

The Impact of Batching Advanced Imaging Tests in Emergency Departments

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Using detailed electronic health record data from two major U.S. emergency departments (EDs), we use practice variation across physicians to uncover the operational impact of discretionary batch ordering of imaging tests. We find that quasi-random assignment of a patient to an ED physician who is a “batcher” (top decile) versus a “sequencer” (bottom decile) causally increases the patient’s length of stay, time to disposition, and the number of imaging tests endured. Instrumental variable results show that discretionary batching increases length of stay by approximately 65%, increases imaging tests by 88%, and has no effect on 72-hour returns. We find evidence that the impact of batching on length of stay is heavily mediated by additional imaging tests performed and the probability of admission to the hospital post-ED service. Results suggests this ordering strategy may lead to clinical decision-making that introduces bottlenecks in patient flow. Conversely, standard practice, which preserves diagnostic flexibility by allowing information from initial tests to guide subsequent decisions, poses an “information gain” advantage compared to batch ordering: the information obtained from a prior test allows for eliminating the need for ordering some future tests. Put together, our findings indicate that discretionary batch ordering is not an efficient strategy for managing diagnostic imaging in emergency care, and interventions to reduce unnecessary batching may improve both operational performance and resource utilization. blind: false

Key words: Emergency Department operations; Diagnostic imaging; Batch ordering; Physician practice patterns; Patient outcomes; Health care efficiency

1. Introduction

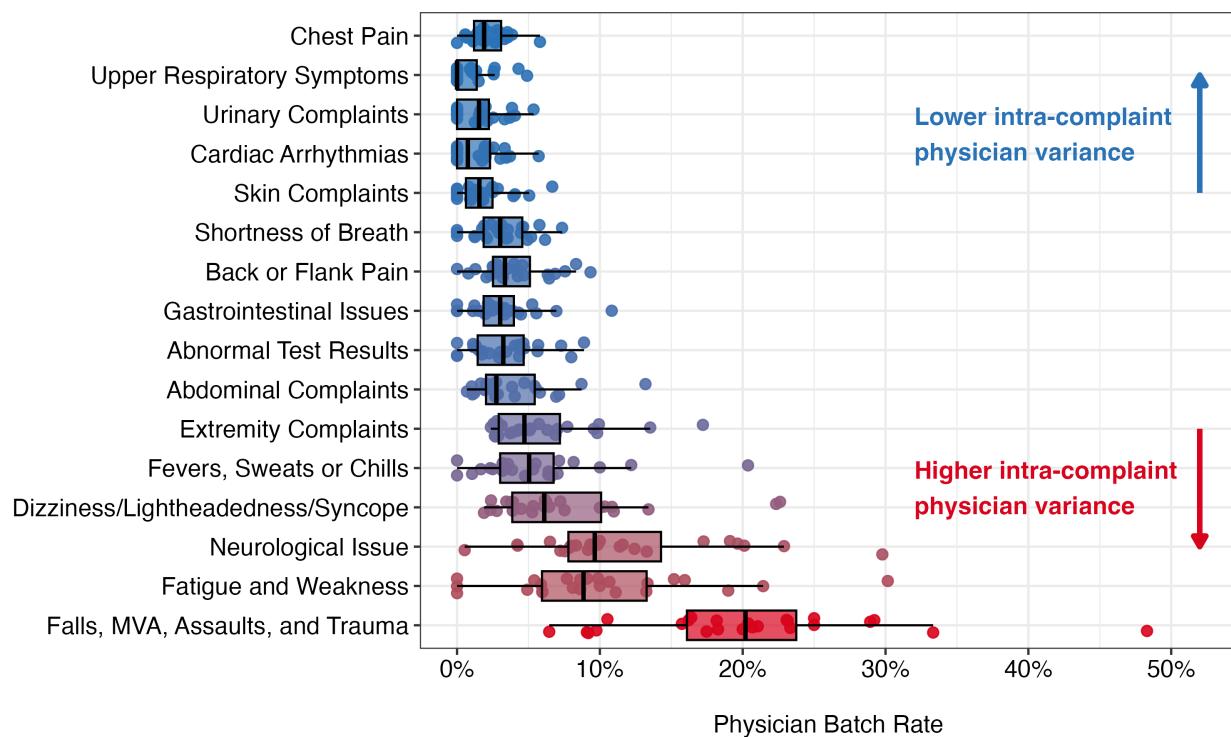
Advanced imaging is simultaneously an emergency department’s (ED) most powerful diagnostic tool and one of its most significant operational bottlenecks (Rogg et al. 2017). Advanced diagnostic imaging has risen dramatically over the past two decades, transforming from a limited resource to

a cornerstone of emergency care (Juliusson et al. 2019, Smith-Bindman et al. (2019)). However, this transformation has intensified operational challenges in EDs, where the complexity stems from multiple modifiable and non-modifiable constraints: limited equipment availability, complex scheduling requirements across different modalities, extended wait times for both image acquisition and interpretation, and growing backlogs in radiologist reading queues. Because of this, diagnostic imaging represents one of the most resource-intensive and operationally complex components of ED care (Mills et al. 2015, Balloescu (2018), Poyiadji et al. (2023)).

Diagnostic imaging is not without consequences for patients. Imaging bottlenecks can significantly impact ED length of stay (LOS) (Cournane et al. 2016), and undergoing advanced imaging may expose patients to higher costs, increased radiation exposure, increased incidental findings that may lead to unnecessary follow-up testing, contrast-induced nephropathy, and contrast-induced allergic reactions (Valtchinov et al. 2019, Raja et al. (2014)). Given these risks and resource constraints, efficient diagnostic testing management is critical for patient outcomes and ED operations (Balogh et al. 2015). Physicians have considerable discretion over how they order these tests, and wide variation in diagnostic test ordering behavior has been well documented (Miller 1994, Solomon et al. (1998), Wennberg (1984), Daniels and Schroeder (1977)). However, little is known about how to manage test ordering strategies when this discretion exists.

We consider an ED physician's decision to order imaging tests for their patient as an optimization problem, where the physician must balance the tradeoffs between the advantages of ordering multiple tests simultaneously (batch) at the start of the patient encounter (e.g., expediting the diagnostic process if the tests are eventually necessary for diagnosis and disposition) and its disadvantages (e.g., increasing the total time spent in the ED because of unnecessary tests) (Tamburrano et al. 2020, Perotte et al. (2018), Lyu et al. (2017), Traub et al. (2018)).

Batch ordering stands in contrast to the more standard practice of physicians sequentially ordering one test at a time, reviewing the results, and then deciding whether to order additional tests based on the information obtained from the previous test. While this standard practice may serve as a natural filter to prevent unnecessary testing, it can also result in longer delays than batching when multiple tests are ultimately needed. This tension between potential efficiency gains and the risk of unnecessary testing is significant, given growing concerns about imaging overutilization in emergency care (Balloescu 2018, Mills et al. (2015)). Beyond avoiding delays, the decision to batch should also be made with consideration of immediate operational implications and broader quality-of-care considerations (Feizi et al. 2023). This decision is inherently complex, requiring physicians to weigh time-sensitive diagnostic needs against resource constraints and the risk of ordering tests that may prove unnecessary once earlier results become available.

Figure 1 Physician Variation in Batch Ordering Imaging Tests

Notes: This figure highlights the marked differences among Mayo Clinic ED physicians in their propensity to batch order imaging tests. Batch rates are crude rates calculated by dividing the number of patient encounters where the physician batch ordered imaging tests for a complaint by the number of patient encounters they had with that complaint.

This paper explores the causal effects of batch ordering advanced imaging tests on operational performance and patient outcomes in the ED. Specifically, we focus on batch orders that include multiple types of imaging tests that cannot be run in a single scanning session. Using data from two leading US hospitals—Mayo Clinic and Massachusetts General Hospital—we first provide evidence of significant variation in emergency physicians’ batching behavior. Batching varies significantly among physicians working in the same ED, treating patients with the same complaint and severity (Figure ??). By making use of this variation, we next investigate whether being seen by a “batcher” or a “sequencer” physician has implications in terms of performance metrics such as length of stay (LOS), number of imaging studies, 72-hr rate of return, and disposition decision (being admitted to the hospital or discharged home post ED service). Finally, we shed light on circumstances in which physicians are more likely to batch-order imaging tests.

