicians take longer to see each patient, but because shift lengths are fixed, they will see fewer patients. Career outcomes will suffer because EM physician compensation is often based on the number and complexity of the patients they see.⁵ Patients will also suffer because even though they will receive the same care and experience the same outcomes, they will have to wait longer if they are seen by a less-trained physician. I compare the impact to career outcomes and patient utility without further adaptations to alternatives where the hospital takes a mitigating action, such as loosening the care quality constraint, increasing the speed of the attendings working independently, and increasing the speed of resident learning.

In the first counterfactual, I quantify the implications on patients of graduating residents of a reduction in training required to achieve a 2% increase in current patient throughput. A desire to increase the number of patients seen could arise from payment reform intended to decrease patient length of stay. This would result in less revenue per patient than the status-quo,

⁴An "order" is any diagnostic or therapeutic procedure that is prescribed for the patient. Diagnostic orders are primarily for gathering information and include procedures such as blood tests, echocardiograms (ECGs), and imaging (CT scans, X-Rays, etc.). Therapeutic orders are primarily for treating and stabilizing the patient, and include pain medication, antibiotics, and surgical procedures.

⁵Compensation tied to Relative Value Units (RVUs) is increasingly popular for EM physicians ([ACEP, 2021](#)). RVUs are a standardized measure of the value of a service or procedure used by the Center for Medicare & Medicaid Services (CMS) and is positively correlated with patient complexity. Therefore, the more patients per shift or complex patients per shift seen, the more RVUs generated and the higher the compensation.

which means that the hospital would need to see additional patients to fulfill its budget constraint.⁶ Assuming that residents go on to a 30-year career, this would result in costs to future career outcomes and patients 17 times larger in present-value than the hospital's gains. However, investing in attending speed—most simply by staffing additional attending physicians so that teaching responsibilities are distributed among additional physicians—such that their aggregate speed increases 5% would greatly reduce the impact on training. With this remedy, training reductions are lowered and future costs decrease by 81%.

In the second counterfactual, I consider the impact and potential responses to a disruption in training. This mirrors the training disruption that affected residents during the Covid-19 pandemic, when both the number and composition of patients seeking emergency care changed.⁷ In the counterfactual, I assume that the disruption causes affected residents enter their final year of training with half of the usual steady-state skill. I find that although the hospital returns to the steady-state the following period such that there is no impact to the entering cohort, the skill of the affected cohort is reduced by 2%. A one-period increase in attending speed by 2.5% allows the hospital to train sufficiently for residents and future patients to recover 88% of the costs relative to the no disruption baseline. As illustrated in both counterfactuals, small decreases in current training can have large consequences for residents' career outcomes and hence for future patients. However, straightforward and feasible actions can greatly mediate the reduction in training.

This work contributes to several strands of literature. First, I add teaching considerations to the literature on private, nonprofit hospitals and the literature on payment reform. Research modeling the objectives of private, nonprofit hospitals began with the seminal theoretical contributions of [Arrow \(1963\)](#), [Newhouse \(1970\)](#), [Feldstein \(1971\)](#), and [Pauly and Redisch \(1973\)](#). Since then, the bulk of the theoretical literature has consisted of models where the hospital maximizes the weighted sum of profits and quality or quantity of care (cf. [Lakdawalla and Philipson \(1998\)](#); see [Gaynor and Town \(2012\)](#) for an overview). These models have the appealing feature that nonprofit hospitals have similar objective functions to their for-profit counterparts, but with a lower marginal cost for quality or quantity ([Gaynor, 2006](#)), and this is consistent with subsequent empirical findings. For instance, nonprofit and for-profit hospitals are very similar in their responses to financial incentives ([Duggan, 2000](#)), CEO compensation incentives ([Brickley and Van Horn, 2015](#)), pricing behavior with regard to competition ([Gaynor and Vogt, 2003](#)), and provision of charitable care ([Capps, et al., 2017](#)). Similarly, the literature on payment reform also typically does not consider teaching. This is true both in the theory (cf. [McClellan, 2011](#)) as well as the empirical evidence (cf. [Clemens and Gottlieb, 2014](#)).

After I add a teaching objective to the nonprofit hospital's utility function, I estimate the parameters of the theoretical model and use it to simulate counterfactuals related to payment reform. Thus, I quantify the extent to which the hospital reduces teaching in response to counterfactual payment policies that reduce its revenue. My findings apply to almost all future physicians and academic medical centers: across specialties, between 83.1% and 96.6% of residency programs were affiliated with nonprofit institutions in 2021 ([Lassner, et al., 2022a](#), [Lassner, et al., 2022b](#)). Additionally, [Kocher and Wachter \(2023\)](#) find that academic hospitals tend to do poorly on measures used in value-based payments, which means that many would stand to lose revenue if commonly-discussed payment reforms to decrease costs and increase quality were implemented. Hence, this paper addresses a shortcoming in the nonprofit hospital literature first raised by [Reder \(1965\)](#): "Still further complications exist:

⁶Alternatively, if the reduction in revenue per patient caused the hospital to decrease the number of patients seen, residents would see fewer patients over the course of the program and the impact on training is identical.

⁷Patients delayed both routine and emergency care ([Czeisler, et al., 2020](#)).

hospitals produce not only current treatment but also train personnel for the production of future treatment. The costs and benefits of this training to the hospitals providing it are not well known.” I go further by not only considering the costs and benefits to the teaching hospital itself, but also the costs and benefits to the graduating resident’s career and their future patients.

Through studying how organizations manage within-firm learning via task allocation, I combine the literatures on task allocation and on learning by doing. Although it has been shown that task allocation to heterogeneous workers may have large implications for productivity (Adhvaryu, et al., 2023) and that productivity differences within sector can be large and persistent (Syverson, 2011), the task allocation literature typically does not incorporate worker learning. Instead, workers have fixed and exogenous skill and the firm allocates heterogeneous tasks to determine each worker’s comparative advantage, as in Adhvaryu, et al. (2023), Bergeron, et al. (2022), Cheng (2019), Cowgill, et al. (2023), Dahlstrand (2023), and Kasy and Teytelboym (2022). Similarly, the literature on learning by doing typically does not consider task assignment. For instance, in medicine, there is work on resident learning in internal medicine (Chan, 2021), learning about match values of patients to procedures (Gong, 2018) and to medications (Currie and MacLeod, 2020), and learning to work in teams (Chen, 2021 and Reagans, et al., 2005). However, although patients may differ in these settings, their arrival to the physician is exogenous.

I explicitly consider both margins, as the hospital chooses the patients to assign to each resident and task-specific resident skill evolves with the history of patients assigned due to learning by doing. The dynamic framework is similar to that in Minni (2023), but the granularity of my data allow me to be more specific. I characterize how residents belonging to the same department and job title differ in skill and show how the organization’s assignment of heterogeneous patients to heterogeneous residents optimally differs. In my setting where the learning margin dominates the comparative advantage margin, considering the impact of learning on future productivity is crucial. If resident skill were fixed, then the empirical patient allocation patterns would suggest that the teaching hospital is making grave errors in task assignment. In that case, reallocating patients would lead to large, permanent improvements in productivity. However, this is not possible in practice because such an allocation strategy would reduce teaching, resulting in much lower future average resident skill and productivity.

Finally, my findings add to the literature studying cohort turnover, the planned simultaneous exit of a large number of experienced workers and similarly sized entry of new workers. In American teaching hospitals, cohort turnover occurs every July 1, the date when the most experienced residents graduate and are replaced by a new class of fresh medical school graduates. The fear that patient outcomes will suffer due to the decrease in average experience is known in the United States⁸ as the “July Effect.” I corroborate Hughes (2017), Wei, et al. (2019), and the recent literature that finds an *absence* of a significant drop in quality in July. I extend the literature by showing that not only patient outcomes but also many process measures related to productivity and efficiency are similarly unchanged on average across July 1. I also add to the findings of Song, et al. (2016) and Hausknecht and Trevor (2011) and describe another method the teaching hospital uses in order to avoid a disruption in output. Notably, this method, strategic patient allocation, is a choice rather than an investment in infrastructure and supervision.

The rest of the paper proceeds as follows: Section 2 gives more details on residency in general and emergency medicine residency at the teaching hospital from which I obtain data. Section 3 describes the electronic health record and audit log data. Section 4 presents empirical results that documents the ways in which residents learn by doing. Section 5 introduces

⁸In the United Kingdom, this occurs on the first Wednesday in August and is known as both “Black Wednesday” and the “killing season.”

the dynamic framework. Section 6 discusses estimation, and Section 7 provides results. Section 8 motivates and presents counterfactual exercises that explore separately the hospital’s response to a change in the shadow cost of training and to a one-time disruption to resident training, as well as the effectiveness of mitigating actions it could take. Section 9 concludes.

2 Medical Residency Background

In the United States, graduates of medical school are required to complete a residency program in order to practice medicine independently. Residency is in a specific predetermined specialty (for example, Radiology, Dermatology, Obstetrics and Gynecology, and Emergency Medicine); medical school students apply to and are accepted to a single program-specialty.⁹ Matching residents to program-specialties is done centrally and is a well-known application of the Gale-Shapley algorithm. Programs last between three and seven years, depending on the specialty, and some medical students choose complete a fellowship after their residency ends to further specialize and become for example Cardiologists and Oncologists, or to sub-specialize, for instance in Pediatric Critical Care or Cardiothoracic Surgery. Notably, residency training is not only for learning facts but also for developing “habits, behaviors, attitudes, and values that will last a professional lifetime” (Ludmerer, 2015).

The focus of this study is Emergency Medicine Residency at the University of California, San Francisco (UCSF). At UCSF, EM Residency is a four-year program.¹⁰ The setup of the program and the day-to-day routine is typical of EM Residency Programs. The majority of patients are seen by a single resident, the trainee, who is supervised by an attending physician, a faculty member. The remaining patients are seen by attendings working independently. Work is shift-based, meaning that once physicians are off-shift, they are no longer responsible for the patients they cared for during their shift. At UCSF, both residents and attendings work eight-hour shifts. The schedule is determined prior to the beginning of the academic year and determined exogenously. All residents and attendings will work day, night, and weekend shifts; there is no sense that seniority or other factors permit attendings or residents to avoid working less-desirable shifts. Teams—groupings of attendings and residents—are ad-hoc, meaning that they change from shift to shift, and throughout the course of the year, all residents will work with all other residents and all attendings.

To be clear on terminology, I will use “resident” to refer to the emergency medicine physician trainees who are the focus of this study. At any point of time, EM residents at UCSF must belong to one of four different cohorts—this is defined as the year that they enter the program. Consistent with nationwide averages, I do not observe any attrition or leaves of absence.¹¹ “Attendings” or attending physicians are faculty members of the medical school, typically on the tenure track, who both supervise residents and see patients independently. I will use the terms “physician” and “provider” interchangeably to refer to residents, attendings, and nurse practitioners, who are also seeing patients independently but do not have supervisory responsibilities. I will use the term “care team” to refer to all providers, nurses, and other medical and non-medical staff (e.g. social workers) who interact with the patient. An “order” is any diagnostic or therapeutic procedure that the care team prescribes for the patient. Diagnostic orders are primarily for gathering information and include procedures such as blood tests, echocardiograms

⁹Students apply to multiple programs but typically a single specialty: among students who successfully match, the average number of specialties ranked is 1.2 (AMA, 2019)

¹⁰Most EM Residency programs are three years; four-year programs tend to be located at prestigious and highly-ranked programs such as Johns Hopkins, Massachusetts General Hospital (Harvard Medical School), UCLA, and the University of Washington.

¹¹The median EM Residency attrition rate from 2010-2020 is 0.83% (Wang, et al., 2022)

(ECGs), and imaging (CT scans, X-Rays, etc.). Therapeutic orders are primarily for treating and stabilizing the patient and include pain medication, antibiotics, and surgical procedures.

The typical workflow in the ED is depicted in Figure 1. When a patient arrives, a triage nurse will interview them, take their vital signs, and estimate their acuity using a five-point scale called the Emergency Severity Index (ESI). This is done independently from the physicians who will subsequently care for the patient. The patient will then return to the waiting room. A resident who is available will select a patient from the waiting room with guidance from the supervising attending. The resident will independently examine the patient and present their findings and plan of care to the attending. The attending will examine the patient, also typically independently, and confer with the resident. An agreement on the plan of care is reached and a set of diagnostic and therapeutic orders are signed. Order results are reviewed, typically independently, and if necessary, predetermined follow-up orders are sent and additional examinations and revisions to the plan are agreed upon and executed. The resident and attending will then make a disposition decision: admit the patient to the hospital for additional care or discharge them home. In the event the patient was discharged home, there is a chance they will return to the ED within 14 days. This is called an ED Readmission and is suggestive that the physicians overlooked something important.

Care quality in the ED is multi-dimensional. Broadly, once the patient is stabilized, the goal is to quickly and efficiently assess the patient's condition. The disposition decision is the crucial element of patient condition: are they healthy enough to send home, or do they need to remain in the hospital for further care? Therefore, the primary measure of ED quality is the accuracy of the disposition decision. A common measure used to evaluate the accuracy of this decision is the 14-day readmission rate (cf. [Chan, 2018](#)): among patients who were deemed healthy enough to discharge, at what rate did they return to the ED within 14 days? A second category of quality relates to speed. Doing things faster with no loss in accuracy is also important. Speed is utility-enhancing for patients because they spend less time suffering from their complaint and being in the hospital. It is also efficient for the hospital because it frees up the examination room for the next patient, thereby increasing patient throughput. Important measures of speed I will consider include process measures such as time to first order and patient length of stay in the ED. Finally, I will consider resource utilization as a measure of efficiency. Resources are both costly orders ("materials") as well as labor in the form of supervision and consults by specialists, and being able to achieve the same patient outcomes with fewer orders or consults represents higher efficiency.

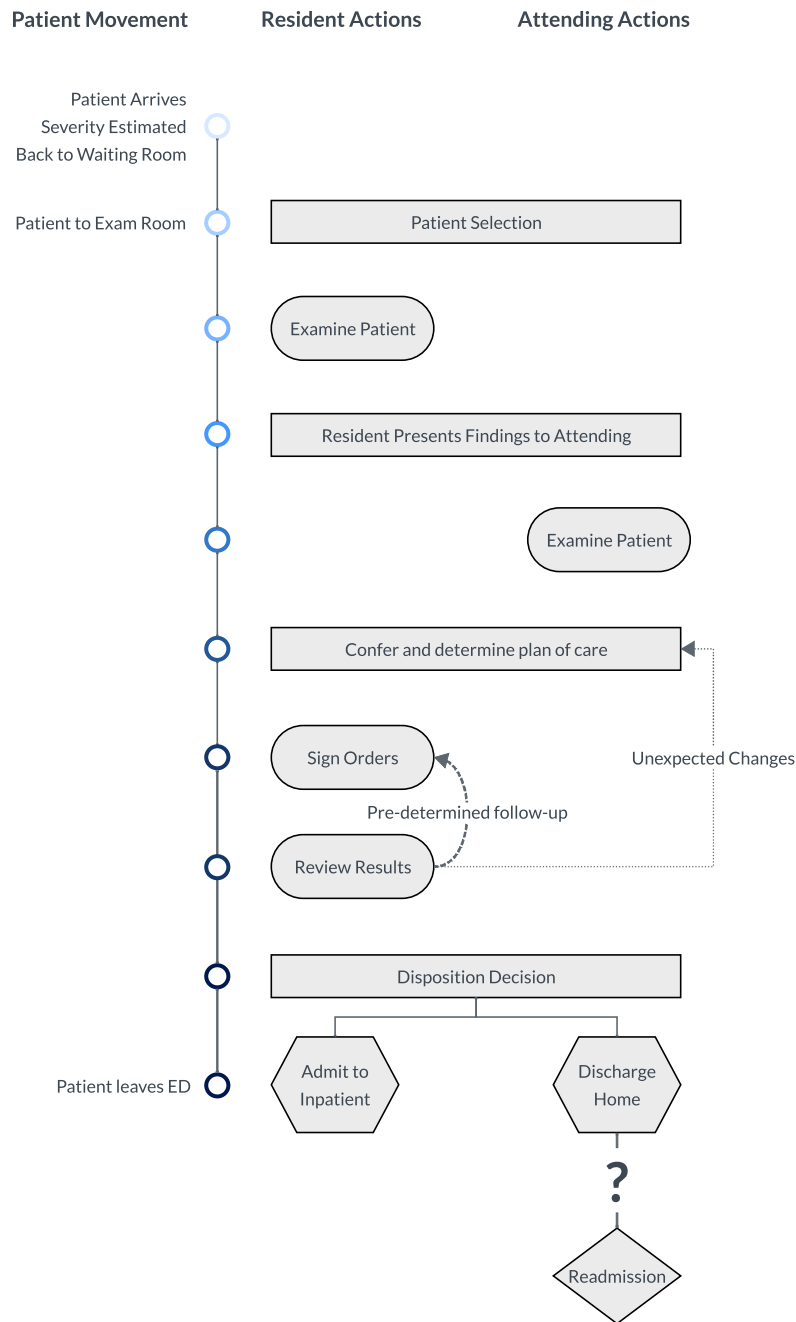
3 Data and Sample Construction

3.1 Data

This research leverages highly granular electronic health record and audit log data from UCSF. This data cover the universe of ED arrivals for patients ages 18-90 over a 24 month period from 2017 to 2019. In total, there are 85,990 patient encounters.¹² In essence, these data record every interaction the physician has with a computer, which is used for gathering information (reading past clinical notes and order results), producing a diagnosis and treating and stabilizing the patient (sending, revising, and canceling orders), and recording information (writing the clinical note summarizing the patient's condition and what was

¹²The unit of observation is an encounter rather than a patient because the same patient may visit the ED multiple times during the sample period. When this occurs, they are assigned a new encounter_id for each visit but retain the same patient_id.

Figure 1: Workflow in the Emergency Department



Notes: This flowchart illustrates of the typical workflow in the emergency department. Actions and outcomes are divided into three categories. Left of the timeline are patient movement. To the right of the timeline, actions are classified into those done by residents (left side), attendings (right side), or together (spanning the width of the section). The dotted arrows originating from Review Results indicate that these actions are done only when deemed necessary. Finally, after the disposition decision is made, if and only if the patient is discharged home, they may feel it is necessary to return to the ED within 14 days, which is called an ED Readmission.

done in the ED).

The data contain an entry for every instance that any provider interacts with an order. For each of these order actions, I observe patient and encounter identifiers, actual, unmasked timestamps for when each order was signed, completed (or canceled), and results became available (when applicable). I also observe identifiers for both the physician who signed the order (typically a resident) and the physician who authorized it (must be an attending). These are both unusual features. For physician identifiers, most medical datasets only contain the data of the attending physician, as they are the entity who is financially and legally responsible. As for timestamps, most datasets either only have the date of the encounter or have detailed but de-identified data that preserves the time between actions but scrambles the start dates. Both of these elements are crucial for this analysis as otherwise I would not be able to attribute residents to patients in the correct order and would not be able to examine the speed and duration of important actions.

I also observe the consumption and production of information. Specifically, I observe the time, duration, and provider for each order result view (e.g. reading the radiologist’s report for an MRI; viewing the numerical results of a blood test) and the same information for clinical notes that contain other physicians’ impressions of the patient.¹³ I also observe the time and duration of edits to the patient’s clinical note from the current encounter, as well as the character length of the note. I do not observe any note content.

For patients, in addition to typical covariates such as age, gender, race, and diagnosis codes, I also observe a set of characteristics that I call “ex-ante” characteristics. These are characteristics that are exogenous to the care team who will subsequently care for the patient. Examples include the patient’s chief complaint that induced the ED visit, the acuity level assigned to them by the triage nurse, and indicators for abnormal vital signs upon entry to the ED (ex. abnormal pulse). Contrast these with measures such as the final diagnosis, ED disposition, or patient’s length of stay in the hospital, which may be endogenous to the composition of the care team and most crucially, resident experience. In the analysis, I use the set of ex-ante and immutable patient characteristics (things that cannot be affected by care, such as the patient’s age, gender, and race) to divide patients into those who are ex-ante predicted to require inpatient care and those who are predicted to be safe to discharge home. For simplicity, I refer to these patients as “complex” and “simple.” The predictions have high predictive power and fit the observed patterns of inpatient admission well. See Appendix A for more details on the construction and fit of the prediction.

For providers, I observe a set of basic covariates. I observe the role of all providers: resident, attending, nurse practitioner, etc. I observe the specialty for attendings and NPs only and infer the specialty of residents based on the specialties of the attendings who most frequently authorize their orders, which I take to be their most frequent supervisors. Residents use different templates in the system if they are in their first two years compared to years thereafter. I also observe their start and end dates if they occur within the sample period; with these two pieces of information I infer the cohort and specialty of each resident.

In a separate dataset, I have the administrative schedules for both providers and residents for calendar year 2018. I use this data to validate my sample construction and to provide some sample statistics on the number of shifts worked by EM and non-EM residents. I am unable to match the names in the schedule with the provider identity numbers in the EHR data.

¹³Both order result and note views can be from “historical” visits outside the sample period.

3.2 Sample Construction

I focus on EM Residents and attendings. These providers make up a minority of physicians who ever work in the ED but work a majority of the shifts and see a majority of the patients, especially among complex patients. The reason I restrict the analysis to EM Residents is because the ED may have other learning objectives for the residents from other specialties who make short rotations through the ED as part of their training. For instance, Internal Medicine residents complete a three-week rotation in the ED. Not only is this time period too short for the ED to reap the benefits from training them, but the residents also may have a different set of baseline skills compared to EM residents.¹⁴ Because the incentives and constraints for training other residents may differ from those for training ED residents, I choose to exclude them from my analysis.

During the sample period, there were 15 residents in each cohort of EM residents. I am unable to identify them based on names or identifiers so I classify them using the total number and fraction of orders that were signed in the ED context (as opposed to inpatient or outpatient). For residents belonging to each cohort, I define as EM residents those who sign over 80% of their orders in the ED context and are also one of the top 30 residents in terms of number of orders signed. The discontinuities in at least one of these measures are generally quite sharp. I show two examples in Appendix Figure A1.

Table 1 shows the breakdown of the residents who work in the ED in terms of the number of individuals, shifts worked, and patients seen. My algorithm slightly under-identifies the true number of EM residents, identifying 83 residents instead of the expected 90 in the six cohorts in my data. In calendar year 2018, where I am able to validate my resident selection by comparing shift summary statistics with administrative shift data, I also under-match slightly, identifying 67 of 75 residents. Perhaps as a result, I find that they work 60% of the shifts rather than the 69% as suggested by the 2018 administrative data. As expected, the majority of patients are seen by EM residents: almost 70% in the two years of EHR data.

Table 1: Sample Selection: Residents

	Residents	Shifts (EHR data)	Shifts (admin)	Patients (EHR data)
All Residents	610	9,340		54,217
EM Residents	83	5,802		37,463
EM Residents (%)	14%	62%		69%
2018 Residents	389	4,512	4,012	26,775
2018 EM Residents	67	2,725	2,765	18,044
2018 EM Residents (%)	17%	60%	69%	67%

Notes: This table shows basic sample statistics on the set of residents who work in the emergency department. I focus on EM Residents, who make up 14% of all residents who work in the ED during the two-year sample based on my classification. They work 62% of the shifts worked by residents and see 69% of all patients seen by residents. I compare the share of shifts with the share of shifts in the administrative data that cover one calendar year and find that EM residents worked 69% of all shifts worked by residents, which compares favorably to the 60% I classify in the data.

Table 2 Panel (a) shows sample selection for patient encounters. Over the two years of data, there are a total of 85,990 patient encounters. I first exclude encounters where the patient left early or against medical advice, or passed away in the ED, so that I can be sure that I capture the full extent of the physician's process rather than some interrupted version. These total roughly 7.7% percent of all encounters. Then, I exclude the patients who the triage nurse categorized upon arrival as being the most urgent (Emergency Severity Index category 1) or the least urgent (ESI 5), who together represent about 2.3% of all

¹⁴For instance, they likely completed a different set of clinical rotations while in medical school and focused their research on different topics.

arrivals. This is because the ESI 1 patients represent “codes” where the entire ED team on staff contributes to the patient’s care, so it is an exception to the usual resident-attending pairing and may not represent cases where the resident is directing care. ESI 5 patients are the other extreme: they are cases where the patient does not need urgent medical care, such as patients with a chief complaint of “Medication Refill” and also do not represent resident learning about urgent patients. Next, among the remaining encounters, I am unable to identify the physician in charge (“Primary MD”) for 6.6% of the patients. The next step results in our first sample of interest: EM Residents and Attendings see a total of 65.3% of all patients. Finally, EM Residents see 40.4% of all patients, or about 62% of the patients assigned to EM Residents or Attendings. Panel (b) reveals that the 62% of patients are not evenly distributed among patient types: residents see a greater share of complex patients (about 77%) relative to simple patients (about 58%) by two measures of ex-ante patient complexity.

Table 2: Sample Selection: Encounters

(a) Encounter Selection					
	Number or Percent of Patients				
All ED Arrivals	85,990				
Did not Leave Early	92.4%				
Did not Pass Away	92.3%				
Triage Nurse ESI 2, 3, or 4	90.0%				
Primary MD Identified	83.6%				
Seen by Attending or EM Resident	65.3%				
Seen by EM Resident	40.4%				

(b) Resident Encounters by Complexity					
	All Patients	by Predicted Admission		by Triage Nurse ESI	
		Complex	Simple	Complex	Simple
All with Primary MD identified	71,892	17,916	53,976	14,935	56,957
Seen by Attending or EM Resident	78.1%	73.1%	79.7%	74.1%	79.1%
Seen by EM Resident	48.3%	56.0%	45.8%	58.0%	45.8%
Percent EM / Attending or EM	61.8%	76.6%	57.5%	78.3%	57.9%

Notes: This table shows the sample selection of patient encounters. Panel (a) shows the steps of sample selection. Patients who Leave Early are those who have leave without being seen, against medical advice, or pass away in the ED. Triage Nurse ESI 2, 3, or 4 are the three middle categories of the triage nurse’s assigned Emergency Severity Index. The two excluded categories are extremely severe cases (“codes”) where the entire ED team contributes to the patient’s care, or cases where the patient does not need urgent care, such as patients with a chief complaint of “Medication Refill.” Primary MD Identified means I was able to identify who the primary provider for the patient was. Panel (b) shows the breakdown of the last three steps of Panel (a) by two ex-ante measures of “complex” and “simple” patients. The first is the primary measure I use in the paper: by a prediction of inpatient admission using only ex-ante and immutable patient characteristics. The second is by the triage nurse’s evaluation: ESI category 2 vs. 3 and 4. The bottom row of Panel (b) shows the percent of patients of each patient type seen by EM residents relative to the patients seen by EM Residents and Attendings and reveals that residents see a greater share of complex patients than of simple patients.

These tables show that EM residents are doing a plurality of work in the ED and a majority of the work for complex patients. It is not the case that they are only being used as low-cost labor by seeing only the low-risk patients they know how to manage and leaving the complex ones for attendings to care for. In the following section I show how patient outcomes, process measures, and the allocation of complex and simple patients vary with resident experience.

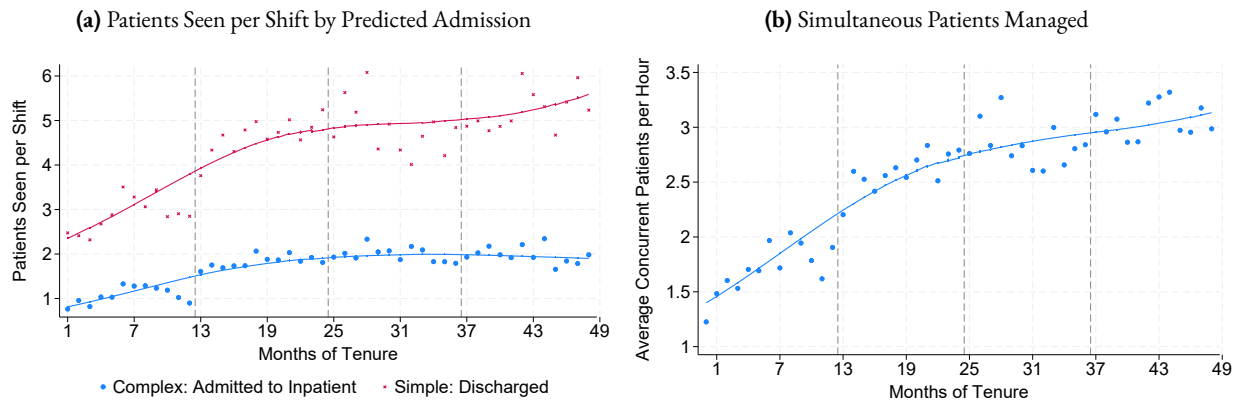
4 Documenting Resident Learning

I begin by documenting the ways that residents improve during the four year program. I first show measures related to overall productivity. Then, I present results on within-patient improvement both graphically via binned scatterplots and in regression form with additional specifications and patient heterogeneity and perform robustness checks. Third, I present evidence that when making patient allocation choices, the hospital is aware of the trade-offs between care quality and learning. Finally, I relate the findings to the literature on cohort turnover and summarize the important takeaways.

4.1 Overall Productivity: Patients Seen per Shift

The number of patients each resident sees per shift is a basic measure of productivity. Since shifts are always eight hours long regardless of experience, this measure is analogous to each resident's units produced per hour. Figure 2, Panel (a) plots the relationship between the average number of patients seen per shift seen by residents and resident experience in months. Patients are grouped by their ex-ante predicted complexity: whether or not they are predicted to be admitted to inpatient care. Panel (b) depicts the growth in the average number of patients managed per hour of each shift for residents of each month in the program. It shows that residents only average about 1.5 patients per hour when they begin residency and improve such that they are managing about 3 patients per hour by the fourth year of residency. Comparing the two panels reveals that the growth in patients seen per shift is mainly in the "simple" category of patients and that it appears to be driven by managing additional patients in parallel rather than large increases in speed per patient, a fact corroborated in Figure 3. Overall, residents make significant gains in productivity, going from seeing about three patients per shift in the first month of the program to seeing almost eight patients per shift in the month prior to graduation. However, growth in this productivity measure is mainly in simple patients. Differences between complex and simple patients will be a recurring theme in this section.

Figure 2: Patient Load Breakdown



Notes: These figures show the evolution of patient load over the 48 months of the EM residency program. Panel (a) shows the breakdown of total number of patients managed during the shift. Patients are grouped by their ex-ante predicted complexity: whether or not they are predicted to be admitted to inpatient care. Panel (b) depicts the average number of patients managed per hour of each shift for residents of each month in the program. Comparing the two panels reveals that the growth in patients seen per shift is mainly in the "simple" category of patients and that it is driven by managing additional patients in parallel rather than large increases in speed per patient, a fact corroborated in Figure 3.

4.2 Within-Patient Quality, Efficiency, and Productivity

While they indicate significant improvement, the previous set of results do not capture within-patient differences with experience. Therefore, the results may either understate or overstate the degree of improvements in productivity. For example, if the quality of care also increases with experience even as residents are seeing more patients per shift, then the results understate productivity improvements. On the other hand, if quality suffers with the additional patient load then the results overstate productivity improvements. This subsection investigates the evolution of a variety of patient-level measures of quality and efficiency with resident experience and finds that learning how to treat patients mainly occurs in complex patients.

I begin with a graphical depiction of resident improvement via binned scatterplots of various patient outcomes and process measures in Figure 3. For each outcome of interest, I regress both the outcome and resident experience on selected patient covariates P_i and show a binned scatterplot of the residuals. I add the overall outcome mean back to the outcome residuals so that the values are more easily interpretable. The slope and standard error of the regression line displayed correspond via Frisch-Waugh-Lovell to the coefficient on experience β in the regression given by

$$Y_i = \beta \text{Experience}_{j(i)} + P_i' \gamma + \varepsilon_i \quad (1)$$

In this regression, i indexes encounters, and $\text{Experience}_{j(i)}$ is the experience of resident j who is in charge of patient i in years. In the binned scatterplots, I select the ex-ante and immutable patient characteristics P_i by hand. The covariates include fixed effects for 10-year bins of patient age, the Charlson comorbidity index, Medicaid status, nonwhite, an interaction of broad chief complaint category and triage nurse assigned emergency severity index, an interaction of indicators for if the encounter began on a weekday and during business hours, and continuous ex-ante predictions of patient complexity and its square from [Chu, et al. \(2023\)](#). The residency program lasts four years, but because my data span two years, I observe each resident for a maximum of two years. Hence, the data is an unbalanced synthetic panel.