1.1. Challenges and Empirical Strategy

While the importance of understanding batching behavior in EDs is evident, generating causal evidence of its effects on patient outcomes presents several empirical challenges. First, physicians' decisions to batch order tests are endogenous. For example, the choice to batch may be correlated with unobservable patient characteristics, physician workload, or ED conditions that independently affect outcomes. Second, studying the timing and sequencing of diagnostic testing requires granular operational data that captures precise timestamps of test orders, completions, and clinical decisions, many of which are not tracked in traditional claims databases. Third, while prior studies have leveraged quasi-random patient assignment in EDs (Eichmeyer and Zhang 2022, Gowrisankaran et al. (2022), Coussens and Ly (2024)), establishing true quasi-randomization requires a detailed understanding of institutional assignment mechanisms that may vary across settings. Thus, providing causal claims that can be generalized beyond a single ED is not straightforward.

Our study addresses these challenges through several unique features. First, we utilize detailed electronic health record data from two leading U.S. hospitals (Mayo Clinic and Massachusetts General Hospital (MGH)) that capture the complete temporal sequence of clinical decisions, including exact timestamps of test orders, results availability, and disposition decisions (Table 1). This granularity allows us to precisely measure batch ordering behavior and its downstream effects on patient flow. Second, our primary analysis leverages Mayo Clinic's rotational patient assignment system, which verifies that patients are randomly assigned to physicians via a round-robin algorithm that does not consider patient characteristics or physician workload (Traub et al. 2016b, Traub et al. (2016a)). We use this random assignment at the Mayo Clinic to gain deeper insights into the causal impacts of being seen by a "batcher." We then validate our findings using data from MGH, which employs a wholly different and non-random patient-to-physician assignment. We do so by creating suitable controls that enable us to construct a quasi-random assignment mechanism and to investigate the validity of our main findings across two different study sites.

Our empirical strategy closely follows the literature that relies on the quasi-random assignment of agents to cases, often referred to as the "judges design." (Dahl et al. 2014a, Dobbie et al. (2018)). Studies in this literature typically exploit variation in judges' sentencing leniency within the same court. Similarly, we exploit variation in batching across physicians working in the same ED through a measure we define as "batch tendency." In its reduced form, under the assumption of random or quasi-random assignment, this approach allows us to identify the causal effect of being assigned to different types of physicians (i.e., batcher or sequencer). Under additional assumptions, an instrumental variable (as we will define it) allows us to estimate the causal effect of the decision to batch on various measures of ED performance.

Table 1 Descriptive Statistics of Emergency Department Encounters

Variable	Mayo Clinic (Median [IQR]) n = 48,854	MGH (Median [IQR]) n = 111,710
Patients encounters ^a		
<i>Panel A. Patient Severity</i>		
Tachycardic	19.2%	21.3%
Tachypneic	8.8%	5.4%
Febrile	2.2%	1.5%
Hypotensive	1.4%	1.0%
Emergency Severity Index	2.8 [2, 3]	2.8 [2, 3]
<i>Panel B. Patient Demographics</i>		
Male	46.5%	51.3%
Race: White	88.4%	61.3%
Race: Black	4.2%	12.3%
Race: Asian	3.05%	4.89%
Arrival age	57.7 [43, 74]	49.6 [32, 65]
<i>Panel C. Diagnostic Tests and Outcomes</i>		
X-ray performed	43.3%	40.1%
Ultrasound performed	11.3%	18.3%
Non-contrast CT performed	35.5%	30.5%
Contrast CT performed	17.7%	13.0%
MRI performed ^b	—	6.3%
Labs ordered	73.7%	84.9%
Time from arrival to triage (mins)	8.0 [4, 10]	12.2 [3, 13]
LOS (min)	246 [152, 306]	426 [241, 1006]
Time to disposition (min)	246 [152, 306]	426 [241, 1006]
Treatment Time (min)	246 [152, 306]	426 [241, 1006]
Patient discharged	66.8%	65.1%
Patient admitted	18.7%	22.8%
Patients revisited within 72 hours	3.8%	3.1%
Order to result ^c : X-Ray (mins)	67.2 [36, 79]	63.4 [31.4, 111.7]
Order to result: Ultrasound (mins)	165 [71, 150]	119 [71, 213]
Order to result: Contrast CT (mins)	142 [86, 153]	167.3 [112.0, 260.6]
Order to result: Non-Contrast CT (mins)	89.7 [50, 102]	185.3 [116.0, 290.2]
Order to result: MRI (mins)	—	374.7 [229.5, 683.7]

Notes: This table reports summary statistics for emergency department visits during the study period. Values are presented as mean (IQR) when available. Vital signs were categorized as follows: tachycardia (pulse more significant than 100), tachypnea (respiratory rate greater than 20), fever (temperature greater than 38°C), and hypotension (systolic blood pressure less than 90). ^aThe number of patient encounters is calculated as the number of unique patient visits during the study period. ^bMRI data is only available for MGH. ^cOrder to result times are calculated as the difference between the time the test was ordered and the time the result was available in the electronic health record. This does not account for the time it takes for the radiologist to review the results.

Our instrumental variables approach provides a local average treatment effect (LATE) for batch ordering, the effect of batch ordering on the subset of patients whose batching decision depends on which physician they are randomly assigned to. This is particularly important in the context of the ED, where there are clear cases where batch ordering is necessary (e.g., when multiple tests are essential and almost every physician would batch) and cases where it is not (e.g., when one or no tests are needed and virtually no physician would batch). By estimating the effect for marginal patients whose batching decisions depend on the provider, we gain deeper insights into the critical implications of batch ordering driven by physician discretion.

1.2. Main Findings and Contributions

Whether batch ordering improves or hinders ED efficiency is an active debate among emergency physicians. Proponents argue that initiating multiple diagnostic processes simultaneously reduces total processing time when multiple tests are ultimately needed; skeptics contend that this approach foregoes the information value of sequential results and leads to unnecessary testing. Our results provide causal evidence that, at least for discretionary decisions at the margin of physician judgment, batch ordering negatively impacts operational metrics. In particular, our results show that the marginal batched patient experiences a 65% increase in total ED LOS and a 69% increase in time to disposition compared to patients managed through standard practice. Furthermore, discretionary batch ordering leads to 1.2 additional imaging tests per patient encounter (an 88% increase) and a 40 percentage point increase in admission probability. These effects remain robust even after adjusting for patient and physician characteristics, laboratory testing intensity, and ED capacity. Through mediation analysis, we find that increased testing volume is a key driver of the higher LOS caused by discretionary batch ordering. We find evidence that this effect is further mediated by the higher likelihood of admission, which can increase LOS through boarding time.

Examining the drivers of batch ordering, we find that physicians are more likely to batch-order tests earlier in their shifts and for patients with higher acuity and more complex chief complaints. This batching tendency, however, varies systematically across physicians and persists even after controlling for patient mix, ED conditions, and observable physician characteristics. Finally, we observe that batching rates decline modestly during periods of major overcapacity (12.4% vs. 14.8% during normal operations), suggesting physicians may become more selective in their batching decisions under resource constraints.

Our results indicate that, despite the perceived workflow advantages of initiating multiple diagnostic processes simultaneously, batch ordering results in significantly longer processing times and increased resource utilization without corresponding improvements in patient outcomes. We validate these findings through heterogeneity analyses across seven high-batching chief complaint

categories, finding consistent patterns — increased imaging without efficiency gains or quality improvements — across all clinical scenarios. These findings have important implications, highlighting that ED managers should consider strategies to reduce discretionary batching to improve diagnostic testing workflows. We shed light on these strategies and provide actionable insights on how ED managers can achieve them.

2. Related Literature

In EDs, physicians face a fundamental choice in how they sequence diagnostic imaging tests: they can order multiple tests simultaneously (“batch ordering”) or order them sequentially as information accumulates. Batch ordering occurs when a physician orders a comprehensive set of diagnostic tests at the start of a patient encounter, typically covering a broad range of potential diagnoses. This contrasts with standard practice, where tests are ordered one at a time, with each subsequent test decision informed by prior test results.

2.1. Physician Decision-Making Under Constraints:

ED physicians operate under significant time pressure and heavy workload, which substantially influences their decision-making. Workload management and carefully balancing the tradeoffs between speed and quality of care are of high importance for physicians making decisions in a complex environment, such as the ED (Saghafian et al. 2018, Leppink and Hanham (2019)), and these decisions lead to multiple documented effects on physician performance. For instance, physicians may resort to ordering additional diagnostic tests when faced with limited patient interaction time, a practice that requires less immediate critical thinking than direct clinical assessment (Batt and Terwiesch 2016, Pines (2009)).

Moreover, increased stress and frequent interruptions can disrupt systematic decision-making and impair complex diagnostic reasoning (Chisholm et al. 2000, Bendoly (2011)). Frequent task switching to manage multiple simultaneous demands can exacerbate cognitive strain and decision fatigue, prompting physicians to batch diagnostic tests and defer intricate diagnostic decisions until comprehensive results are available (KC 2013, Skaugset et al. (2016), Berry Jaeker and Tucker (2020)). By ordering multiple tests upfront, physicians can defer complex diagnostic reasoning until all results are available, potentially reducing the cognitive strain of repeated task-switching and decision-making under uncertainty. A cognitive load theory of batching suggests that batching is more prevalent during periods of high workload or complexity.

Significant variation in ED physician testing and admitting practices has also been documented (Hodgson et al. 2018, Coussens and Ly (2024), Smulowitz et al. (2021)). This variation also extends to batch ordering, where physicians differ systematically in their propensity to order multiple imaging tests simultaneously (Jameson et al. 2024). However, understanding the drivers and operational

impact of this variation remains a significant gap in the literature. Our study aims to fill this gap by examining the factors that drive batch ordering behavior and exploiting physician variation to identify the causal effects of batch ordering on ED operations and patient outcomes.

2.2. Discretionary Behavior and Task Scheduling in Healthcare Operations

Recent work has examined how operational factors influence physicians' discretionary behavior in test ordering, revealing that decisions about diagnostic intensity are shaped by multiple operational pressures (Soltani et al. 2022). Studies have found that test utilization varies with peer observation (Song et al. 2017), workload (Deo and Jain 2019), and the presence of justification requirements (Berry Jaeker and Tucker 2020). While additional tests can improve diagnostic accuracy, they also extend ED LOS and potentially exacerbate congestion (Chan 2018). This tension is particularly acute in imaging decisions, where test sequencing can significantly impact patient flow and resource utilization (Cournane et al. 2016).

The decision to batch order tests represents a specific form of discretionary task ordering that has received limited attention in healthcare operations. While prior work has examined discretionary task ordering in other contexts (Ibanez et al. 2018, Ibanez and Toffel (2020)), the unique constraints of ED imaging—including capacity limitations, varying processing times across modalities, and the inability to run different imaging types on a patient simultaneously—make these decisions particularly consequential. A growing literature examines how workers exercise discretion over task ordering to improve system performance (van Donselaar et al. 2010, Campbell and Frei (2011)) but also how such discretion can sometimes lead workers to “choose the wrong task operationally” (Boudreau et al. 2003).

The implications of batch ordering also connect to broader theoretical work on task scheduling in resource-constrained environments. While batching strategies often reduce setup times and improve throughput in manufacturing settings (Fowler and Mönch 2022), applying these principles to healthcare operations introduces unique complexities. While batching may streamline the diagnostic process by initiating multiple diagnostic processes simultaneously (Song et al. 2017), recent evidence suggests it may lead to increased testing volumes that could overwhelm imaging departments and extend wait times (Jessome 2020, Saghafian et al. (2015)). The information value of sequential testing —where results from initial tests inform the need for subsequent ones—creates a fundamental tension between operational and diagnostic efficiency that has not been well-studied. Our analysis provides novel evidence on this tradeoff, showing how different test ordering strategies affect operational metrics and clinical decision-making. Our study advances this literature by providing causal evidence on how physicians' test sequencing decisions affect ED performance. Furthermore, we identify specific mechanisms through which batch ordering affects operational performance, allowing us to distinguish between efficiency gains from parallel processing and potential losses from increased diagnostic intensity.

2.3. Hypothesis Development

Building on the literature reviewed above, we develop formal hypotheses about how batch ordering affects ED operations. While prior work has identified the mechanisms driving batching behavior and its potential consequences, the net effects remain an open empirical question. Our theoretical framework centers on the fundamental tradeoff between the perceived efficiency of parallel processing and the information value of sequential testing.

2.3.1. Information Value and Test Volume The decision to batch or sequence tests fundamentally involves whether to preserve the option value of information. Sequential testing allows each test result to inform subsequent decisions, potentially eliminating unnecessary tests. When physicians batch tests upfront, they commit to a diagnostic pathway before information unfolds, thereby forfeiting this option value.

Physicians under high workload face cognitive strain from task switching and may batch tests to defer complex diagnostic reasoning (KC 2013, Skaugset et al. (2016)). However, this cognitive convenience comes at a cost. Without the filtering mechanism of sequential information revelation, physicians must rely solely on their initial assessment. (Lam et al. 2020) identify this as a key driver of overtesting—when facing diagnostic uncertainty, physicians order comprehensive test batteries rather than allowing initial results to guide subsequent testing. Given the documented variation in physician testing intensity (Hodgson et al. 2018), with some physicians ordering twice as many tests as their peers, batching likely amplifies these tendencies by removing the natural stopping points that sequential results provide. Therefore:

Hypothesis 1. Batch ordering will increase the total number of imaging tests performed compared to standard practice due to the loss of information value from initial test results.

2.3.2. Processing Time and Operational Flow While batching strategies reduce setup times in manufacturing (Fowler and Mönch 2022), the ED imaging context presents unique operational constraints as noted in our review. Different imaging modalities require separate equipment and cannot be performed simultaneously (Jessome 2020). This creates a fundamental bottleneck: batched orders must still be executed sequentially, but with a larger committed workload that cannot be adjusted based on emerging information.

Moreover, the cognitive load literature suggests that processing multiple test results simultaneously increases decision complexity (KC 2013). When physicians receive multiple results at once rather than sequentially, they must integrate more information simultaneously, potentially lengthening the diagnostic reasoning process. This “information overload” effect, combined with the additional tests ordered as predicted in H1, suggests that batching may paradoxically increase rather than decrease processing times:

Hypothesis 2. *Batch ordering will increase patient length of stay and time to disposition compared to standard practice, as the operational constraints of imaging and increased test volume outweigh any potential benefits of parallel processing.*

2.3.3. Clinical Decision-Making and Disposition The medical literature documents “diagnostic momentum”—where abnormal findings, even if clinically insignificant, drive further workup and more conservative clinical decisions (Coen et al. 2022, Featherston et al. (2020)). When physicians batch order and receive multiple results simultaneously, they encounter more opportunities for incidental findings that may influence disposition decisions (Lumbreras et al. 2010, Berlin (2011)). As our review noted, physicians facing uncertainty and potential legal consequences may opt for more conservative disposition decisions (Rao and Levin 2012, Lam et al. (2020)). The simultaneous arrival of multiple test results, particularly with incidental findings, may trigger defensive medicine behaviors:

Hypothesis 3. Batch ordering will increase hospital admission rates through increased diagnostic intensity and the influence of incidental findings on clinical decision-making.

2.3.4. Contextual Moderators The literature on physician behavior under capacity constraints consistently shows that resource scarcity forces more selective decision-making (Kuntz et al. 2014, KC and Terwiesch (2009)). When EDs face severe overcrowding, the operational pressures documented in our review intensify. Under these conditions, physicians may reserve batching for cases where it is clinically essential rather than convenient:

Hypothesis 4. The effects of batch ordering on LOS and test volume will be attenuated under conditions of major ED overcapacity, as physicians become more selective in their batching decisions.

These hypotheses provide testable predictions that we examine using our quasi-experimental design. By leveraging variation in physicians’ batching tendencies under random patient assignment, we can determine whether these theoretical mechanisms manifest in actual ED operations.

3. Setting, Data, and Models

3.1. Empirical Setting

Our study uses data from two large U.S. emergency departments (EDs): the Mayo Clinic of Arizona and Massachusetts General Hospital (MGH). The MGH dataset, which includes 129,489 patient encounters from November 10, 2021, through December 10, 2022, provides a robust sample for validating the generalizability of our findings. However, our primary analysis focuses on the Mayo Clinic data due to its unique feature of random patient-physician assignment, which allows for stronger causal inference. More specifically, the Mayo Clinic ED employs a sophisticated computerized rotational patient assignment algorithm that addresses many of the empirical challenges previously identified (Traub et al. 2016a,b, 2018). The system automatically assigns patients to

physicians 60 seconds after registration through the electronic health record system, following a strict rotational protocol. At shift start, each physician receives four consecutive patients to establish an initial patient load, after which they enter rotation with other on-duty physicians. Critically, these assignments are based solely on arrival time—the algorithm does not consider patient demographics, chief complaint, Emergency Severity Index score, physician workload, or the acuity of recently assigned patients. To maintain system integrity, physicians receive no new patients during their final 120 minutes and are capped at 18 patients per shift. The rotation order follows a predetermined schedule that varies across shifts to ensure fairness over time.