The various panels of Figure 3 break down resident learning into various components. I first examine improvements in two key measures of care quality and efficiency. I observe in Panel (a) that there does not appear to be a statistically or economically significant decrease in 14-day ED Readmissions, suggesting that conditional on patient observables, the accuracy of the disposition decision made by inexperienced and experienced residents is similar. Similarly, in Panel (b), I find that there is also no relationship between experience and the number of costly diagnostic and therapeutic resources signed. Therefore, I conclude that neither patient outcomes nor efficiency in costly resource utilization is a cost of training.

But does that mean that residents do not learn? Panels (c) and (d) refute this. Panel (c) plots the fraction of orders signed by the resident in charge of the patient, rather than the supervising attending, other attendings such as consulting physicians from other specialties, nurses, or other residents. This measure of resident independence increases linearly with experience, and the magnitude over four years is approximately 10% of the mean of 59.5%. This implies that with experience, residents gain independence and are less apt to leave out important orders. Panel (d) plots a measure of speed: how long does it take providers to sign the first order after the patient enters the examination room? Over four years, this decreases approximately 15% of the mean of about 34 minutes. This means that residents become faster at discerning the patient's underlying condition through history-taking and physical examination and determining which set of orders are appropriate for treating and refining the

working diagnosis. Becoming faster and more thorough are important clinical skills that affect care quality after the resident graduates and begins practicing independently.

I find that the increases in independence and speed only flow through to the total length of stay for complex patients. Panels (e) and (f) show the evolution of the natural logarithm of the number of hours the patient spends in the ED with resident experience. The patient sample is split by whether I predict that they were admitted to the hospital (“complex”) or were discharged home (“simple”). While there is no change for simple patients, there is a significant and meaningful improvement for complex patients. Under the assumption of linear learning, the four-year improvement of 9.2 log points is almost 25% of the standard deviation of $\log(\text{length of stay})$ conditional on patient covariates and is relative to a mean length of stay of about 6.6 hours.¹⁵ Therefore, experience greatly decreases time spent in the ED for complex patients but has limited effects for simple patients. The difference in learning for simple and complex patients motivates examining heterogeneity for the other process measures and the design of the structural model.

The previous findings are supported by the regression results in Table 3. The regression specification differs slightly from the binned scatterplots in Figure 3. First, the regressor of interest is the natural logarithm of days in the program. I tend to prefer this over the linear specification because the literature generally finds that learning exhibits diminishing returns (cf. Benkard, 2000 and Levitt, et al., 2013). Second, I include resident fixed effects in all regressions to focus on within-resident learning. With these fixed effects, estimates are not subject to bias from individuals in earlier cohorts (e.g. starting residency in 2015) being inherently “better” or “worse” than individuals in later cohorts (e.g. starting residency in 2018). Third, when I include patient covariates, I select them using the post-double-selection LASSO method of Belloni, et al. (2014). Inspection of the covariates chosen by the algorithm reveal that they are more sparse than the set that I manually selected, and tend to include indicators for the number of abnormal vital signs upon entry, which I did not include in the binned scatterplots.

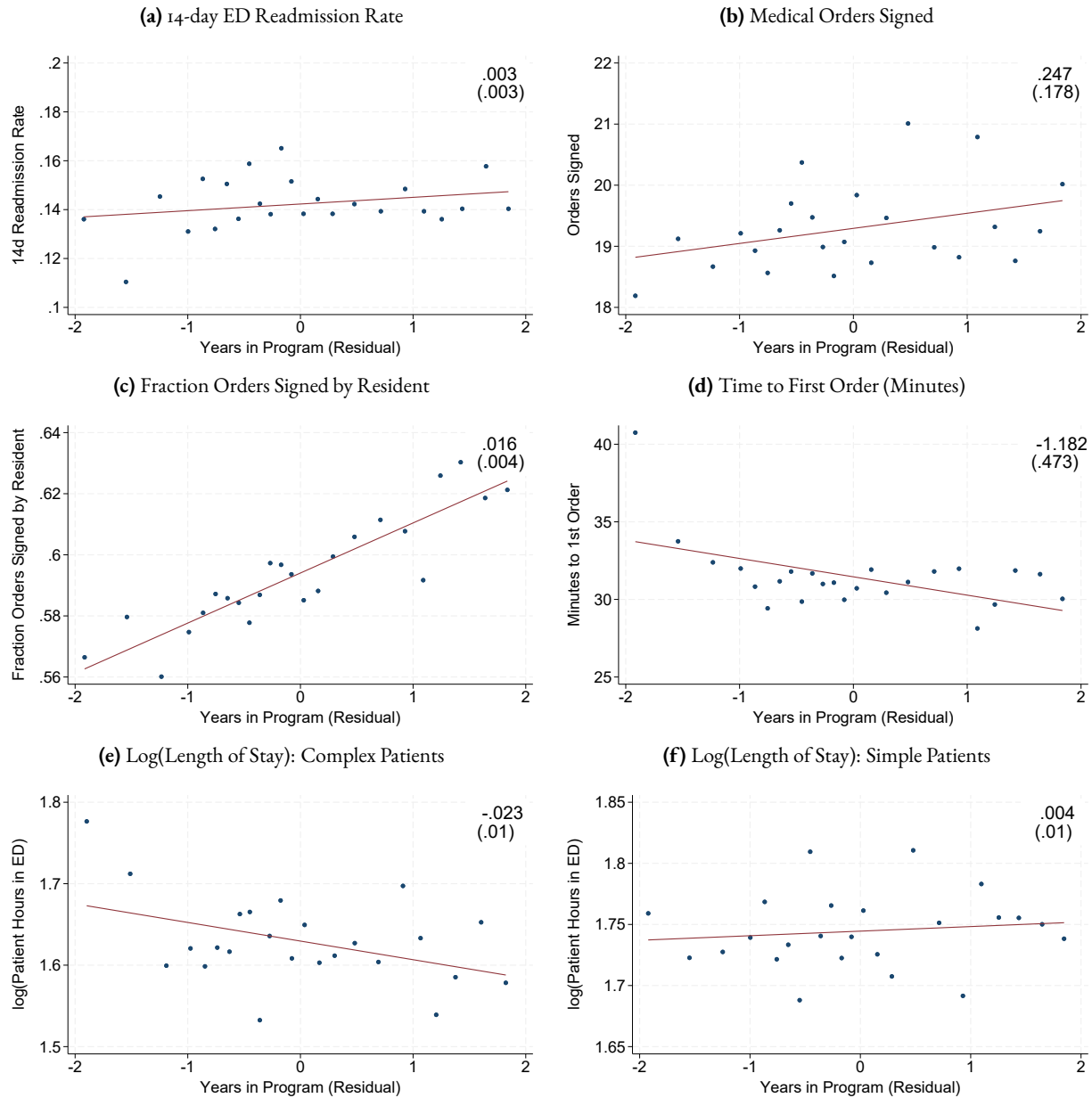
Table 3 Panel (a), shows that the results in Figure 3 are generally robust to the more sophisticated selection of patient covariates and the inclusion of resident fixed effects. Notably, as in the figures, the $\log(\text{Length of Stay})$ relationship is only statistically and economically significant for complex patients. In Panel (b), I examine heterogeneity by patient complexity for the other process measures.¹⁶ For the natural logarithm of medical orders signed, I find that the small positive effect in Panel (a) masked offsetting effects for complex patients and simple patients. One potential explanation, supported by the results on diagnostic orders only shown in Appendix Table A2, is that with experience, residents obtain less diffuse priors for complex patients, but they substitute effort with costly resources for simple patients in order to save time.¹⁷ Next, we observe that the increase in fraction of orders signed by the resident is also primarily driven by improvements for complex patients, but that decreases in the minutes to the first order are proportionally similar for complex patients compared to for simple patients. Overall, these results suggest that the bulk of the learning that occurs during the residency relate to learning how to treat complex patients and that there is relatively little learning for simple patients.

¹⁵The reason the mean for complex patients is less than the mean for simple patients is because for admitted patients, I end the the length of stay at the moment the patient is confirmed for inpatient upgrade. At that moment, the patient may not leave the ED, but the ED care team’s involvement has concluded and the patient is now the responsibility of the admitting department, whether it be cardiology, surgery, hospital medicine, or something else. Unfortunately, there is no consistent analogous marker for discharged patients (discharge orders are inconsistently signed and disappear entirely midway through the sample period). Both relationships are similar if I instead use total time in the ED for both sets of patients.

¹⁶By definition, ED Readmissions are only possible for discharged patients, so a breakdown by complexity is not appropriate.

¹⁷This finding may facilitate the increase in managing additional patients simultaneously with experience shown in Figure 2.

Figure 3: Learning over Time: Binned Scatterplots



Notes: These figures are binned scatterplots with 24 bins of patient outcomes and process measures of interest on the residual of years in the program by the resident in charge of the patient. The sample is all sample patients seen by EM residents. Residuals are after removing selected patient covariates. The coefficient and standard error, clustered by physician, are displayed. The 14-day ED readmission rate is the rate at which patients who are discharged home from the ED have a repeat visit within 14 days. Medical Orders signed is the sum of diagnostic and therapeutic orders signed in the ED. Fraction Orders Signed by Resident is the fraction of medical orders that are signed by the resident, rather than the attending, nurses, or other residents assisting. Time to First Order is the time between the moment the patient is moved from the waiting room to an exam room and the time that the first medical order is signed. Log(Length of Stay) is the natural logarithm of the hours the patient spent in the ED under the care of EM providers. It is split into “complex” and “simple” patients based on an ex-ante prediction of inpatient admission. See text for more details.

Table 3: Learning over Time: Regressions

(a) Main Results												
	Readmissions		log(Medical Orders)		Frac. Signed by Resident		log(Mins to 1st Order)		log(Length of Stay, Hours)			
log(Days in Program)	-0.001 (0.004)	0.002 (0.004)	0.039** (0.016)	0.024** (0.011)	0.010** (0.005)	0.013*** (0.004)	-0.117*** (0.028)	-0.101*** (0.016)	-0.055*** (0.015)	-0.048*** (0.015)	0.002 (0.011)	0.004 (0.009)
DepVar Mean	0.140		19.307		0.596		39.485		6.669		7.653	
ED Disposition	Discharged		All		All		All		Complex		Simple	
Controls	X		X		X		X		X		X	
Obs	22,863	22,824	31,775	31,712	31,775	31,712	27,384	27,330	8,930	8,906	22,863	22,824

(b) Resident Progress by Patient Heterogeneity												
	log(Medical Orders)				Frac. Orders Signed by Resident				log(Minutes to 1st Order)			
log(Days in Program)	-0.040*** (0.014)	-0.041*** (0.015)	0.047** (0.020)	0.052*** (0.012)	0.025*** (0.008)	0.024*** (0.006)	0.008 (0.005)	0.007* (0.004)	-0.129*** (0.040)	-0.118*** (0.033)	-0.102*** (0.030)	-0.094*** (0.018)
DepVar Mean	29.138				0.488				27.626			
ED Disposition	Complex				Complex				Complex			
Controls	X				X				X			
Obs	8,913	8,889	22,862	22,823	8,913	8,889	22,862	22,823	7,467	7,448	19,917	19,882

Notes: Regressions of selected patient outcome and process measures on various measures of resident experience. The sample consists of all patients seen by EM residents. Every regression includes provider fixed effects. Standard errors are clustered by physician. Patient Controls are chosen from the set of immutable and ex-ante patient covariates using the post-double-selection LASSO method of Belloni, et al. (2014) and differ from the covariates used in the binned scatterplots. The 14-day ED readmission rate is the rate at which patients who are discharged home from the ED have a repeat visit within 14 days. By definition, the measure only exists for discharged patients. log(Medical Orders) is the natural logarithm of the sum of diagnostic and therapeutic orders signed in the ED. Frac. Orders Signed by Resident is the fraction of medical orders that are signed by the resident, rather than the attending, nurses, or other residents assisting. log(Mins to 1st Order) is the time between the moment the patient is moved from the waiting room to an exam room and the time that the first medical order is signed. This value is missing if the first order is signed prior to being roomed; see Appendix Table A1 for the extensive margin. log(Length of Stay) is the natural logarithm of the hours the patient spent in the ED under the care of EM providers. It is split into “complex” and “simple” patients based on an ex-ante prediction of inpatient admission. Dependent variable means are listed, always in levels. Panel (b) shows progress split by ex-ante predicted patient complexity. See text and Appendix A for additional details.

4.2.1 Robustness

The main threat to the within-patient analyses is that they are biased by selection on unobserved patient characteristics. Specifically, if more experienced residents are assigned patients who are unobservably more complex, my estimates will be biased towards zero. Similarly, if they are assigned unobservably less complex patients because they are seeing additional patients simultaneously, then my estimates will be larger in magnitude than the true improvement with experience. I believe this is unlikely in my setting for two reasons. First, providers observe a limited amount of information when allocating patients, and I am able to control for almost all of these covariates. The main thing I do not observe are the patient’s appearance and answers to brief questions, but to the extent that is captured in the triage nurse’s estimation of the patient’s severity, I do control for it. Second, other than for the first six months of the program, observable patient severity averages per patient are stable across the four years of experience as can be seen in Appendix Figure A2, Panel (b). Therefore, in terms of ex-ante patient assignment patterns, I believe I sufficiently control for selection on observables, and that unobservables are of limited importance.

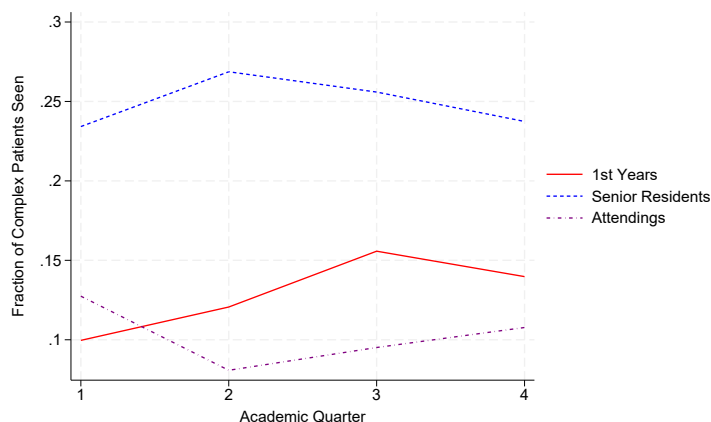
It is not entirely straightforward to confirm this formally. I would like to perform the test proposed in [Oster \(2019\)](#) and [Altonji, et al. \(2011\)](#), but that requires the use of a measure of model fit such as R^2 . Because I use LASSO to select covariates, the reported R^2 is not correct because it does not take into account uncertainty in covariate selection. I proceed regardless of this limitation and use the R^2 as if there was no uncertainty. This means that the test results will be biased towards rejecting the null of no treatment effect due to omitted variables bias because I will be overestimating the improvement in model fit from including observable covariates. With these caveats in mind, results suggest that the size of omitted variables bias in this context are small. For instance, when considering length of stay for complex patients, the improvement in R^2 from going from a specification with only physician fixed effects to the covariates chosen by post-double-selection is from 0.0206 to 0.1057, and the coefficient on experience decreases in magnitude from -0.055 to -0.048. If I assume that the maximum R^2 that can be explained by the model is 0.3 (in other words, outside “randomness” such as ED congestion explains the other 0.7), then we would need the omitted variables to have 3.21 times the amount of selection as the observable factors to obtain the results I have if the true effect was zero. If I assume the maximum R^2 is 0.5, then the omitted variables would need to have 1.66 the amount of proportional selection, whereas if the maximum R^2 is 1, then the omitted variables would need to have 0.75 the amount of proportional selection to obtain the results I have if the true effect is zero. Based on the qualitative arguments based on the context I outlined previously, I find these magnitudes to be unlikely and conclude that selection on unobservables should not meaningfully affect the results.

4.3 Hospital Awareness of Trade Off between Quality and Learning

Because learning is mostly in complex patients, attendings can control the trade-off between care quality and training by changing the allocation of complex and simple patients to residents of varying experience and themselves. But are attendings aware of the trade-off? The answer appears to be yes. Figure 4 plots the average fraction of complex patients seen by individual providers during each shift across the four quarters of the academic year. This figure illustrates three interesting facts. First, the fraction of complex patients seen increases from 10% to 15% during the first year (solid red line), corroborating the results of Figure 2. Second, again in line with Figure 2, the fraction seen by the other three cohorts of residents is relatively stable during the year (dashed blue line). Third, it is attendings who “pick up the slack” in July through September and see the patients that

the first year residents are unable to treat (dotted and dashed purple line).¹⁸

Figure 4: Average Fraction of Complex Patients Seen, by Role



Notes: This figure depicts the average fraction of complex patients seen per shift, by role, for each quarter of the academic year. Complex patients are those with the highest values of ex-ante predicted admission. “Senior Residents” are the average shares of residents in years 2-4. This choice is informed by the results in Figure 2, Panel (b) and Appendix Figure A2, Panel (b), where the share of “Most Urgent” and Admitted patients does not continue growing after the first year. The figure shows that first year residents see more patients as they gain experience, but that the patients they are not able to see in quarter 1 are seen by attending physicians rather than other residents. Not shown is that there are no meaningful differences in staffing or arriving patient composition across the academic year.