This rotational mechanism achieves the quasi-randomization necessary for causal inference. Unlike settings where patient-physician matching may be influenced by triage decisions, physician preferences, or informal routing practices, the Mayo Clinic's algorithmic assignment removes discretion from the matching process. We establish that, conditional on arrival time, patient-physician matching is effectively random—a critical requirement for our identification strategy that distinguishes our study from observational analyses where endogenous matching could confound the effects of physician discretion.

The data contain information on the timing of test orders, test results, and patient disposition, among various other important triage metrics and demographic features. We focus on imaging tests (x-rays, contrast CT scans, non-contrast CT scans, and ultrasound) because, unlike laboratory tests, these tests cannot be run simultaneously on a given patient due to the different equipment and settings required. Therefore, the operational implications of batch ordering imaging tests are more pronounced. We exclude MRI from our Mayo analysis due to an institutional policy requiring either inpatient admission for urgent MRIs or outpatient ordering for non-urgent cases, resulting in negligible ED MRI usage. MGH does not have this policy, so we included MRI in their generalizability analysis.

3.2. Data

Our primary data comes from the Mayo Clinic of Arizona ED, a tertiary care hospital without obstetrical services, an inpatient pediatrics unit, or a trauma designation. During the study period (October 6, 2018, through December 31, 2019) the ED recorded 48,854 visits during the study period, managed across 26 treatment rooms and up to 9 hallway spaces. The department is exclusively staffed by board-eligible or board-certified emergency physicians (EPs), a rare but ideal setting for our study. Many EDs are staffed by a mix of EPs and non-EPs (e.g., Nurse Practitioners and Physician Assistants), both responsible for ordering tests, which may introduce confounding factors. The Mayo Clinic ED is unique in that only EPs can order tests, eliminating the potential for confounding by provider type. Furthermore, as mentioned earlier, the ED makes uses of a randomized patient to EP assignment, eliminating some other potential sources of confounding.

We conducted a retrospective review of the comprehensive ED operations data, coinciding with the initiation of a new electronic medical record. The data includes detailed patient demographics, chief complaints, vital signs, emergency severity index (ESI), LOS, timestamps, and resource utilization metrics. This period was chosen to provide a robust data set while excluding the influence of the coronavirus pandemic. The data is summarized in Table 1. Hourly patient arrival rates to the ED are shown in Appendix Figure A1. LOS is measured from the time of arrival to departure from the ED. During periods when inpatient beds are filled to capacity (i.e., when patients requiring inpatient admission must “board” in the ED due to lack of inpatient beds), the Mayo Clinic converts ED beds into temporary inpatient beds, making the endpoint for LOS for ED boarders when they are moved from their ED bed to their assigned “inpatient” boarding bed within the ED¹.

To improve power in our analyses, we drop encounters with rare “reasons for visit” (RVF) (defined as those with less than 1000 total encounters) as well as complaints where either a batch order occurs less than 5% of the time across all patients or no imaging is ordered. Since batch orders are rare for these cases, our physician batch tendency instrument could suffer from a weak instrument problem if we included them. Examples of complaints dropped include skin and urinary complaints, as well as other complaints where multiple imaging modalities are unlikely to occur. Excluding these conditions does not introduce selection bias because of the random assignment. Finally, to estimate a precise measure of physician-level batch tendency, we restrict our sample to the encounters only involving full-time physicians. Our final sample includes 11,404 encounters consisting of chief complaints from the following categories: Neurological Issue, Abdominal Complaints, Fevers, Sweats or Chills, Falls, Motor Vehicle Crashes, Assaults, and Trauma, Dizziness/Lightheadedness/Syncope, Extremity Complaints, and Fatigue and Weakness.

3.2.1. Treatment Variable Our treatment variable, $Batched_{i,t}$, is an indicator taking the value of 1 if patient i has their tests batch ordered during their ED encounter, which took place on date t , and 0 otherwise. Batching occurs when a physician simultaneously orders a comprehensive set of diagnostic tests, typically covering a broad range of potential diagnoses. This contrasts with standard care, where a single test is ordered and subsequent tests are ordered in sequence on an as-needed basis.

We define “batching” in line with standard emergency medicine practices and focus on batches that include two or more different imaging modalities where the time between orders is within

¹ The Mayo Clinic hospital operations team views ED crowding and boarding as a hospital-wide problem and not an “ED problem,” and they have elected to convert multiple sites around the hospital including pre-operative areas into boarding areas during hospital overcapacity instead of the ED, assigning ED to be the location of boarders as a true last resort.

5 minutes, occurring as the first imaging tests ordered for the patient encounter (Su et al. 2025, Jameson et al. (2024)). We focus on batches that concern the first imaging tests ordered during the patient encounter because this represents the moment of maximum diagnostic uncertainty when physicians must decide their testing strategy before clinical information unfolds. Physicians cannot know ex-ante which patients will ultimately require multiple tests, making early batching a discretionary choice based on practice style rather than clinical necessity. Each imaging modality, such as X-ray, contrast CT scan, non-contrast CT, and ultrasound, is considered a separate and distinct test for our study. In particular, we focus on batching instances where the physician orders different imaging tests because such tests cannot be done in a single scanning session (due to differences in equipment and setting). Encounters where a single test precedes subsequent batched tests (1.91% of multi-test cases) are classified as sequential in our primary analysis, as the physician has initiated sequential information gathering before placing additional orders. Sensitivity analyses conducted around this time window, batch size threshold, and the timing of the batch show that our results are robust to variations in these values.

3.2.2. Dependent Variables The primary outcomes of interest are the ED's efficiency and effectiveness measures. The first is patient length of stay, which we measure in two ways. First, we measure the time from patient arrival until the attending physician completes care and determines disposition, capturing the duration until a decision is made to admit, discharge, or transfer the patient (Feizi et al. 2023). This metric excludes delays related to inpatient bed availability, providing a more transparent measure of ED operational efficiency. Second, we measure a patient's total time in the ED from arrival until physical departure (Lim et al. 2024). This total time for admitted patients includes the duration until transfer to an "inpatient" bed, whether in the main hospital or designated ED areas converted for inpatient use, encompassing boarding time and discharge processing (Feizi et al. 2023). Given the documented right-skewed nature of ED time metrics (Song et al. 2015), we log-transform both time measurements to achieve approximately normal distributions (Brown et al. 2005, Saghatian et al. (2024)), meeting the assumptions required for our regression analyses.

Beyond time-based metrics, we examine resource utilization through the number of distinct imaging tests ordered during each ED encounter. This count variable helps us understand how batch ordering practices influence the diagnostic workload. To assess the quality of care, we track whether patients return to the ED within 72 hours of their initial visit and require hospital admission (Lerman and Kobernick 1987). This binary indicator is a crucial quality metric, as returns within this timeframe may signal potential issues with initial treatment decisions, premature discharges, or missed diagnoses. These measures are widely used and validated in the emergency medicine

literature and are also of significant concern to our partner EDs. Furthermore, they allow us to evaluate ED performance across three critical dimensions: operational efficiency through time-based measurements, resource utilization via imaging orders, and care quality through return visit patterns. By examining these outcomes together, we can assess how batching behaviors and related process changes affect the efficiency and effectiveness of care delivery.