Next, I provide suggestive evidence that attendings are aware of the trade-off on a more micro level via correlational logit regressions. In these regressions, I regress the probability that a first year resident is assigned a complex patient on the number of complex patients currently being seen in the ED, the number of patients in the waiting room, fixed effects for the patient’s chief complaint, and other characteristics of the physicians on staff and the index patient. Results are in Appendix Table A4. I find that first year residents are much less likely to be assigned complex patients when there are many patients in the waiting room. As the number of patients in the waiting room increases from the 25th to 75th percentile, the probability that first year residents are assigned a complex patient decreases by 15%. To conserve space, I do not show the coefficients on patient chief complaint, but these estimates are meaningful. I find that *ceteris paribus*, first year residents are much more likely to be assigned patients from more common chief complaints (e.g. chest pain, abdominal pain, and shortness of breath) compared to the pooled “less common” category.

Taken together, these findings suggest that the hospital is aware of the costs of teaching because they teach less when the costs are higher due to congestion, and that the hospital is aware of the benefits because they first train residents in the patients they are most likely to encounter.

4.4 Summary of Resident Learning

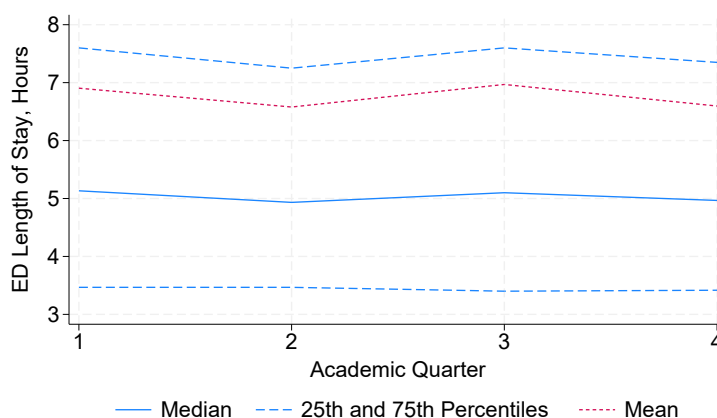
Based on the combination of the results on shift-level efficiency and within-patient outcomes, I conclude that EM residents improve in two dimensions. The first is in medical skill for individual patients: the processes of gathering, synthesizing, and interpreting information about each patient’s underlying state and signing the correct set of orders given that information.

¹⁸Indeed, there is no difference in the composition of arriving patients across the year.

Table 3 Panel (b) shows that these improvements are primarily for treating complex patients. The second is improvement in “bandwidth” or cognitive capacity: residents become able to manage additional patients simultaneously. Most of the growth in capacity is for less complex patients, as shown in Figure 2. I am primarily interested in the improvement in medical skill for individual patients, which I believe is a more appropriate application of the learning by doing and task allocation frameworks. Because the majority of improvement in within-patient medical skill is for complex patients, attendings can affect the trade-off between care quality and training by changing the allocation of complex and simple patients among residents of varying experience and themselves.

The within-patient results relate to the literature on cohort turnover in residency programs. Hughes (2017), Wei, et al. (2019), and the recent literature finds an absence of a significant drop in care quality in July, when the most experienced residents graduate and are replaced by new medical school graduates. In my findings, this follows from the lack of a gradient with respect to ED readmissions and resource utilization: if inexperienced residents achieve the same outcomes as experienced residents, there cannot be a drop-off in quality. But what about complex patient length of stay? I show that there is a notable decrease in length of stay over the four-year program. Therefore, outcomes for individual patients can change during the academic year. But recall that attendings see more patients in July through September, when the experience cost is greatest (Figure 4). Figure 5 shows that average length of stay is unchanged throughout the academic year as a result of the patient allocation strategy. This method of reducing the impact of cohort turnover complements the investments in infrastructure studied by Song, et al. (2016) and Hausknecht and Trevor (2011), such as better nurses, a transition period for continuing residents in June prior to turnover, and better attending supervision. Hospitals can also strategically allocate patients to physicians of varying skill in order to maintain average outcomes. Notably, unlike better infrastructure and training practices, this method is a choice that does not require costly investment.

Figure 5: Average Length of Stay, Complex Patients



Notes: This figure plots summary statistics of patient length of stay over the four quarters of the academic year for patients seen by EM residents and attending physicians. These are raw summary statistics without any patient or physician controls. The median ED length of stay is very stable with respect to academic quarter. The mean is slightly less stable, but that is driven by the top 25 percent of patient encounters.

Broadly, resident progress for complex patients can be divided into two categories: patient-relevant and not patient-relevant. The main patient-relevant change is complex patients’ length of stay in the ED, which decreases by approximately

9.2% over the four-year program. Crucial patient outcomes, as measured through ED readmissions, are unchanged. The time to first order does decrease, but the average magnitude is only about five minutes, so it is relatively unimportant. Patients are not affected by who signs orders for them, so the fraction of orders signed by the resident is not a patient-relevant outcome. Arguably, they are also relatively insensitive to the number of orders signed, insofar as it does not affect their outcomes and the change in out-of-pocket cost is small due to insurance coverage. It is also ambiguous whether the hospital desires a reduction in orders signed as this depends on how the payer will reimburse them. I return to reimbursements in the first counterfactual.

Therefore, the training environment can be described as follows: residents are more or less capable of treating simple patients when they begin the residency program. However, they need to learn how to diagnose and treat complex patients, but the only way to learn is to learn by doing: by seeing complex patients. Attendings are aware of this, and also of the primary trade-off: inexperienced residents are slower than experienced residents. But because learning is concave, inexperienced residents gain more from seeing each patient. Furthermore, there is additional time left in the program for the hospital to benefit from their increased skill compared to more senior residents. Therefore, the benefits of training inexperienced residents may be greater than the benefits of training experienced residents. The hospital must take these trade-offs into account and strategically allocate complex and simple patients to inexperienced residents, experienced residents, and attendings working independently in order to maximize the discounted sum of its stream of payoffs. I formally describe and estimate the nonprofit teaching hospital's dynamic optimization problem in the next sections.

5 Dynamic Framework

In this section, I present a dynamic model of patient allocation. It is necessary to consider dynamics because I am interested in estimating how the hospital allocates patients to trade off current care quantity and quality and future care quantity and quality via training. Unless the hospital acts myopically, a static model cannot capture these trade offs because it does not take into account future benefits of training. In other words, forward-looking hospitals take opportunity costs and future benefits into account when optimizing patient allocation. The dynamic choice model is a discrete-time, infinite-horizon model, where the state-space, resident skill, evolves akin to overlapping-generations models.

Each shift, attendings first observe the the skill of residents who were assigned to work. An infinitesimally divisible unit mass of complex patients arrives and attendings choose a share of patients to assign to each resident and themselves. Attendings help residents see patients and may also see some patients independently. Patient utility, a function of length of stay and therefore a function of resident skill, is realized. At the end of the shift, resident skill increases by the share of patients they saw. Each July 1, 4th years graduate and are replaced by new 1st years with zero skill. Attending skill is fixed.

This means that skill X is a four-dimensional vector where each element represents the experience of one of the four resident cohorts—first years, second years, third years, and fourth years. I do not need to track attending skill because it is fixed. Within the academic year, skill in the next period is simply skill in the current period plus the share of patients seen in the current period. On July 1, the fourth years graduate, the continuing three cohorts are promoted, and the new first years who join enter with zero skill. This structure for the evolution of skill is similar to the structure in [Bloesch and Weber \(2023\)](#) and [Jovanovic \(2014\)](#).

The hospital's choice of patient allocation share is the path of allocations $\{S_t\}_{t=0}^{\infty}$ that maximizes

$$\begin{aligned} & \sum_{t=0}^{\infty} \beta^t [u(S_t|X_t) + \varepsilon_{S_t}] \\ \text{subject to } X_{t+1} = & \begin{cases} (0, x_{t1} + s_{t1}, x_{t2} + s_{t2}, x_{t3} + s_{t3}) & \text{if } t = \text{June 30} \\ X_t + S_t & \text{otherwise} \end{cases} \end{aligned} \quad (2)$$

Flow utility u is a function of the choice of patient allocation shares in period t and is conditional on the state of resident skill X_t and also includes a component that is observable to the hospital staff but not to the econometrician, ε_{S_t} . This term is different for every allocation choice S and period t and could reflect things such as congestion or features of the patient that make them particularly suitable or costly for training that I do not observe.

This setup leads to the standard Bellman equation describing the value of being in any particular state X given by

$$V(X, q) = E_{\varepsilon} \left[\max_S \{u(S|X) + \varepsilon_{S_t} + \beta V(X', q')\} \right] \quad (3)$$

where I now explicitly separate out the resident's knowledge state X and the current quarter of the academic year q . I do this to make clear that the value of being in state X differs based on which academic quarter q the current period t is. That the quarter q affects the value of being in knowledge state X is intuitive: consider a state $X = [0, 0]$. In this case, it is far less undesirable for the hospital to be in this state in the first quarter, where it can still train the residents, than it would be for the hospital to be in this state in quarter four, where the training utility for the senior residents are about to be realized.

This model is very general and can accommodate any objective function. Motivated by the stable average patient length of stay in the data shown in Figure 5 and the finding that length of stay is the main patient-relevant outcome that improves with experience, I consider a utility function where the hospital maximizes training subject to a lower bound of utility from length of stay.

$$\begin{aligned} & \max_S \sum_{t=0}^{\infty} \beta^t [K(S_t; X_t, q(t)) + \varepsilon_{S_t}] \\ \text{such that } & L(S_t; X_t) \geq L^* \text{ for all } t \end{aligned} \quad (4)$$

L is the hospital's utility from patient length of stay and is the average length of stay utility f for patients, given allocation S and skill X .

$$L(S_t; X_t) = s_j f(x_{tj}) + s_s f(x_{ts}) + (1 - s_{tj} - s_{ts}) f(x_A) \quad (5)$$

This is simply the share of patients allocated to the junior residents, senior residents, and attendings in each period t , times the length of stay utility f for providers of each skill. Length of stay utility f is increasing and concave in provider skill x . Given L^* , the hospital conditionally maximizes the discounted sum of K , the utility from training. The minimum quality threshold L^* must be satisfied in every period and is to be estimated.

Flow utility from training K is the cumulative skill of the graduating senior residents in academic quarter four. That is,

$$K(S_t; X_t, q(t)) = \begin{cases} 0 & \text{if } q(t) \neq 4 \\ f(x_{ts} + s_{ts}) & \text{if } q(t) = 4 \end{cases} \quad (6)$$

In this specification, K is only nonzero in academic quarter four. Note that this does not automatically mean the hospital chooses not to train if it is not in academic quarter four because the value function $V(X, q)$ will generally be increasing in the state X within each quarter: higher levels of skill at any point enable the residents to achieve a higher skill upon graduation. It only means that the hospital does not directly derive utility from resident skill within the academic year—it does not benefit from increased resident skill within the academic year above its impact on length of stay utility L .

This model nests many potential theoretical models of hospital behavior. First, patients clearly demand care quality and may view speed of care as an important component of quality. Second, given the time cost of training, teaching hospitals face a trade-off between patient revenue and training. That said, many hospital administrators view training as the more important goal: “Trustees and administrators of teaching hospitals were charged with making their institutions academic leaders, not financial profit-centers. Fiscal responsibility was required for the institutions to do good work, but ultimately teaching hospitals were measured by their academic and professional accomplishments rather than their balance sheets” (Ludmerer, 2005). The model is able to accommodate the full range of potential weights between revenue and training. Setting $L^* = -\infty$ represents the extreme where hospitals only care about maximizing training. On the other extreme, if they only care about care quality or revenue, then they would choose L^* corresponding to the level of quality that would be provided if attendings provided all care independently such that training is impossible if the quality constraint is to be achieved. Convex combinations of the two objectives are accommodated with intermediate values of L^* .

This objective function is similar to the canonical specifications of Newhouse (1970) and Lakdawalla and Philipson (1998). I include revenue through the hospital utility channel, which is a function of patient length of stay. But length of stay is inextricably linked with revenue: in general, hospitals receive more revenue for each additional patient they see. Because facility size is fixed, the only way to increase revenue is to increase patient throughput via shorter length of stay. I do not separately include revenue to avoid double-counting care quality and revenue. In Appendix B, I consider an alternative flow utility function where the hospital maximizes a weighted sum of throughput and training, with the weight to be estimated, but reject it because it is inconsistent with the data: the optimal patient assignment rule does not result in a stable steady-state.

Note that even with constrained maximization, the dynamic problem does not reduce to a static problem. This is because training today and training tomorrow are intertemporal complements. More training today means that residents are faster tomorrow, and if residents are faster tomorrow, then the cost of additional training tomorrow is lower and more training is possible. Therefore, the myopic or static approach of maximizing the senior cohort’s training and ignoring the junior cohort in each period is not optimal. With that approach, training for the current seniors will be maximized, but future cohorts will suffer. Instead, the hospital must take into account the intertemporal complementarities and train both cohorts in every period. The optimal division of training across cohorts and time is the result of solving the dynamic problem.

Next, I describe how the model incorporates the key trade-off between care quality and training. For each level of minimum patient care utility L^* , there is a corresponding maximum level of training that can be achieved. Therefore, one way that the hospital can control the trade-off between care quality and training is by tightening or relaxing the care quality threshold.

If the hospital relaxes the care quality threshold, then more patients can be allocated to slow, inexperienced residents, who will then become faster in later periods and have higher skill upon graduation. Increasing attending skill x_A has a similar effect as relaxing the threshold L^* . Faster attendings allow for additional patients to be allocated to lower-skilled residents while maintaining mean care quality above L^* . Finally, if the slope of care utility with respect to skill $\frac{df}{dx}$ increases, then the benefits to patient allocation to residents increase. In this case, the hospital will desire to allocate additional patients to residents, but the degree to which it can do so is limited by the quality constraint L^* . In the first counterfactual, I quantify the amount that training decreases when L^* is tightened and consider the effectiveness of mitigating changes such as increasing attending skill and increasing the speed of learning.

Because the hospital maximizes training subject to the quality constraint, it maximizes the sum of discounted outcomes of graduating residents and the patients the residents see in the future. But the objective is one of pure efficiency: if there is a disruption to training that results in one cohort being trained less than the steady-state, the hospital will not take action to “smooth out” resident skill across cohorts beyond what is optimal given the concavity of training utility K . The shape of the optimal training function for each cohort given the skill of continuing cohorts and the corresponding impulse response function govern how many future cohorts are affected by disruptions to a single cohort’s training. These are empirical questions where the answers may vary based on the estimated parameters of the model. I quantify the impact in the second counterfactual and consider how one-time changes to the learning environment, such as a temporary relaxation of L^* , increase in x_A , and increase in the slope of care utility with respect to skill mitigate the impact of a training disruption.

6 Estimation and Identification

6.1 Simplifying Assumptions and Parameterizations

In order to make progress, I make some simplifying assumptions and parameterizations that keep the problem manageable and facilitate estimation. I describe these assumptions and the rationale behind them in this subsection.

The first set of simplifying assumptions I make keeps the state-space and action-space manageable. I assume that the program lasts for two years, so that there are only two cohorts: new residents, or “juniors,” who I denote with subscript j , and residents who will graduate at the end of the academic year, or “seniors,” who I denote with subscript s . I further assume that there is no within-cohort variation in skill. I take the time period t to be a quarter of the academic year. Without loss of generality, I impose that a mass of measure 0.25 complex patients arrives each quarter, so that each academic year a unit mass of patients arrives. Consequently, the maximum steady-state value of resident knowledge is 1.0, achieved when every patient is assigned to one of the cohorts. I discretize both the state space of resident knowledge and the choice variable of the share of patients assigned to each cohort and to attendings working independently.