3.3. Identification Strategy

Our empirical strategy closely follows the literature that relies on the quasi-random assignment of agents to cases, often referred to as the “judges design.” Papers in this literature typically exploit variation in the sentencing leniency of judges who work in the same court. Similarly, we explore batching variation across physicians who work in the same ED via a measure that we term “batch tendency.” We use each physician’s residualized leave-out average batch rate to measure physician batch tendency. We use this residualized measure of physician batch tendency because if certain physicians are more likely to work afternoon or weekend shifts (Figure A1 shows to be the busiest shifts), the simple leave-out mean will be biased. A residualized measure of physician batch tendency accounts for this potential selection. This measure is derived from two steps following a similar approach used in other applications (e.g., Doyle et al. (2015), Dobbie et al. (2018), and Eichmeyer and Zhang (2022)). First, we obtain residuals from a regression model, which includes all ED encounters in our sample period:

$$\text{Batched}_{i,t} = \alpha_0 + \alpha_{ym} + \alpha_{dt} + \beta \mathbf{X}_{i,t} + \varepsilon_{i,t}, \quad (1)$$

where $\text{Batched}_{i,t}$ is a dummy variable equal to one if patient i had their imaging tests batch ordered on an encounter on date t . Fixed effects include year-month fixed effects, α_{ym} , to control for time and seasonal variation in batching, hospital-specific policies (e.g., initiatives to eliminate excess testing during a flu season), or seasonality in ED visits. We also control for “shift-level” variations that include both physician scheduling and patient arrival with day of week-time of day fixed effects, α_{dt} ². A vector of patient characteristics, $\mathbf{X}_{i,t}$, including chief complaint by ESI, vital signs, age, race, and sex, was included to increase precision. As stated in 3.1, these controls are more than required for our quasi-random assignment assumption. Under the assumption that we have captured the observables under which quasi-random assignment occurs in the ED, the unexplained variation—the physician’s contribution—resides in the error term, $\varepsilon_{i,t}$.

In step two, the tendency measure for patient i seen by physician j is computed as the average residual across all other patients seen by the physician during the study period:

² Day of week takes on seven values: Sunday, Monday, etc., and time of day are six mutually exclusive four-hour bins: 8 am–12 pm, 12 pm–4 pm, etc.

$$BatchTendency_{i,j}^{phys} = \frac{1}{N_{-i,j}} \sum_{i' \in \{\mathbb{J} \setminus i\}} \hat{\varepsilon}_{i'} \quad (2)$$

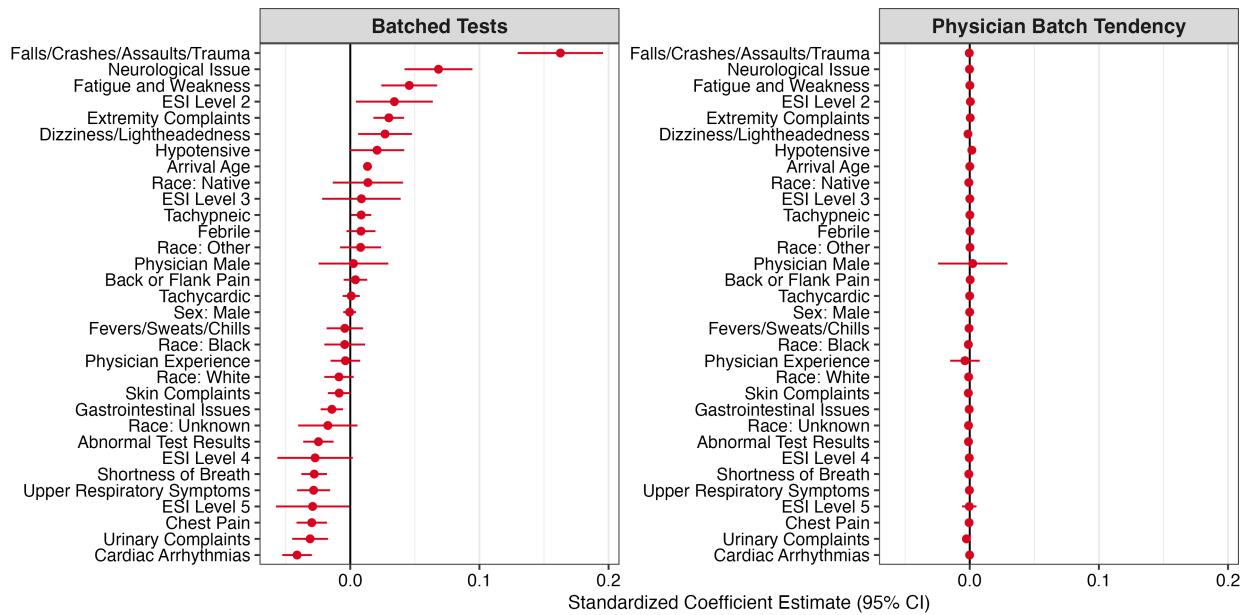
where $\hat{\varepsilon}_{i'} = \hat{Batch}_{i'} - Batch_{i'}$ is the residual from Eq. (1); \mathbb{J} is the set of all ED encounters treated by physician j ; and $N_{-i,j} = |\{\mathbb{J} \setminus i\}|$, the number of cases that physician has seen that year, excluding patient i . This leave-out mean eliminates the mechanical bias that stems from patient i 's case entering into the instrument. The measure is interpreted as the average (leave-out) batch rate of patient i 's physician relative to other physicians in that hospital-year-month, hospital-day of week-time of day.

Figure 2 provides empirical verification that, while the decision to batch depends on patient characteristics, our measure—batch tendency—is plausibly exogenous. The left panel uses a linear probability model to test whether encounter, patient, ED, and physician characteristics predict the batching decision, controlling for shift-level fixed effects with standard errors clustered at the physician level. As expected, patient characteristics strongly predict batching decisions; for instance, patients with Falls/Assaults/Trauma complaints are 16.2 percentage points more likely to be batched compared to similar patients under similar ED capacity. The right panel assesses whether these same characteristics predict assignment to physicians with different batch tendencies. Importantly, we find that patient characteristics do not significantly predict assignment to high versus low batch-tendency physicians. The coefficients are near zero with confidence intervals crossing zero for all patient characteristics, confirming that, conditional on shift fixed effects (which account for the mechanical rotation), the assignment of patients to physicians with different batching tendencies is effectively random. This validates the rotational assignment mechanism and establishes batch tendency as an exogenous source of variation for identifying causal effects.

We further document that (a) there is significant variation in this measure, and (b) the measure is highly predictive of the decision to batch. Figure 3 shows the distribution of physician batch tendency and the relationship between batch tendency and batching, where the relationship is illustrated via local linear regression of batching against physician tendency. As can be seen, the probability of batching is monotonically and approximately linearly, increasing in our tendency measure (see Table 2 for more formal results).

Together, we observe that batch tendency likely satisfies the conditions required for a valid IV. In the next section, we formalize our IV analysis questions and more formally establish the validity of our IV.

3.3.1. IV Analysis To estimate the reduced-form effects of being treated by a batch-preferring physician (batcher), we estimate the following equation:

Figure 2 Batch Tendency by Patient Characteristics

Notes: This figure plots a test for quasi-random assignment of patients to physicians in the Mayo Clinic ED.

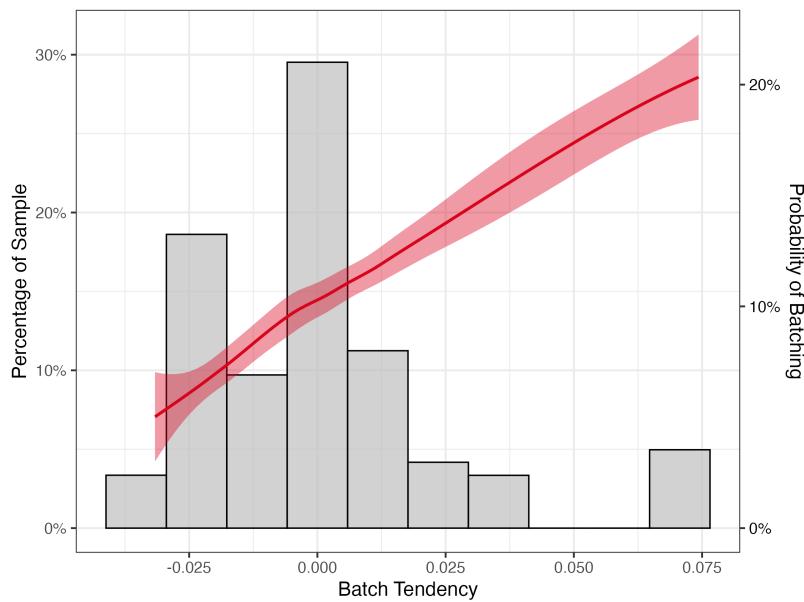
Residualization fixed effects include hospital-year-month, hospital-day of week-time of day. Robust standard errors are clustered at the physician level.