These simplifications are necessary for the following reasons. First, managing a continuous choice of patient share and experience is intractable when taking first-order conditions is not possible, which applies here because the value function is unknown (V in Equation (3)). Instead, I consider an interval of knowledge space $[0.01, 1.2]$ and discretize it into 250 evenly-spaced values. I choose 0.01 as the starting value because residents begin transitioning into the program in June prior to their first year and they see a share of complex patients that is equivalent to about 0.01 when dividing by the full quarter. This is

also necessary because I need a finite value for the natural logarithm of experience. I censor the upper bound of the knowledge space to 1.2 because the maximum steady-state allocation for rising senior residents is 1.0 (achieved if every patient in every quarter is assigned to them). I choose 1.2 rather than 1.0 because this reduces estimation error when rising senior skill is near 1.0: otherwise, the hospital will begin allocating fewer patients to senior residents because it cannot benefit from the increased skill. For example, if the upper bound was 1.0 and rising seniors had 0.9 starting knowledge, the hospital's incentives to allocate more than 0.1 patients to the seniors is drastically reduced because there is no additional training benefit to doing so. In keeping with the discretization of the state-space, I constrain the hospital to dividing the mass of arriving patients into increments that correspond to the grid of valid knowledge values. This means the hospital chooses one of 52 values evenly spaced from 0 to 0.25 to allocate to each cohort and to the attendings such that the sum of allocations to all providers equals 0.25. The full state-space must contain one dimension for each cohort, and must have one such array for each time period.¹⁹ Even with just two cohorts and time in quarters, the state space array with my discretization has dimension [250, 250, 4].

The second set of assumptions concerns the steady-state. I assume that the hospital is in the steady-state and that the steady-state is such that training each year is identical to training every other year. The first assumption facilitates estimation because it does not require me to infer the skill of the rising seniors—this is not data because I do not observe their full patient history. The assumption of a stable steady-state is consistent with the patient assignment data. In Appendix Figure A3, I show that patient assignment shares are similar for each class across the two years of data, suggesting that cohorts are treated similarly. It also is consistent with the intuition that a teaching hospital would treat all cohorts similarly. The assumption rules out models and parameters where in the optimal solution the hospital alternates between training cohorts that enter during even years and ignoring the cohorts that enter on odd years.

Estimation proceeds in two steps in the spirit of Hotz and Miller (1993), Bajari, et al. (2007), and Pakes, et al. (2007). The unknowns and methodology are summarized in Table 4 Panel (a). In the first, “offline,” step, I estimate the parameters relating to the learning rate $\{\alpha_0, \alpha_1\}$ using OLS in the panel data, and infer attending speed x_A using the estimates $\hat{\alpha}$. Then, for three candidate values of the discount rate²⁰ β , I find via iteration the lower bound on quality in the utility function given by Equation (4) that produces optimal patient assignment shares most similar to the observed shares. I consider three functional forms for the length of stay flow utility f that vary in concavity: linear, quadratic, and log, as delineated in Table 4 Panel (b). Note that the linear and quadratic parameterizations of f differ because the shape parameters α are determined in the offline estimation.

6.2 Step 1: Offline Parameter Estimation

I begin by estimating the learning parameters outside of the dynamics, or “offline,” via OLS. The goal is to recover how patient length of stay improves with experience with complex patients, as measured with the share of complex patients and to estimate the skill of attendings working alone. Two factors make this not entirely straightforward. First, I must restrict to the subset of residents who begin the program during the sample period because I do not observe the resident's full patient history otherwise. Second, the residency schedule is such that the residents do work at another hospital in the city that I do not have

¹⁹This is because the value to the hospital of any level of resident skill is potentially different depending on when in the academic year it is.

²⁰I choose not to estimate the discount rate, which is a common choice in the dynamic model literature. For instance, Pakes, et al. (2007) writes, “We usually think that the prior information we have on δ [the discount rate] is likely to swamp the information on δ available from estimating an entry model.”

Table 4: Summary of Estimation Parameterizations and Methodology

(a) Parameters to Estimate and Methodology		
Category	Unknowns	Estimation Methodology
Learning rate	$\{\alpha_0, \alpha_1\}$	OLS in panel data, “offline”
Attending speed	x_A	Back out from panel data using $\hat{\alpha}$
Discount rate	β	Calibrated; yearly $\beta = \{0.90, 0.95, 0.99\}$
Weight on quality vs. training	ϕ	Dynamic, match patient shares averages
Lower bound on quality	L^*	Dynamic, match patient shares averages

(b) Parameterizations of Length of Stay Utility f	
Linear	$f(x) = -\alpha_0 x^{\alpha_1}$
Quadratic	$f(x) = -(\alpha_0 x^{\alpha_1})^2$
Log	$f(x) = \log(C - \alpha_0 x^{\alpha_1})$

Notes: This table enumerates the unknown parameters and the estimation method employed in order to estimate them, as well as the functional forms for the length of stay utility function f . In Panel (a), the first section lists the parameters to be estimated in “offline” in panel data without any dynamics. The middle sections shows that the discount rate is calibrated using various reasonable yearly values, as it is not well-identified in the dynamic model. The final section shows the two parameters that are estimated using the dynamic model and take the offline parameters as fixed; these come from two different utility functions that the hospital may use. Panel (b) lists the three functional forms used for the length of stay utility f . Note that the linear and quadratic parameterizations do differ because the shape parameters α are fixed in the offline estimation. C is a constant chosen to ensure that $C - \alpha_0 x^{\alpha_1}$ is positive for all values of skill x . See text for additional details, as well as Subsection 6.2 for more details on offline estimation and Subsection 6.3 for more details on the dynamic estimation.

data from so I must infer the total fraction of complex patients seen. I first describe the assumptions I make and then the tests I do in order to test the validity of the assumptions.

The coefficients recovered by OLS are unbiased under the same assumptions on omitted variables as outlined in Section 4. Two additional assumptions are necessary in this setting. First, I assume that the natural logarithm is the correct functional form for resident progress with respect to the cumulative fraction of complex patients seen. Second, I assume that patient assignment inference is in expectation correct. In other words, residents who see “excess” patients relative to their peers at UCSF also see similar “excess” patients at ZSFG. Both assumptions are fundamentally untestable but I offer arguments in favor of accepting them.

First, to test the validity of the functional form assumption, I compare the quarterly patient share results for the subset of residents with the results using years in the program as the measure for experience. The rationale behind this is that years in the program is a “reduced-form” measure of share of complex patients, as much of the variation is in the time-series rather than in the cross-section. I test the validity of my assumptions in Table 5 by seeing if the results for continuous tenure are similar to that of quarterly patient share.

Next, because UCSF EM residents work in two locations but I only have data from one, I must infer patient assignment at the other location. The assumption I make is that patient assignment at the other location (Zuckerberg San Francisco General Hospital, ZSFG) mirrors patient assignment at the observed location (UCSF). In other words, if a resident sees 12% of patients at UCSF within a period, I assume they are also seeing 12% of patients at ZSFG. Importantly, this means that attendings are

not assigning patients in a mean-reverting manner or that observed differences at UCSF are not magnified or diminished at ZSFG.

I find evidence consistent with this assumption in Appendix Table A7, which shows that the standard deviation of complex patients seen per shift is relatively stable across the academic year. The rationale is that if residents were assigned more patients at UCSF to “make up” for seeing fewer patients at ZSFG for exogenous reasons such as ED congestion, then I would expect to see more dispersion in the number of patients per shift in earlier academic quarters compared to later quarters. This is because of the law of large numbers: in later quarters, variation in exogenous factors should be more similar across residents and any additional variation will have a smaller impact on the total number of patients seen. Furthermore, I believe factors such as the ad-hoc team structure and variation in congestion and patient arrivals make this assumption reasonable, as it is difficult for the rotating attendings to know the resident’s history and adjust their assignment instructions accordingly.²¹ To lessen the impact of this assumption as well as differences due to exogenous factors such as congestion, I use as the measure of patient-specific experience the average share of complex patients seen during the calendar quarter. This measure has considerably less variation than experience at the two-week level, but still contains some variation, as can be seen in Appendix Figure A4.

Now, I describe how I infer attending skill with the learning parameters in hand. Conceptually, this is simple as I observe the length of stay for complex patients seen by attending physicians and I know the functional form of learning, so I can just take the inverse of that function. However, the inclusion of physician fixed effects makes this complicated as the concept of the regression constant is not well-defined. Therefore, what I do is I infer attending skill for every estimated physician fixed effect and patient seen by an attending, and use the grand mean of the estimates as the estimate for attending skill.

6.3 Step 2: Dynamic Parameters

The goal of estimation is to find the unknown parameter L^* that gives the best fit between the model-predicted optimal quarterly patient shares and the observed quarterly patient shares. The metric of fit used is RMSE, with each quarter receiving equal weight. In other words, I find the value of L^* that minimizes:

$$\sum_{t=1}^4 \sum_{r \in \{j,s,a\}} \sqrt{(s_{tr} - MSS(L^*; \beta)_{tr})^2} \quad (7)$$

where the subscripts j , s , and a represent the shares assigned to each role: the junior resident, senior resident, and attending. s_t are the observed patient allocation shares, and MSS_t is the model-predicted steady-state shares given the parameter L^* and discount rate β in period t .

In order to find the value of L^* that minimizes Equation (7), I perform a grid search over values of L^* . For each value of L^* and choice of β , I first perform value function iteration on Equation (3) in order to solve for $V(X, q; L^*, \beta)$, the value of being in knowledge state X in academic quarter q given L^* and β . I then use the estimated $V(X, q; L^*, \beta)$ in conjunction with the flow utility K to find the optimal patient allocation choice S for each X and quarter q : $S(X, q; L^*, \beta)$. Finally, I find the steady-state given the allocation choices S . That is, I search for a value of rising senior knowledge $\sum_{t=t'}^{t'+4} s_{tj}^*$, the

²¹ According to EM residents at UCSF, many decisions regarding progress are made at the cohort level. For example, at the beginning of second year all residents are expected to take on additional patients and there is limited “personalization” of this directive based on individual progress. This is unsurprising because of the ad-hoc team status and because there are 60 EM residents for the various attendings to keep track of.

cumulative share of patients seen in their first year, such that the optimal training results in the new cohort of junior residents finishes the first year with the same knowledge. In my notation, I search for $\sum_{t=t'}^{t'+4} s_{tj}^*$ that satisfies for all t' :

$$\sum_{t=t'}^{t'+4} s_{tj}^* = \sum_{t=t'+5}^{t'+8} S(X_t^*, q(t); L^*, \beta)_j$$

such that $X_{t+1}^* = X_t^* + S(X_t^*, q(t); L^*, \beta)$

and t' is the beginning of an academic year

(8)

The left hand side is the starting knowledge of the rising seniors, which is equal to the cumulative share of patients seen in their first year. The right hand side is the sum of patient shares seen by the new juniors in the next academic year, because S is the function that maps knowledge X and time q to a vector of optimal patient assignment decisions and skill X accumulates in the usual way.

I iterate until the average L2-norm (Euclidean distance) between successive elements of the value function is less than 10^{-6} . Although the grid search over possible values of L^* is slightly cumbersome, this method has the advantage that I in theory do not risk finding a local minimum rather than the global minimum. In practice, I begin with a relatively coarse grid and perform a finer grid search around the minimum given by the coarse grid.

7 Results

In this section, I first present and discuss estimates of the offline estimation and provide evidence in support of my assumptions. Then, I discuss the results for the dynamic model.

Results of the offline OLS estimation of the learning parameters are in Table 5. My preferred estimates are the bolded set in the rightmost column, which are the results using the natural logarithm of quarterly patient share with physician fixed effects and patient controls. Starting from the bottom row, the results suggest that the average attending physician has skill similar to a resident with a cumulative experience share of 0.89 patients (recall that a mass of 1 patient arrives each year). While this may be lower than expected, this measure includes interruptions to attending speed due to supervisory duties so it is not a measure of pure attending skill. Next, for learning speed, the results suggest that for each 1% increase in cumulative quarterly patient share, patient length of stay will decrease by about 0.04%.

The remaining columns of Table 5 are tests of the assumptions necessary for the patient share results to be valid. I compare those estimates to estimates from the full sample of residents and for continuous measures of experience. The first pair of columns presents the results using years in the program as a continuous measure and for the full sample of residents, which represent the baseline. Next, I restrict to full history residents and find minimal changes in the estimated coefficients. Coarsening the years of experience measure to quarterly snapshots results in coefficient estimates of increased magnitude, but the standard errors are large enough that I cannot reject that they are equal to the coefficients from the continuous measures. Similarly, changing the measure of experience to patient share does not create a large difference in the estimates. The estimated attending skill is similar for all specifications other than the full resident sample, which I believe is due to some imprecisely estimated resident fixed effects that have outsize influence on the grand mean of inferred attending skill. Values across the

other specifications with patient controls are all similar.

Table 5: Offline Parameter Estimates of Learning Speed and Attending Skill

Experience Type	log(Patient Length of Stay, Hours)							
	Tenure (continuous)				Tenure (quarterly)		Patient Share (quarterly)	
α_1 : log("Experience")	-0.030 (0.013)	-0.050 (0.015)	-0.073 (0.015)	-0.059 (0.019)	-0.127 (0.029)	-0.105 (0.036)	-0.054 (0.012)	-0.043 (0.015)
α_0 : Constant	1.674 (0.013)	1.692 (0.013)	1.652 (0.025)	1.694 (0.025)	1.665 (0.025)	1.711 (0.025)	1.606 (0.030)	1.623 (0.030)
Sample	All				Full History Residents			
User ID and Patient Ctrls	Y		Y		Y		Y	
Observations	11,520	11,520	1,202	1,202	1,202	1,202	1,202	1,202
Inferred x_A	1.47	1.39	0.86	0.88	1.02	0.77	0.37	0.89

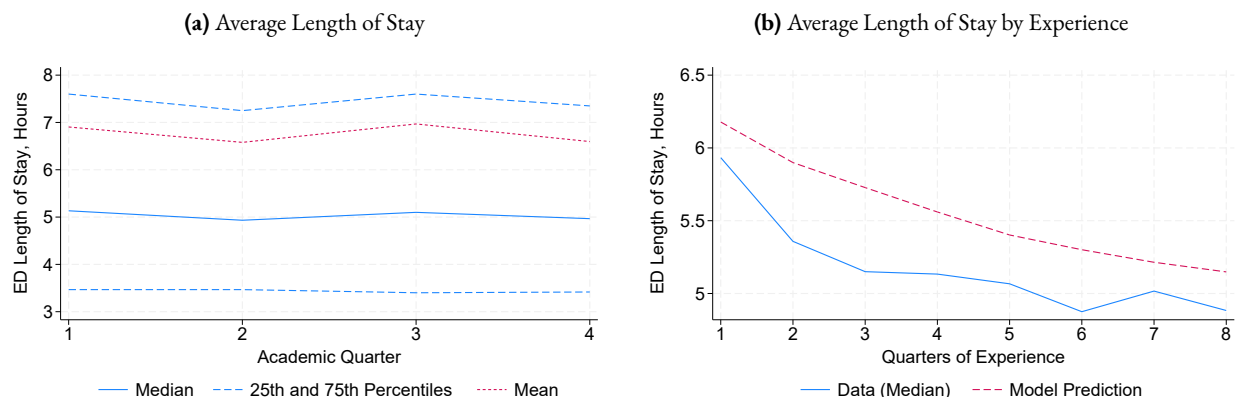
Notes: This table shows the results of the offline estimates for the parameters governing learning speed as well as the value of attending skill inferred using these estimates. The bolded estimates in the final column are what are used in the dynamic estimation as they use the desired measure of experience: share of complex patient seen. This measure is only available for residents who begin the program during the sample (the 2018 and 2019 cohorts). In order to test that this sample of residents is not significantly different from the full sample and that discretizing experience to quarterly intervals similarly does not result in different estimates, I begin with the full sample of residents and a continuous measure related to patient share: years in the program. This first pair of regressions is similar to the regressions in Table 3. I then restrict to the 2018 and 2019 cohorts and find that the coefficients do not change much in the specification with physician fixed effects and patient controls. Similarly, I cannot reject equality of coefficients when I only allow tenure to change each quarter, and again when using the quarterly patient share definition of experience. Standard errors are clustered by physician in the first two columns but are the greater of the clustered and robust otherwise because there are fewer than 40 physicians.

Results for the dynamic model are similar across specifications and discount rates. Regardless of the specification or discount rate, the estimated lower bound, converted from utils into hours, is always around 5.33 hours per patient. The model that fits the data best is the specification with quadratic utility from length of stay and a yearly discount rate of $\beta = 0.95$. Full results can be seen in Appendix Table A6. The model fits the qualitative patterns of increasing allocation to first year residents and decreasing allocation to attendings well, but the gradient for both is steeper than observed in the data. This can be seen in Appendix Figure A5.

I next evaluate model fit by examining how well it fits non-targeted moments. Specifically, I examine how the length of stay predictions compare to length of stay averages in the data. First, I examine the average length of stay across the academic year. The estimated quality bound of 5.33 hours is less than the raw mean and median length of stay in the data. The reason it differs is related to the fact that the inferred constant is using the set of first year residents, but the data contains additional residents that are not used in the estimation. Therefore, when assessing model fit, I will focus on matches with changes over calendar time. The model predicts that length of stay is stable over the academic year, as the quality bound binds in every quarter. Figure 6 Panel (a) shows that the median ED length of stay is very stable with respect to academic quarter, just as the model predicts. The mean shows more movement, but that is driven by the top 25 percent of encounters and potentially related to encounters where patients were in worse condition than expected or the affected by the arrival of a code patient in critical condition who demanded the attention of the entire ED. Next, I examine how average length of stay varies across quarters of experience, and compare it to the model predicted values. Figure 6 Panel (b) shows that see that average length of

stay by experience has similar shape as the median length of stay for residents with each level of experience. The similarities between average length of stay in the data and predicted length of stay in the model were not a moment that was targeted in the estimation—only patient share assignment was—and the comparisons give me more confidence in the model.

Figure 6: Model Fit: Non-Targeted Moments



Notes: These figures show how well the model fits the non-targeted moments relating to patient length of stay. In Panel (a), a reproduction of Figure 4, we see that the median ED length of stay is very stable with respect to academic quarter, just as the model predicts. The mean is slightly less stable, but that is driven by the top 25 percent of encounters. In Panel (b), we see that average length of stay by experience has approximately the same shape as the median length of stay for residents with each level of experience, as well as attendings who in the figure have “experience” equal to 9 quarters. All of the empirical averages shown are raw averages without any patient or physician controls.

8 Counterfactuals

I use the model to assess the consequences of a policy change and of a training disruption on both patient care quality and resident skill. In addition to quantifying the impact of the change, I consider the effectiveness of various remedies that the hospital may enact in order to counteract the effects of the counterfactual changes.

First, I consider an increase in the speed at which attendings see patients independently, which in the model is represented by x_A . This is a feasible action because it does not necessarily require that the hospital hire higher-skilled attendings. Instead, they can simply staff more attending physicians on each shift. This works because x_A includes the supervision portion of the attending’s duties. If there are additional attendings working on each shift, then supervisory duties will be split among more physicians, thereby reducing the number of disruptions each attending faces when caring for patients individually. This will reduce length of stay for patients assigned to attendings and increase their effective speed x_A . This remedy is also realistic: a similar change was proposed by the Institute of Medicine in 2009: they estimated that \$1.7 billion was required to improve residency, with the bulk of the spending for more providers to assume some of the patient load currently seen by residents, thereby allowing them more time to reflect, study, and learn (Ulmer, et al., 2009).

Second, I consider an increase in the learning rate of residents. This is potentially more difficult to implement because it would likely involve redesigning the curriculum or partnering with additional hospitals so that residents see additional patients.²² On the other hand, it could also have significant returns because residency shapes the habits and approaches that

²²EM Residents typically are not constrained by the ACGME’s hours limit so this change would be legal, but it ignores general equilibrium effects, such

physicians will continue to use throughout their careers (Ludmerer, 2015).

For the first counterfactual, I consider permanent changes, but in the second counterfactual, the changes are for one period only. In the second counterfactual, I also explore the effectiveness of a temporary relaxing of the care quality constraint. To simulate the counterfactuals, I change the relevant parameters and re-solve the model with other parameters held fixed. I find the new optimal patient assignment function (both counterfactuals) and the new steady-state (first counterfactual only) following the same procedure as outlined in Section 6.3.

The two teaching outcomes I consider are average patient length of stay and the total number of patients seen over the resident's career. For now, I make the extreme assumption that no further learning occurs after the resident graduates from the program.²³ Under this assumption, calculating average patient length of stay is straightforward: it is simply the average length of stay given by the resident's skill upon graduation. This is equivalent to the intensive margin of patient utility: for each patient the resident sees, what is the difference in their length of stay? Estimating the total number of patients seen requires making additional assumptions. I assume that graduates see $\frac{8}{\alpha_0 X^{\alpha_1}}$ patients per shift, where X is the skill they leave residency with, and that they go on to work 18 8-hour shifts per month (AMA, 2017) for 30 years. Differences in total patients seen represent the extensive margin of the change.

8.1 Increasing the Bound on Quality

In the first counterfactual, the hospital decides to increase the lower bound of care quality. In the model, this is governed by an increase in L^* . There are real reasons for why hospital administrators may choose to make this change. The first is that length of stay is an important part of Medicare's Hospital Report Cards.²⁴ Hospital administrators may care about these ratings both because higher ratings help attract more patients and for intrinsic or reputational concerns (Kolstad, 2013). The second may be due to payment reform, which is a heavily-discussed policy lever to reduce healthcare costs (see McClellan, 2011). I next explain how payment reform may interact with the hospital's choice of care quality bound L^* .

Generally, payments have been trending away from the traditional fee-for-service (FFS) system to alternatives such as value-based payments and capitated, prospective payment systems (PPS). Under FFS, providers are paid for every procedure, order, and service they provide to the patient. One of the issues with this system is that providers are not incentivized to reduce utilization or cost and have financial incentives to provide marginally necessary care (cf. Marmor and Gordon, 2021). Two leading alternatives are value-based care and PPS. In value-based care, providers are paid more if they realize better quality outcomes regardless of utilization, for example, for lower rates of complications from surgery or shorter ED length of stay. Because payment is independent of utilization, conditional on care quality, value-based care incentivizes physicians to reduce cost and improve quality. PPS works similarly in that providers are paid the same amount for every patient type regardless of utilization, so again providers have incentives to reduce costs.

Issues may arise for teaching hospitals if the reimbursement rates for value-based care and PPS are set uniformly across hospital types. An example would be if under the two systems, the average hospital's revenue is identical. Teaching hospitals

as the possibility of slower learning due to increased fatigue or a change in selection into specialties (cf. Wasserman, 2023).

²³In progress is a version where graduating residents learn at half the speed as they did during residency. This approximation takes into account the facts that attendings work fewer shifts per month than residents and they no longer have formal supervision for every patient.

²⁴See the "Timely and Effective Care" subsection of Medicare's Care Compare website (accessed October 25, 2023): <https://www.medicare.gov/care-compare/>

would lose revenue due to a change like this because they tend to do poorly on many typical quality and efficiency metrics (Kocher and Wachter, 2023). Furthermore, teaching hospitals currently have very high FFS reimbursement rates, estimated at 10-20% above FFS payments at non-teaching hospitals, although quality of care is higher for some patient types, which offsets that somewhat (Sloan, 2021). In any case, if the switch from FFS to PPS or value-based care occurs without sufficient accommodations for teaching hospitals, they would stand to lose significant revenue from patient care. This is the spirit of the first counterfactual.

Consider a very simple payment model where instead of being paid for each hour with patients (similar to FFS), hospitals are instead paid a fixed amount for each patient (similar to PPS). Further assume that all hospitals began with the same FFS rates and that the PPS rate is set so that the average hospital in the nation does not experience a change in revenue. My results suggest that UCSF could see at least 5% more patients each day if they did not train at all and instead had attendings see all of the patients.²⁵ Therefore, under this simple payment structure, they would lose 5% of revenue.²⁶ The hospital could recover some of the lost revenue by increasing patient throughput via increasing the quality constraint L^* . Particularly in the short run, the hospital must reduce training since residents are slower than attendings in order to increase throughput, and this is precisely what occurred in the 1980s when the first PPS reforms were implemented (Ludmerer, 2015). However, there are two mitigating actions the hospital can take. First, they could increase the rate of learning α_1 so that residents gain more skill with each patient seen. Second, they could increase the speed of attendings seeing patients independently. In the counterfactual, I assume that the hospital chooses to become 2% faster at caring for complex patients.

Table 6 shows the impact of the increase in the patient quality constraint alone and in combination with mitigating actions. The figures presented compare the new steady-state with the current steady-state, and ignores contributions to revenue, patients seen, and minutes per patient during the transition period. The first row reports current outcomes. Under the assumptions on speed and shifts worked described above, residents see 10,141 complex patients over the course of their career and spend 307 minutes per patient. If the hospital adjusts training to increase the length of stay by 2% and makes no further changes, then in the new steady-state graduating residents see 520 fewer patients during their career and are almost 17 minutes slower for each individual patient. The 2% gain in teaching hospital revenue from seeing patients faster is paid by the hospital that employs the resident after graduation because its new physicians are slower, and this cost is almost 17 times larger than the revenue gain. This future cost is an externality from the teaching hospital's point of view because it undervalues the future productivity of their graduating residents when making the decision to reduce training.

However, the social planner can induce the teaching hospital to take mitigating actions and reduce the impact on training required by the 2% stricter length of stay requirement. For instance, teaching hospitals can increase the speed that attendings see patients independently by 5%. This is very effective in reducing the difference in counterfactual training from the current training level, making up 81% of the loss relative to when no other actions are taken. The intuition behind this is that the hospital desires to maximize training given a constraint, and increasing the speed at which attendings work in effect makes the

²⁵This is calculated from the model predictions for average length of stay during the academic year given optimal patient assignment under the current parameters, and the inferred value of attending skill. It is a lower bound because the current attending skill measure assumes that attendings also have teaching and supervisory duties, which would be reduced if the hospital reduced teaching.

²⁶If the teaching hospital had higher FFS reimbursement rates than non-teaching hospitals prior to the policy change, then it would stand to lose even more revenue. Additionally, while it is true that even in the current world, the hospital could increase revenue by training less, it has chosen not to. This is because the hospital has chosen L^* at the current level from maximizing preferences over care quality, quantity, revenue, and teaching. I take this choice given and do not model it. As long as revenue is a normal good, changes that decrease revenue will cause it to seek ways to increase it.

constraint less binding. This allows them to increase training while still meeting the quality constraint. On the other hand, increasing the rate of learning by 5% has a much smaller effect, only allowing the hospital to make up 24% of the loss. This is again due to the constrained maximization problem faced by the hospital. Although the benefits of training are increased, the hospital has difficulty taking advantage of this and increasing the fraction of patients allocated to residents because it still must meet the same care quality constraint in every quarter. In other words, the hospital is not permitted to intertemporally substitute decreased speed in earlier quarters due to increased allocation of patients to residents with increased speed in later quarters because residents have gained more skill as it would in the absence of the constraint. Only in the later quarters of the academic year, when residents who learn faster are more skilled can the hospital actually increase patient allocation relative to current levels, and even then it is not by much. Finally, taking both actions actually has the effect of improving future outcomes, as now the hospital is able to take advantage of the increased benefits of faster learning and actually allocate additional patients to residents.

Table 6: Quality Bound Changes: Steady-State Counterfactual Resident Training and Mitigating Factors

Plan	Revenue “Externality”	Lifetime Patients	Minutes per Patient
Current Outcomes		10,141	307
Decrease length of stay 2% and...			
No other changes	-16.7:1	-520	+16.6
Attending Speed +5%	-3.1:1	-97	+3.0
Learning Rate +5%	-12.7:1	-396	+12.5
Learning Rate +5% & Att +5%	+1.8:1	+57	-1.7

Notes: This table shows the loss for future patients of senior residents if UCSF decides to decrease patient length of stay by 2%, adjust the care quality utility constraint by the corresponding amount, and take the listed mitigating action. The revenue externality captures only the financial cost and is the ratio of the change in the present value of future patient revenue to the current patient revenue increase due to the policy change, assuming no changes in reimbursements. For example, if no other changes are taken, the present value of the cost to future employers of the resident is 16.7 times the additional revenue generated by UCSF by speeding up, because the graduating residents have less skill. This is in essence the discounted difference in lifetime patients seen and assumes that residents go on to work 18 shifts per month, as is typical for EM attendings, for 30 years. Lifetime patients is the total difference in patients seen (extensive margin), and minutes per patient is the length of stay difference for each patient (intensive margin) given graduating resident skill. For now, I make the extreme assumption that no further learning occurs post-residency.

These results show that small changes in training by the teaching hospital can have outside effects for future patients and future employers of residents. It is important for policymakers to consider these externalities when designing payment systems so that future patients do not end up paying orders of magnitude greater in costs in order to save a little today. Fortunately, there are feasible and straightforward remedies available that can mitigate these costs. The counterfactual shows that increasing the speed at which attendings see patients individually by just 5% can recover 81% of the loss in training resulting from a desire to increase patient throughput by 2%. This can be satisfied by staffing additional attending physicians, which admittedly may be difficult if general equilibrium effects are considered, but is likely far easier and more effective than finding ways to redesign the resident curriculum or having them work additional hours in order to learn faster. Another possibility that I have not discussed is to increase Medicare’s Indirect Medical Education Payment to cover non-Medicare patients. These payments are

a lump-sum bonus paid by Medicare to Medicare PPS academic hospitals, which CMS recognizes have higher costs than non-teaching hospitals due to the teaching responsibility. Increasing the IME Payments would also be effective as it would decrease the hospital's need to gain more revenue from patients due to payment reform, thereby reducing the need to increase patient throughput by decreasing training.

8.2 Unexpected One-Time Training Disruption

In the second counterfactual, I consider the consequences and effectiveness of policy responses to a one-time, unexpected disruption in training. This scenario resembles disruptions during the Covid-19 Pandemic, which affected residents in at least two general ways. First, the composition of patients who went to the hospital changed as patients delayed and avoided both routine and urgent or emergency care (Czeisler, et al., 2020). This, in addition to the influx of Covid patients, changed the pool of patients that residents could see and learn from, decreasing effective patient share in every period. Second, medical workers were under extreme stress during this period (HHS, 2022), which also likely reduced residents' ability to learn.²⁷

I ask three questions. First, how many incoming classes of residents will the one-time disruption affect through spillovers? Second, for affected residents, what are the long-run effects of the disruption on their future careers? Third, what temporary mitigating factors could reduce the impact on residents affected by the training disruption? For simplicity, I assume that future incoming cohorts are equally skilled as their historical counterparts even though this is contrary to evidence (Jhajj, et al., 2022).

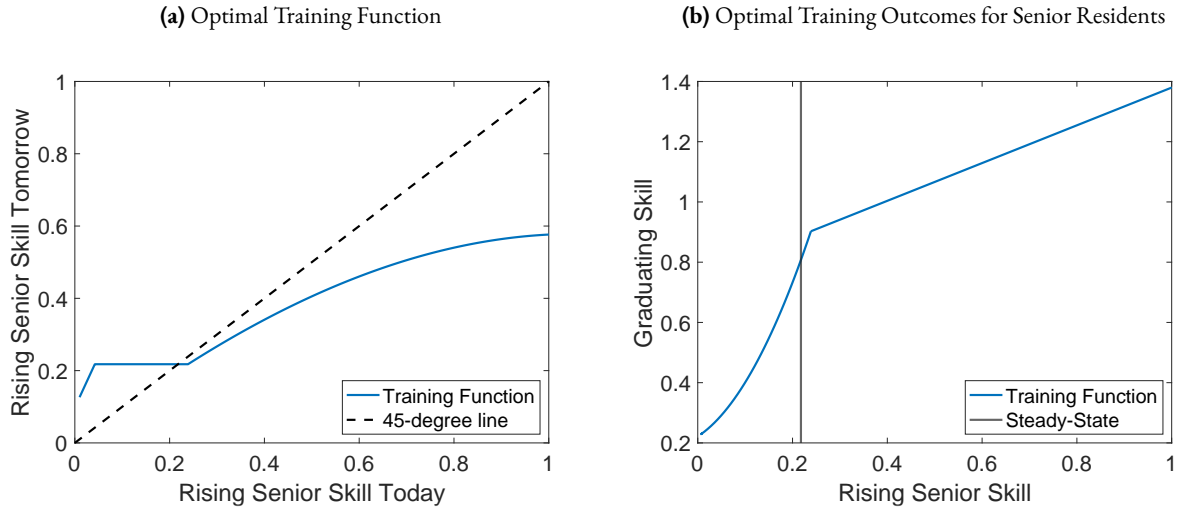
Under no additional changes, how long does the hospital take to return to the steady-state of training? This is simply the impulse response function of the system. In this case, it is very simple and easily inferred from the Optimal Training Function presented in Figure 7 Panel (a). The figure illustrates the utility-maximizing choice of patient allocation during the incoming cohort's first year (vertical axis) as a function of the skill of the rising senior (horizontal axis). The steady-state of the system is when rising senior skill today is equal to the resulting rising senior skill tomorrow, which occurs at the point which the optimal training function intersects the 45-degree line (the dashed line in the figure). In the figure, we observe that for most decreases in rising senior skill today, the hospital trains the incoming cohort exactly as much as it would have if there was no disruption, therefore returning to the steady-state the very next period. That means that aside from the senior residents at the time of the disruption, the disruption only affects the continuing cohort of rising seniors and does not affect future incoming residents.