$$Y_i = \mu_0 + \mu_1 \text{BatchTendency}_{i,j}^{phys} + \gamma \mathbf{X}_i + \nu_i \quad (3)$$

To study the effects of test batching on outcomes, Y_i , we estimate the following Two-Stage Least Squares (2SLS) equations:

$$\left\{ \begin{array}{l} \text{First Stage: } \text{Batched}_i = \delta_0 + \delta_1 \text{BatchTendency}_{i,j}^{phys} + \delta_2 \mathbf{X}_i + \nu_i \\ \text{Second Stage: } Y_i = \beta_0 + \beta_1 \hat{\text{Batched}}_i + \theta \mathbf{X}_i + \varepsilon_i \end{array} \right. \quad (4)$$

In all cases, Y_i represents our primary outcomes of interest, and \mathbf{X}_i includes the same covariates as in Eq. 1 and additional controls for physician experience, physician sex, and ED capacity level (ED capacity guidelines for Mayo Clinic are in Appendix Table A1. The variable Batched_i may suffer from potential endogeneity concerns; for example, injury severity may be unobserved and correlated with the need to run multiple tests, length of stay, and return with admission likelihood. Hence, we instrument Batched_i with the assigned physician j 's underlying tendency to batch, $\text{BatchTendency}_{i,j}^{phys}$. We cluster robust standard errors at the physician level to account for the assignment process of patients to physicians.

Figure 3 Distribution and First Stage of Instrument

Notes: This figure plots the histogram of physician batch tendency along the x-axis and the left y-axis for all patient encounters. A local-linear regression of the fitted probability of batching on batch tendency after residualizing (see text for baseline fixed effects and controls in residualization) is overlaid and displayed on the right y-axis. Ninety-five percent confidence bands are also shown.

Table 2 presents formal first-stage results from Eq. (4). Column 1 of Table 2 presents the mean crude batch rate. Column 2 begins by reporting results only with year-month and day-of-week-time-of-day fixed effects. Column 3 adds our baseline patient and hospital condition controls. Consistent with Figure 3, our residualized physician instrument is highly predictive of whether a patient will have their imaging tests batch ordered. Including controls in column 3 does not change the magnitude of the estimated first-stage effect, consistent with the quasi-randomness of patients to physicians with different batching tendencies.

Furthermore, the batch tendency measure reasonably predicts the batching decision and the IV is not weak (F values are 520.4 and 227.6 for columns 2 and 3, respectively). For example, with all controls (column 3), our results show that a patient assigned to a physician that is at the 90th percentile of batch tendency (0.023) relative to a physician at the 10th percentile (-0.024) is 8.7 percentage points more likely to have their tests batched. The coefficient is greater than one because all emergency visits are used to construct the tendency instrument. The first stage is calculated using only the baseline sample, excluding the rare and rarely batched complaints.

3.3.2. UJIVE Construction Following Goldsmith-Pinkham et al. (2025), we implement the Unbiased Jackknife Instrumental Variables Estimator (UJIVE) as a robustness check for our main 2SLS specification. Our primary IV design uses a single continuous instrument—physician batch

Table 2 First-Stage Results: Batch Tendency and Batching

	Sample Mean	Batched	
		(1)	(2)
Batch Tendency	0.137 (0.343)	1.837*** (0.138)	1.752*** (0.134)
<i>Controls</i>			
Necessary controls	—	Yes	Yes
Precision controls	—	No	Yes
Adj. R^2	—	0.022	0.74
F-stat	—	171.9	171.9
Observations	11,679	11,679	11,679

Notes: This table reports first-stage results for the regression of batch tendency on the likelihood of batching. Column 1 reports the sample mean and standard deviation of the dependent variable. Column 2 includes fixed effects for year-month and day of week-time of day. Column 3 adds baseline controls, including patient characteristics (age, vital signs like tachycardia, tachypnea, febrile, hypotensive status), hospital characteristics (capacity level), and physician characteristics (physician sex and physician experience). Robust standard errors are clustered at the physician level. *** $p < 0.01$.

tendency—but UJIVE requires the full set of physician indicator variables as instruments. Using these indicators allows us to assess whether our 2SLS estimates suffer from the mechanical many-instrument bias documented in the leniency-design literature, without altering the core empirical strategy.

Let Z_i denote the vector of physician indicator variables for encounter i , and let P be the projection matrix onto the column space of all controls in the first stage. Define $M = I - P$ as the residual-maker matrix. For each observation i , UJIVE estimates the physician effects leaving out that observation:

$$\hat{\pi}_{-i} = \arg \min_{\pi} \sum_{k \neq i} (MB_k - Z'_k \pi)^2, \quad (5)$$

where B_k is the observed batching decision. We then compute the leave-one-out predicted instrument

$$\hat{\ell}_{i,-i} = Z'_i \hat{\pi}_{-i}.$$

Because $\hat{\pi}_{-i}$ is estimated using all observations *except* i , these predictions are orthogonal to the structural error and therefore eliminate the mechanical correlation that contaminates the conventional 2SLS first stage when each physician dummy enters the model as a separate instrument.

The UJIVE estimate is then obtained in standard IV/Wald form:

$$\hat{\beta}_{UJIVE} = \frac{\sum_i \hat{\ell}_{i,-i} Y_i}{\sum_i \hat{\ell}_{i,-i} \text{Batched}_i} = \frac{\widehat{\text{Cov}}(\hat{\ell}_{i,-i}, Y_i)}{\widehat{\text{Cov}}(\hat{\ell}_{i,-i}, \text{Batched}_i)}.$$

This estimator is asymptotically unbiased in many-instrument leniency designs and yields valid standard errors even when conventional 2SLS understates uncertainty. We report UJIVE results as a robustness check alongside our baseline 2SLS estimates, which remain interpretable and more straightforward given our single-instrument batch-tendency design.

3.3.3. Identifying Assumptions The reduced-form approach delivers an unbiased estimate of the causal effect of being treated by a physician with a higher tendency to batch since patient assignment to ED physicians is random and conditional on seasonality and shift (“conditional independence”). The residualization in Eq. (1) allows for further statistical precision in measuring physician tendency to batch.

Our instrumental variable approach, which aims to recover the causal effect of having diagnostic tests batch ordered, relies on three additional assumptions: relevance, exclusion, and monotonicity. We reported a strong first stage (i.e., relevance) at the end of the previous section. The exclusion restriction requires the instrument to influence the outcome of interest only through its effect on test batching. This is our strongest assumption and is, at its core, untestable. Nevertheless, we take this assumption seriously and perform a placebo check in Appendix D1 and various robustness checks in Section 4.8.

However, several features of the ED setting suggest that such violations may likely only have a small impact and may be less concerning than in other healthcare settings. First, unlike in primary care settings, where the patient and primary care provider have many repeated encounters, the scope of what the emergency physician can do to impact medium-term outcomes is limited and well-observed by the researcher. Second, any exclusion restriction violation must directly affect the specific outcome of interest. The channel by which ED physicians can influence the outcomes of interest is likely through testing and diagnosis. To the extent that the exclusion restriction is violated, our reduced form estimates can be interpreted as the causal impact of being assigned to a more or less likely to batch physician. Table 3 shows these reduced form results.

Finally, the monotonicity assumption is necessary for interpreting the coefficient estimates obtained from the IV approach as LATEs if there are heterogeneous treatment effects. It requires that any patient whom a low batch tendency physician batches would also be batched by a high batch tendency physician. The literature leveraging the judges design typically performs two informal tests for its implications. The first one provides that the first stage should be weakly positive for all subsamples (Dobbie et al. (2018)). The second implication asserts that the instrument constructed by leaving out a particular subsample has predictive power over that same left-out

subsample (Bhuller et al. (2020)). Appendix Figure D1 presents both of these tests for various subsamples of interest. In the left panel, our residualized measure of batch tendency is consistently positive and sizable in all subsamples, which aligns with the monotonicity assumption. In the right panel, we also find that our additional first-stage results are consistently same-signed and sizable across all subsamples. The coefficient magnitudes differ across subgroups because rates of batching differ.