But that does not mean the training disruption has no impact on training: clearly the training of the affected cohort must be reduced as a result in order to maintain the quality bound. This is exactly what we observe in Figure 7 Panel (b), which plots the graduating skill of the senior residents as a function of their skill when they become seniors. Below the steady-state, depicted by the vertical line, there is a very steep gradient in training, but it flattens substantially when rising senior skill exceeds the previous steady-state. Therefore, even though incoming cohorts are not affected by the one-period training disruption, senior residents receive drastically less training.

The intuition behind these findings is as follows. Because the rising seniors are less skilled than usual, the hospital is limited in the total fraction of patients it can assign to residents and maintain the care quality constraint. Therefore, it is very costly for the hospital to train the disrupted cohort because it not only means that the incoming cohort receives less training, but

²⁷ As with K-12 education, medical student education during this time also suffered (Jhajj, et al., 2022) so it is reasonable to infer that residents were also affected.

Figure 7: Optimal Training Function and Outcomes



Notes: This figure depicts the hospital's optimal choice of total training for the two cohorts given the training the current senior residents received in their first year. Panel (a) depicts the total first-year training for tomorrow's junior residents in their first year given the training the current senior residents received in their first year. The steady-state is where the optimal training choice intersects with the dotted 45-degree line. Panel (a) illustrates how for many values of current rising senior resident skill below the steady-state, the hospital chooses to train the next cohort of junior residents at exactly the steady-state quantity. If today's rising senior resident skill is greater than the steady-state, the hospital increases training in a diminishing way, and skill remains elevated for a few periods as it steps back down to the steady-state. The reason the second kink around 0.25 is not at the steady-state is due to the discount rate: here it is optimal to realize the gains immediately rather than realize small gains for the next few periods. Panel (b) depicts the hospital's optimal choice of total training for senior residents conditional on their skill acquired during their first year. The steady-state is depicted by the vertical line. This figure illustrates that below the steady-state, there is a very steep gradient in training, but the slope is flatter above the steady-state. When combined with Panel (a), one notices that below the steady-state the hospital prioritizes training the junior residents to return to the steady-state and trains the seniors minimally. This is due to the value of training the junior resident in the next period: the higher skilled the junior resident, the more training both cohorts can receive and still meet the quality constraint.

also means that future incoming cohorts would also receive less training. The combination of the yearly discount factor of $\beta = 0.95$ and the concavity of the training utility with respect to patient share means that the hospital is patient enough to sacrifice training in the current period in order to return to the steady-state immediately, rather than spreading the cost of the disruption over multiple periods.

For the counterfactual outcomes, I assume that the result of the disruption is that the affected rising seniors begin the academic year with half of the steady-state skill, but that the incoming cohort is identical to all other incoming cohorts. For the temporary changes, I find the optimal patient allocation with the different model parameters and the lower-than-usual starting value of rising senior skill. Motivated by the previous finding that the hospital returns to the steady-state the very next period, I consider combinations of six one-time, temporary policy changes: relaxing the care quality bound by 0.25% and 0.5% in length of stay, increasing attending speed by 2.5%, increasing the rate of learning by 2.5%, and combining an increase in attending speed with either a relaxation of the lower bound or an increase in the learning speed.

Results are in Table 7. As before, I compare outcomes with the steady-state outcomes in lifetime patients seen and minutes per patient. Those outcomes are represented in the first row of the table. The remaining rows (under the single dividing line) display the outcomes under various one-time changes when the rising senior class begins with half the knowledge as in the

steady-state. As we saw in Figure 7, there is a significant training cost in the Status Quo—if no other actions are taken. Under the same assumptions on resident careers as the first counterfactual, residents see 224 fewer complex patients during their career and spend 7 additional minutes on each patient they see. Temporarily relaxing care quality by 0.25% roughly halves both decreases, while temporarily relaxing care quality by 0.5% actually makes the affected cohort slightly more skilled than usual. Attending speed increases again prove to be quite effective as the senior residents recover 88% of the difference in lifetime patients seen under the Status Quo compared to the steady-state. Similar to before, learning rate increases also have limited effect. Curiously, increasing attending speed and lowering the care quality threshold is not particularly effective, but as before, increasing both the attending speed and the learning rate is very effective as now the hospital is able to take advantage of the increased benefits of training.

Table 7: Training Disruption: Counterfactual Resident Training and Mitigating Factors

Counterfactual	Lifetime Patients	Minutes per Patient
Steady-State	10,141	307
Status Quo	-224	+6.9
Relax L^* 0.25%	-113	+3.4
Relax L^* 0.5%	+23	-0.7
Att Speed +2.5%	-26	+0.8
Learning Rate +2.5%	-58	+1.8
A.S. \uparrow & L^* \downarrow 0.25% [†]	-51	+1.6
A.S. \uparrow & Learning	+21	-1.6

Notes: This table shows the loss for future patients of senior residents given that their training in their first year was disrupted. I assume they enter their second year with half of the knowledge they otherwise would have. In the status quo, the hospital does not adjust anything and behaves as depicted in Figure 7. The other entries show the outcome if the hospital makes a one-time change in behavior as indicated. The outcomes are relative to the steady-state outcome and compare the total number of patients the physician can see after the graduate (extensive margin) and the extra time per patient seen (intensive margin). [†] The combination of increasing attending speed and decreasing care quality has a benefit not depicted in the table: although outcomes for the affected cohort are not as good as before, the hospital over-trains the incoming cohort in anticipation of the higher steady-state given by the increase in attending skill. See text and notes to Table 6 for more details.

This counterfactual shows that a disruption in training for residents has large effects on future patients that the teaching hospital may not internalize. But as in the first counterfactual, there exist straightforward remedies, and in this case they only need to be enacted temporarily. If the hospital is willing to temporarily reduce throughput, then a reduction of just 0.5%, or approximately two minutes, is sufficient for these residents to “catch up.” If that is not acceptable, a small increase in attending speed of just 2.5% makes up 88% of the difference in training compared to the steady-state. In the event of future disruptions, both local and national, policymakers should consider stepping in to ensure that resident education does not suffer.

9 Discussion and Conclusion

Especially when profit maximization is not the primary goal, how multi-product nonprofit firms adjust the production of their products due to changes in revenue from one product is ambiguous. I study nonprofit teaching hospitals, which have the dual role of providing health services and training the next generation of physicians. Because the teaching component in this environment requires learning by doing, the hospital faces a trade-off between care quality and teaching. I study how the hospital allocates complex patients to residents and attendings to make this trade-off. I find that short-run increases in quality achieved with reducing training are dwarfed by long-run quality decreases because residents see many patients over the rest of their career. Policies that use revenue to incentivize quality improvements to current patients such as value-based care and prospective payment systems are an increasingly popular tool among both public and private insurers (Sokol, 2020). I show that when designing such policies, policymakers should be aware of potential unintended reductions in teaching: in response to the decrease in revenue, academic hospitals may reduce teaching and the resulting reductions in physician skill may result in costs for future patients orders of magnitude larger than the savings for current patients.

I examine and quantify these trade-offs in the emergency department of a large, urban teaching hospital. I first investigate at a granular level the costs of training and find that despite substantial increases in independence and the ability to manage additional patients simultaneously, there are no differences in patient outcomes or costly resource utilization. I find notable differences in patient throughput, but only for complex patients who are predicted to require inpatient admission: the median fourth-year is able to arrive at a disposition decision and complete these patients 9.4 % faster than the median first-year. The improvement in length of stay means that the hospital trades off patient throughput today with patient throughput tomorrow. To quantify this trade-off, I develop and estimate a dynamic model of training and find that the hospital acts as if it maximizes training conditional on a minimum average patient throughput level in each quarter. In counterfactuals, I find that if hospital administrators increase throughput by 2%, the required reduction in training will result in lower future throughput losses 17 times larger than the current gains. However, there exist simple and feasible changes that can reduce the externality. For instance, I find that a 5% increase in attending speed would mitigate the training reduction and reduce the future costs by 81%.

Even though my focus is on the emergency department of a single, top-ranked teaching hospital, there are key lessons for the broader healthcare sector. First, the link between throughput and revenue applies to all departments. Second, time is essential for teaching: Ludmerer writes, “Time was the irreducible element of good medical education, whatever clinical setting happened to be used.” Third, speed is an important quality measure across medical care, even in non-urgent situations. For instance, in the surgical context, it has been shown that longer operative time is associated with increased odds of complications (Jackson, et al., 2011). Next, although there may be some variation in care correlated with teaching hospital rankings, prior work has shown that the basic production function of health services does not differ in outcomes with respect to residency program prestige (Doyle, et al., 2010).

CMS is aware of the increased costs faced by teaching hospitals. The Medicare Prospective Payment System (PPS) includes a bonus paid to academic hospitals, known as the Indirect Medical Education Payment (IME). Although my findings show that patient throughput costs may be significant, they should not be used as the sole basis for determining the size of these payments. I believe that a large part of the reason that patient outcomes and resource utilization do not change with experience is due to the success of attending supervision. Staffing high-quality attendings can be very expensive, especially when they are

also spending significant time engaged in research, and the IME Payments should account for this cost. My hypothesis is supported by the workflow, in which attendings and residents confer to determine the plan of care for each patient, as well as the empirical results, which show that resident independence increases most notably and significantly in the first hour of the patient's encounter. Further research exploring the ways in which variation in supervision affects both patient outcomes and teaching quality could be valuable in improving both care quality and training outcomes. After all, and the degree to which policy can improve patient outcomes and reduce costs is reliant on improvements in physician habits and practice, much of which is taught and absorbed during residency ([Ludmerer, 2015](#)).

Finally, while teaching hospitals are a single example of a specialized organization, they constitute an outsize share of both the economy and individual utility. The United States spent 17.8% of GDP on healthcare in 2021, and in 2019, teaching hospitals contributed 45% to Health Care and Social Assistance GDP.²⁸ Preserving life and increasing the quality of life, the main functions of hospitals, are arguably the most important components of individual utility, well-being, and happiness, and the continued production of high-quality health services requires continued investment in teaching. That said, the model and empirical strategy can be applied to related settings as many nonprofit institutions are in essence multi-product firms. Most notably, this group includes research universities, which through their research are principal drivers of innovation in the modern economy ([Lerner, et al., 2023](#)) yet are also responsible for educating undergraduate, professional, and graduate students. Studying how they make this trade-off and respond to changes in government funding could be a fruitful area for future research.

²⁸[Gunja, et al. \(2023\)](#) and the author's calculations using statistics from the [BEA](#) and [AAMC](#)

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A Prediction of Inpatient Admission

In this section I provide a brief overview of the ex-ante prediction of inpatient admission. The key feature of this prediction is that only factors that are immutable (e.g. patient age) and determined prior to the physician's involvement (e.g. abnormal vital signs upon entry; chief complaint as recorded by the triage nurse) are included in the prediction. Therefore, it is by construction exogenous to the providers who will subsequently care for the patient.

I use LASSO to select among the large set of ex-ante and immutable patient covariates, with a logit functional form because inpatient admission is a binary outcome. The predictions fit observed patterns of inpatient admission well: the area under the receiver operating characteristic curve (AUC) is around 0.97. One way to interpret AUC is that it is the probability that the model ranks a random positive example more highly than a random negative example. The maximum value is 1, so a value of 0.97 indicates that the model is very successful at predicting the observed outcome.

Similar results are obtained whether the functional form is a linear probability model or a probit.

B Alternative Hospital Objective Function

An alternative flow utility function I consider is where the hospital maximizes a weighted sum of patient care quality and resident training.

$$\max_S \sum_{t=0}^{\infty} \beta^t [\phi L(S_t; X_t) + (1 - \phi)K(S_t; X_t, q(t)) + \varepsilon_{S_t}] \quad (9)$$

L is the hospital's utility from length of stay (care quality). This is a function of the allocation of patients S_t and the state variable of resident knowledge X_t . K is the hospital's utility from training ("knowledge"), which depends on the allocation of patients S_t , the state variable X_t , and the result of a function q that maps time t to quarter of the academic year. I write K in this manner in order for it to depend on the quarter. The weight on care quality ϕ is to be estimated.

It turns out that the weighted average specification of Equation (9) actually does not result in a stable steady state of training. Instead, the steady-state utility-maximizing patient allocation is a two-year cycle where every other cohort is trained. The result holds for all chosen values of the discount rate, as well as all three concavities of utility from length of stay and making the utility from learning more concave than the utility from patient care. This is because for each cohort, training today and training tomorrow are intertemporal complements. A larger amount of training today means that the cost of training tomorrow is decreased because the residents have higher skill. The presence of attending physicians amplifies this feature: instead of distributing training among the two cohorts, it is better to focus it on one cohort and give the remaining patients to the attending to maximize patient utility.

To build intuition for this result, consider a model where there is only one period per academic year. In the first year, if the senior cohort received training in year zero, then it is cheaper to train them further than to train the new cohort, and it is better for patient outcomes if the hospital allocates patients only between the senior cohort and the attendings. In the second year, the senior residents have zero skill because they received no training when they were junior residents. The hospital chooses to ignore them, trains only the new cohort, and gives the remaining patients to the attendings to maximize the patient utility

portion of utility. Then, in year three, it trains the senior cohort, because it has already trained them in the previous year, and again ignores the new cohort. Consequently, every other year, both training utility and patient utility are high and we have a two-year cycle.

C Additional Tables

Table A1: Learning Over Time: Immediate Orders Upon ED Admission

	First Order Upon Admission					
Years in Program	0.010** (0.005)	0.010*** (0.004)	0.013 (0.010)	0.011 (0.008)	0.008 (0.005)	0.011** (0.004)
log(Days in Program)	0.006 (0.005)	0.006 (0.004)	0.014 (0.011)	0.008 (0.008)	0.002 (0.005)	0.005 (0.004)
DepVar Mean	0.138		0.162		0.128	
ED Disposition	All Patients		Complex		Simple	
Controls	X		X		X	
Obs	31,628	31,565	8,877	8,853	22,751	22,712

Notes: Separate regressions of a binary indicator for first medical order upon admission to the ED on measures of resident experience, split by ex-ante predicted patient complexity. This process measure is a complement to the log(Minutes to First Order) outcome in Table 3, which is undefined when orders are immediate. The dependent variable is equal to one if the first medical order is signed at or before the patient is moved from the waiting room to an examination room and zero otherwise. Standard errors are clustered by physician. See text and corresponding Table Notes for additional details.

Table A2: Learning Over Time: Diagnostic Orders

	Any Diagnostic Order						log(Diagnostic Orders)					
Days in Program	-0.001 (0.003)	-0.000 (0.003)	-0.001 (0.002)	-0.001 (0.002)	-0.002 (0.004)	0.002 (0.004)	0.012 (0.014)	0.014 (0.010)	-0.021 (0.016)	-0.014 (0.014)	0.014 (0.016)	0.034*** (0.012)
log(Days in Program)	0.005 (0.004)	0.004 (0.003)	-0.001 (0.002)	-0.001 (0.002)	0.006 (0.006)	0.007 (0.004)	0.023* (0.013)	0.010 (0.011)	-0.030** (0.014)	-0.032** (0.015)	0.024 (0.016)	0.032** (0.013)
DepVar Mean	0.939		0.993		0.918		12.067		19.655		9.103	
ED Disposition	All Patients		Complex		Simple		All Patients		Complex		Simple	
Controls	X		X		X		X		X		X	
Obs	31,793	31,730	8,930	8,906	22,863	22,824	29,859	29,798	8,871	8,847	20,988	20,951

Notes: This table presents regressions of outcomes related to diagnostic orders signed on two parameterizations of resident experience, split by ex-ante predicted patient complexity. It is similar to Table 3. Dependent variable means are listed, always in levels. Diagnostic Orders are medical orders primarily for gathering information about the patient, such as lab tests and imaging, rather than for treating or stabilizing the patient. Any Diagnostic Order Signed is a binary variable equal to one if at least one diagnostic order was signed and zero otherwise. log(Diagnostic Orders Signed) is the natural logarithm of the number of diagnostic orders signed and is undefined when zero orders are signed (for instance, if the patient required stitches but did not receive an X-Ray prior to the procedure). Standard errors are clustered by physician. See text and notes to Table 3 for additional details.