3.3.4. More Details on Our LATE Estimates Our two-stage least squares estimates represent the LATE of batch ordering for ‘compliers’—patients whose testing strategy depends on the assigned physician’s practice style. This effect compares early batching to standard practice, which includes both sequential ordering and single tests. While this involves a composite counterfactual, it provides the policy-relevant parameter: the effect of encouraging comprehensive upfront testing versus allowing diagnostic information to guide testing decisions for patients at the margin of clinical discretion—those whose testing strategy is not dictated by clear clinical necessity but rather depends on physician practice style and judgment. To better understand this LATE, we characterize the number of compliers and their characteristics following the approach developed by Abadie and Gardeazabal (2003) and extended by Dahl et al. (2014b).

Specifically, compliers are defined as patients whose batched status depends on whether their physician has the highest batch tendency (\bar{z}) or the lowest batch tendency (\underline{z}). Mathematically, the fraction of compliers (π_c) is given by:

$$\pi_c = P(\text{Batched}|Z = \bar{z}) - P(\text{Batched}|Z = \underline{z}),$$

where Z represents the batch tendency of the physician. Using the first-stage regression model, we predict the probabilities of being batched under the most lenient (\bar{z}) and strict (\underline{z}) physicians.

Approximately 13 percent of patients in our sample are “compliers,” meaning they would have received batched tests if their physician had higher batch tendency but sequenced tests otherwise. In comparison, 5 percent of patients are “always takers,” meaning they would receive batched tests regardless of the physician’s batch tendency, and 82 percent are “never takers,” meaning they would never receive batched tests regardless of the physician’s batch tendency. Appendix B provides more details on complier estimates and their characteristics.

4. Results and Discussion

4.1. Reduced-Form Results

In this sub-section, we explore the causal influence of physician batch tendency on patient outcomes and resource utilization in the ED. We find statistically and operationally significant effects of assignment to a high batch tendency physician on every outcome except 72-hour return with

Table 3 Reduced Form: Batch Tendency and Patient Outcomes

	Dependent variable			
	Log time to disposition (1)	Log LOS (2)	Number of distinct imaging tests (3)	72hr return with admission (4)
Batch tendency	1.526* (0.6825)	1.589* (0.5811)	2.561*** (0.2614)	-0.0222 (0.0364)
Mean dependent variable	5.247 (0.487)	5.501 (0.445)	1.450 (0.623)	0.0122 (0.110)
Time FE	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes
Adj R^2	0.152	0.104	0.236	0.011
Observations	11,404	11,404	11,404	11,404

Notes: This table reports the estimated coefficients of a reduced-form regression of our main outcomes on physician batch tendency. The dependent variables are log time to disposition, log LOS, number of distinct imaging tests, and 72-hour return with admission. Robust standard errors are clustered at the physician level. * $p < 0.05$, *** $p < 0.001$

admission (Table 3). Scaling our coefficients by the difference in tendency going from the lowest decile to the highest decile in physician tendency—equal to a 4.7 percentage point increase—for interpretability, we find that assignment to a physician in the top batching decile (relative to one in the bottom decile) is associated with an 7.8% increase in LOS, an 7.4% increase in time to disposition, and an additional 12.8 imaging tests ordered per 100 patient encounters. These findings highlight ED physicians' substantial role in putting patients on a path toward longer LOS and increased resource utilization³.

The fact that our primary outcomes respond strongly to physician batch tendency suggests that batching is the underlying mechanism behind the effects. However, physicians could differ in other dimensions of care—some observable and others not—which could be correlated with batch tendency. Appendix D attempts to distinguish between and identify the mechanisms behind the observed reduced-form effects. This mediation analysis provides a crucial step toward a well-identified IV analysis.

4.2. Instrumental Variables Estimation

Next, we examine the effects of batch ordering imaging tests using the IV strategy described above. We first analyze the effects of batching on primary ED operational outcomes before examining its impacts on specific test ordering patterns and disposition decisions.

³ For reduced form results for a less strict sample see, e.g., Jameson et al. (2024), Hodgson et al. (2018), and the references therein.

Panel A of Table 4 presents OLS and 2SLS estimates of batching's impact on key operational metrics. Column 1 reports the dependent variable means for patients who had their tests ordered sequentially. Columns 2 and 3 report OLS estimates with increasing controls to understand potential sources of bias. Columns 4 and 5 report results for two-stage least squares estimates using our physician batch tendency instrument, without and with baseline controls, respectively.

The 2SLS estimates with full controls (column 5) indicate that batching substantially increases ED length of stay. The marginal batched patient experiences an 130% increase in total ED length of stay and an 123% increase in time to disposition. These significant effects suggest that in contrast to the fact that batching may seem efficient by initiating multiple diagnostic processes simultaneously, it significantly extends patient average processing times. Batching also leads to more intensive diagnostic testing. Specifically, the marginal batched patient receives 1.4 more distinct imaging tests, representing a 105% increase from the mean for sequentially tested patients. However, this increased testing intensity does not appear to impact the quality of care, as measured by 72-hour returns with admission, at the typical statistical significance levels. Notably, these findings suggest that the ED's batching behavior results in additional delay-inducing tests but not necessary value-adding. Put differently; they indicate that sequentially ordering diagnostic tests offers an important benefit: the information obtained from prior tests reduces the need to order subsequent, non-value-adding but delay-inducing tests (an “information gain” advantage).

Panel B of Table 4 examines how batching affects the utilization of specific imaging modalities. The two-stage least squares estimates reveal that batching leads to significant increases across several imaging types, with substantial effects on X-rays. With full controls, batched patients are 94.2 percentage points more likely to receive an X-ray ($p<0.001$) and 16.7 percentage points more likely to receive an ultrasound ($p<0.05$). These substantial increases across several modalities suggest that physicians who batch tend to order more comprehensive imaging workups (compared to their non-batching peers) rather than substituting between different types of imaging.

Panel C of Table 4 presents estimates of batching's impact on ED admission decisions. The two-stage least squares results indicate that batching substantially alters clinical decision-making patterns. With full controls, batching leads to a 44.5 percentage point increase in admission probability. This also means that the impact of batching in the EDs likely spills over to other parts of hospitals (e.g., inpatient units), increasing their patient volumes. Increased levels of patient volume, in turn, are known to induce behaviors such as speed-up, which can hurt other quality-of-care metrics, such as 30-day mortality (Song and Saghatian 2019).

These results paint a complex picture of batching's operational implications. While batching is associated with more comprehensive diagnostic workups, it also leads to significantly longer processing times and an increased likelihood of admitting the patient. The similar magnitudes

Table 4 Effect of Batching Tests on Patient Outcomes

	Sequenced mean	<u>2SLS</u> (2)	<u>2SLS</u> (3)	<u>UJIVE</u> (4)	<u>UJIVE</u> (5)
<i>Panel A. Primary Outcomes</i>					
Log time to disposition	5.237 (0.499)	0.659*** (0.103)	0.651*** (0.101)	0.583*** (0.189)	0.522*** (0.177)
Log LOS	5.490 (0.456)	0.717*** (0.094)	0.597*** (0.088)	0.653*** (0.158)	0.503*** (0.144)
Number of distinct imaging tests	1.335 (0.572)	1.385*** (0.118)	1.241*** (0.116)	1.316*** (0.126)	1.174*** (0.119)
72hr return with admission	0.012 (0.110)	-0.0137 (0.018)	-0.0146 (0.019)	-0.0079 (0.020)	-0.0039 (0.022)
72hr return	0.030 (0.170)	-0.0512 (0.029)	-0.0536 (0.031)	-0.0440 (0.032)	-0.0396 (0.034)
<i>Panel B. Test Types</i>					
X-ray	0.576 (0.494)	0.943*** (0.100)	0.989*** (0.101)	0.960*** (0.116)	0.959*** (0.117)
Ultrasound	0.171 (0.377)	0.160** (0.076)	0.087 (0.073)	0.164* (0.082)	0.087 (0.078)
CT without contrast	0.400 (0.490)	0.102 (0.095)	0.062 (0.086)	0.052 (0.112)	0.053 (0.102)
CT with contrast	0.187 (0.390)	0.180* (0.078)	0.102 (0.076)	0.140 (0.087)	0.075 (0.079)
<i>Panel C. Disposition</i>					
Admission	0.279 (0.449)	0.419*** (0.096)	0.404*** (0.088)	0.424*** (0.103)	0.398*** (0.090)
Necessary controls	—	Yes	Yes	Yes	Yes
Precision controls	—	No	Yes	No	Yes
Observations	11,679	11,679	11,679	11,679	11,679

Notes: Column 1 reports means for sequenced patients (standard deviations in parentheses).