Table A3: When does Supervision Occur and Change for Complex Patients?

	Fraction Orders Signed by Resident			
Experience (Years)	0.047*** (0.008)	0.008 (0.011)	0.010 (0.009)	-0.000 (0.006)
Period	1st Hour	2nd Hour	Middle	Last Hour
DepVar Mean	0.430	0.505	0.451	0.176
Num Orders	11.8	4.1	11.1	4.3
Obs	9,196	8,632	7,648	9,196

Notes: Regressions of the fraction of orders signed by the resident during various portions of the patient's stay in the ED on the number of fractional years in the program. If the patient stay is less than or equal to two hours, the second hour is counted only as part of the Last Hour. "Middle" includes all hours after hour three and prior to the last hour before inpatient upgrade (for admitted patients) or discharge (for discharged patients). The dependent variable mean is listed, as is the mean number of orders signed during the period. Most of the change occurs in the first hour, which is also when the bulk of the orders are signed. I select a similar set of patient covariates as in the binned scatterplots of Figure 3, but additionally include the number of simultaneous patients managed by the resident and its square. Standard errors are clustered by physician.

Table A4: Allocation of Complex Patients: Congestion

	Patient Assigned to 1st Year Resident			
# Complex Pt in ED	0.976 (0.017)	0.972 (0.018)	0.973 (0.018)	0.973 (0.018)
# Pt in Waiting Room	0.986 (0.011)	0.971*** (0.010)	0.970*** (0.010)	0.969*** (0.010)
Likely Handoff				0.421** (0.149)
# other EM1 FE	Y	Y	Y	Y
Month FE		Y	Y	Y
Patient Condition FE			Y	Y
Other Controls				Y
Obs	6,903	6,903	6,896	6,896

Notes: Odds ratios reported. Going from the 25th to 75th percentile of patients in the waiting room lowers the probability of assignment to a first year resident by 15 percentage points. # of other EM1 FE are fixed effects for the number of other first year residents on shift at the time of patient allocation: clearly it is more likely to assign a patient to a first year resident when there are more of them working. Not shown are the coefficients for patient condition fixed effects, which include interactions between ex-ante triage nurse estimated severity and chief complaint. Standard errors are clustered by physician.

Table A5: Impact of Excess Patients on Outcomes and Process Measures

	Readmissions	log(LoS)	Any Dx Order	log(Dx Orders)	Frac Orders
EM1 or EM2	-0.017 (0.019)	0.094*** (0.028)	0.007 (0.008)	0.054* (0.031)	-0.174** (0.067)
Excess Pt	-0.025 (0.018)	-0.153*** (0.024)	-0.003 (0.007)	-0.041 (0.033)	-0.055 (0.062)
EM1 or EM2 X Excess Pt	0.017 (0.023)	0.008 (0.039)	0.004 (0.012)	-0.019 (0.042)	0.129 (0.080)
Obs	4,306	8,245	8,127	7,784	8,121

Notes: The coefficients of interest are the coefficients on “Excess Patients” and the interaction “EM1 or EM2 X Excess Patients.” Excess patients is an indicator variable equal to one when the resident is currently managing three or more patients with high values of the triage nurse assigned emergency severity index. This is the 75th percentile of simultaneous patients. EM1 or EM2 is a binary variable equal to one if the resident is in their first two years of the program. All regressions include resident fixed effects and controls for overall ED congestion, ex-ante and immutable patient characteristics, and business hour and weekend fixed effects. Standard errors are clustered by physician.

Table A6: Dynamic Results: Full Estimates

Specification	β	L^*	RMSE	L^* Implied Hrs	Graduating Skill (Hrs)
Linear	0.90	-1.335	.0101	5.339	5.112
	0.95	-1.335	.0095	5.338	5.116
	0.99	-1.332	.0092	5.330	5.113
Quadratic	0.90	-7.144	.0095	5.346	5.112
	0.95	-7.144	.0087	5.346	5.112
	0.99	-7.139	.0091	5.344	5.112
Log	0.90	0.149	.0110	5.363	5.103
	0.95	0.149	.0096	5.361	5.116
	0.99	0.149	.0102	5.362	5.108

Notes: This table shows the full estimation results for the three functional forms of hospital utility for patient length of stay and three values of the discount rate β . The first two columns show the estimated lower bound of patient quality L^* in utils, as well as the model’s root mean squared error compared to the observed patient assignment shares. L^* implied hours converts the utils to hours, and I also show the graduating skill of the resident, also in hours per patient. There is not much of a difference between specifications.

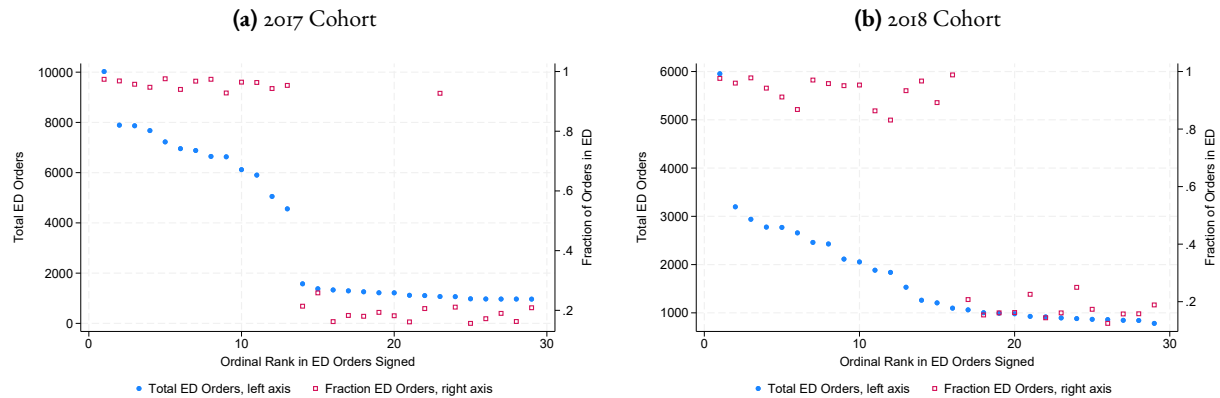
Table A7: Distribution of Average Number of Complex Patients Per Shift, by Quarter

Academic Quarter	Mean Pt/Shift	SD Pt/Shift
1	1.573	.717
2	1.587	.775
3	1.659	.658
4	1.736	.790

Notes: This table shows the mean and standard deviation for the number of complex patients seen per shift by residents during each academic quarter. The mean increases, as expected (see 2), but the standard deviation is relatively stable. The stability in the standard deviation suggests that patient allocation patterns are not mean-reverting in the sense that it is likely that allocation patterns are similar in the hospital where I do not have data from. If they were, then I would expect a lower standard deviation in later academic quarters, where due to the law of large numbers, variation in patients seen due to exogenous factors such as ED congestion should be more similar across residents.

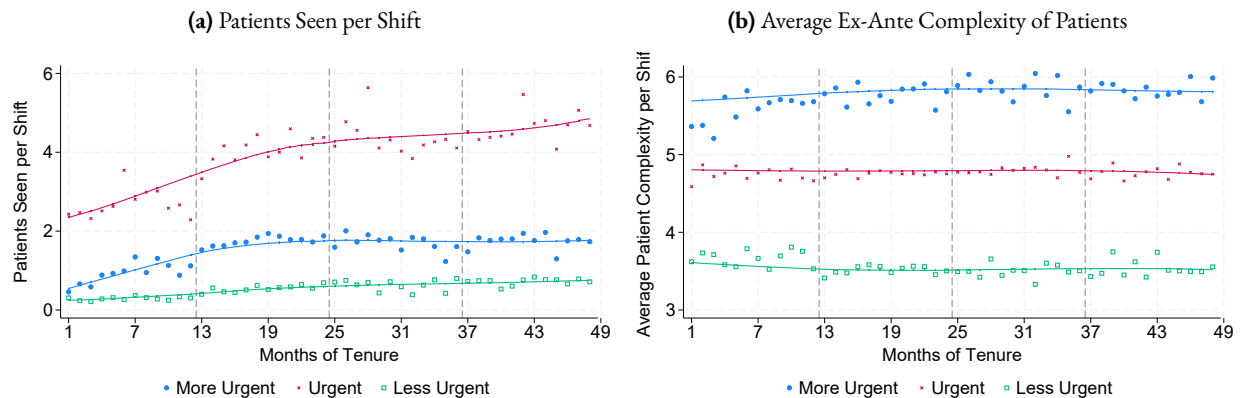
D Additional Figures

Figure A1: Identifying EM Residents Based on Orders Signed



Notes: These figures illustrate the discontinuity in total orders signed in the ED and fraction of orders signed in the ED for residents belonging to two cohorts. Residents are ordered based on the number of ED orders signed, and for each resident both the total number of orders (blue circles) and fraction of orders (hollow red squares) signed in the ED are plotted. Each vertical pair of markers represents one individual resident. Panel (a) shows the relationship for the 2017 cohort, whereas Panel (b) shows the relationship for the 2018 cohort. See text for additional details.

Figure A2: Patients Seen Per Shift



Notes: Panel (a) shows the number of patients seen per shift split by three groups of ex-ante severity, as assigned by the triage nurse upon patient arrival. The blue circles represent the most urgent patients, and comprise about 20% of all arriving patients. We see growth in these complex patients during the first year that levels off after residents enter their second year. The red X's represent the middle category of urgency, which comprise about 60% of all patients, and growth continues throughout the program. The hollow green squares represent the least urgent patients, who comprise the remaining 20% of patients. Growth in these patients is minimal. Panel (b) shows the average predicted ex-ante complexity of patients assigned to residents in the same categories. The complexity measure corresponds to variation in patient severity within ESI category and can be thought of as the “intensive margin” of complexity assignment to residents. “Complexity” is a prediction of patient severity based on ex-ante and immutable patient covariates developed in [Chu, et al. \(2023\)](#). This figure shows that with the exception of residents in the first six months of the program getting slightly simpler patients in the highest complexity category, averages are stable across experience. This means that residents are not assigned less complex patients as they increase the number of patients they see simultaneously with experience.

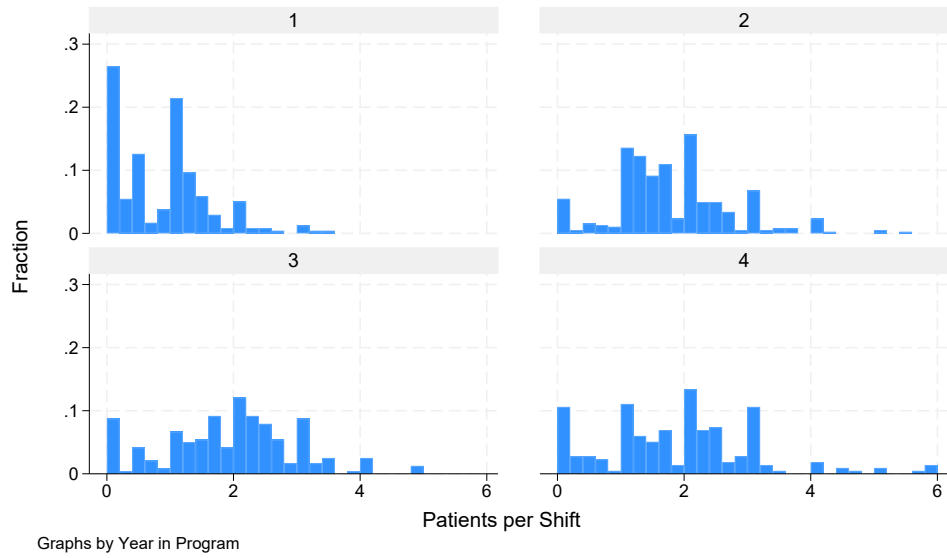
Figure A3: Average Fraction of Complex Patients Seen, by Role in Each Calendar Quarter



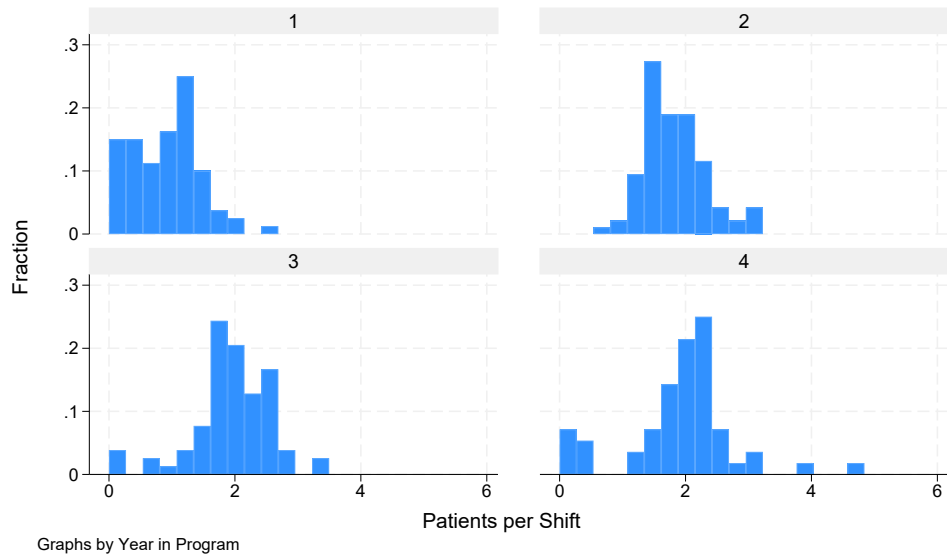
Notes: This figure shows the average fraction of complex patients seen by role for each calendar quarter. The figure shows that the shares are relatively stable across academic years, delineated by the vertical dashed lines, providing evidence supporting the assumption that in the steady-state, the hospital trains the same amount each academic year. See text and notes to Figure 4 for more details.

Figure A4: Cross-Sectional Variation in Average Complex Patients Seen per Shift

(a) Two-Week Averages

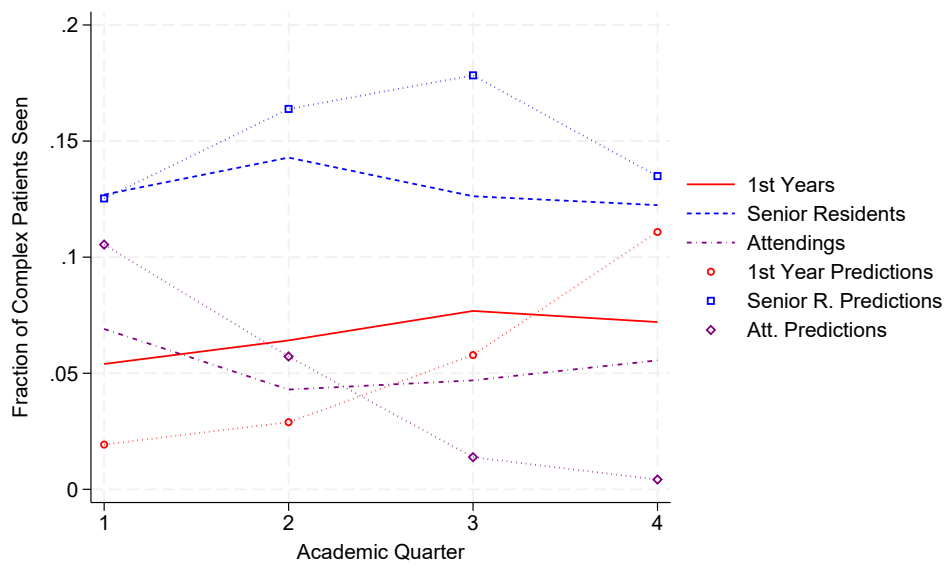


(b) Quarterly Averages



Notes: This figure shows the average number of patients per shift over two different periods of aggregation. Panel (a) shows this over two-week periods, while Panel (b) shows this over calendar quarters. Each observation is a resident-period and variation is shown separately by the resident's year in the program.

Figure A5: Model Fit by Quarter



Notes: This figure plots the actual allocation of complex patients with the model predicted allocation. The scale is different than in Figure 4 and Appendix Figure A3 because I have normalized each quarter to have a mass of 0.25 patients. The data are represented by the heavier lines without markers, and the model predictions are the lighter lines with markers on each quarter. The model fits the qualitative patterns well but the gradient on patients allocated to first year residents and attendings is steeper than in the data. See text for additional details.