Columns 2–3 report 2SLS results using physician batch tendency as the instrument. Columns 4–5 report UJIVE estimates using ED provider identifiers as many weak instruments. All models include day-of-week and month fixed effects. Precision controls described in text. Standard errors are heteroskedasticity-robust.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

between the OLS and two-stage least squares estimates suggest that selection bias may play a more minor role than anticipated in driving these relationships. However, the substantially larger standard errors in the two-stage least squares specifications indicate considerable heterogeneity in batching's effects across patients.

4.3. Potential Mechanism: Mediation Analysis

To better understand the mechanisms through which batching in the ED affects key operational outcomes—LOS and time to disposition—we investigated the mediating roles of imaging volume (number of tests) and admission decisions. Separate analyses were conducted for each operational outcome to ensure a comprehensive assessment of these pathways. These variables were selected as potential mediators for two reasons: (a) our prior analyses demonstrate that batching significantly increases both the number of tests ordered and the likelihood of admission, and (b) there is a strong theoretical basis to believe that these variables contribute to longer LOS and time to disposition. Increased imaging volume can delay patient processing due to the time required to conduct and interpret diagnostic tests. Similarly, resource utilization and diagnostic intensity are known to influence admission decisions, directly impacting ED operational metrics via patients that could be discharged but end up being admitted to the hospital (Hodgson et al. 2018).

We formalized our hypothesized mechanisms using structural equation modeling (SEM) and the underlying directed acyclic graphs (DAGs) depicted in Figure 4. Parts A and B in this figure represent the underlying DAG when LOS and time to disposition are considered to be the main outcome of interest, respectively.⁴ SEM simultaneously estimates multiple interrelated regression equations, explicitly modeling direct and indirect effects through causal pathways identified in a DAG. This approach enables a quantitative evaluation of the theoretical model in which batching influences operational outcomes both directly and indirectly via mediators (Beran and Violato 2010, Zhang (2017)). In our SEM analyses, to control for potential confounding due to time and patient complexity, we first residualized all variables of interest by regressing them on fixed effects, including day of the week, month, and chief complaint severity. This residualization ensures that our estimates reflect associations net of these confounders, enabling a more precise exploration of the relationships among batching tendency, mediators, and outcomes.

The mediation analysis results, detailed in Appendix Tables C1 and C2, shed light on a plausible mechanism by which batching impacts LOS and time to disposition. Our findings suggest that the effects of batching are primarily mediated through increased diagnostic testing intensity. This aligns with the results in Table 4, demonstrating that batching increases imaging volume. This pathway accounts for substantial delays in LOS, as additional imaging requires time for completion, interpretation, and integration into clinical decision-making. For LOS (Figure 4 part A), the indirect effect via imaging volume was estimated at 0.207 ($p < 0.001$), indicating a substantial contribution to the total delay observed. Similarly, for time to disposition (Figure 4 part B), the indirect effect via imaging was 0.085 ($p < 0.001$), underscoring the central role of diagnostic testing intensity in

⁴ Of note, a change in admission decision (discharge vs. admit) in the ED can influence a patients' LOS (part A) but not their time to disposition (part B), since the latter by definition excludes delays after the disposition decision.

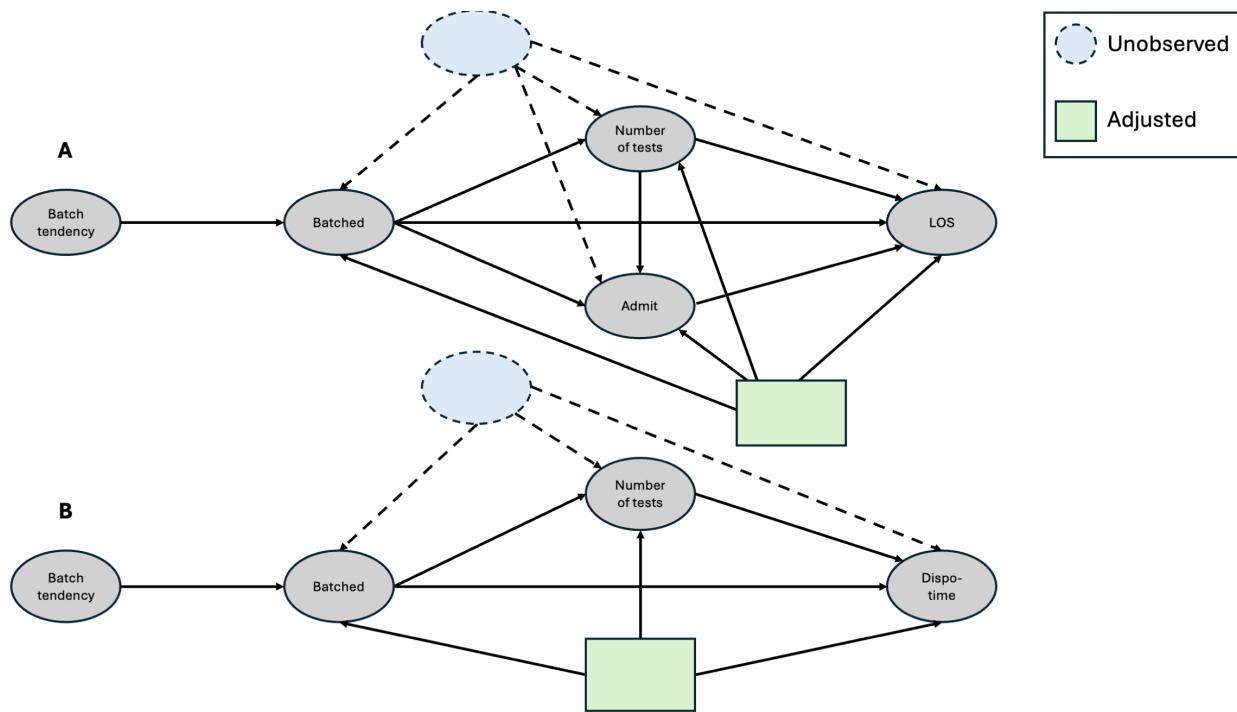


Figure 4 Directed Acyclic Graph (DAG) of the Mediation Analysis

extending processing times. In contrast, the direct effects of batching on both LOS and time to disposition were small and statistically insignificant, as shown in Appendix Tables C1 and C2. This suggests that the delays attributed to batching are driven not by the act of batching itself but rather by the subsequent increase in diagnostic testing activity that batching involves.

For LOS (Figure 4 part A), the role of admission decisions adds complexity to this narrative. Affirming the results in Table 4, the SEM analysis (Table C1) revealed that batching was associated with a significant increase in admission likelihood ($b_2 = 0.327, p < 0.001$). This suggests that increased imaging may contribute to more conservative disposition decisions, potentially due to incidental findings or heightened diagnostic uncertainty, which necessitate further inpatient care. This pathway contributed to additional delays to LOS, as coordinating patient transfers from the ED to inpatient units involves logistical challenges, and further time consumption often accrued because of the lack of bed availability in such units. The total indirect effect for LOS, combining the pathways through imaging tests and admissions, was estimated at 0.256 ($p < 0.001$), while the direct effect of batching remained insignificant ($c' = 0.031, p = 0.662$). This consistency between the 2SLS and SEM results (Table 4, Table C1, and Table C2) reinforces that diagnostic intensity and admission are the key drivers of increased LOS in batched patients.

For time to disposition, where admission is not a mediator, the indirect effect through imaging tests (0.085, $p < 0.001$) remains the predominant pathway, with the direct effect of batching again

nonsignificant ($c' = -0.100$, $p = 0.216$). This further highlights that the perceived efficiency gains from batching outweigh the operational burdens associated with increased diagnostic testing.

4.4. Heterogeneous Effects: ED Capacity Status

Given that ED capacity constraints significantly influence operational decisions, we examine whether batching's effects vary across different capacity levels. Following The Mayo Clinic ED's internal guidelines⁵ (Table A1), we categorize each encounter into three categories: occurring during normal operations, minor overcapacity, or major overcapacity. While our primary analysis controls for capacity status, stratifying by this variable allows us to understand whether the impact of batching on operational performance varies with ED congestion.

Table 5 shows that batching's impact varies significantly across ED congestion levels, with important implications for operational efficiency. During normal operations, batching is most frequent (15.8% of encounters), leading to substantial increases in LOS and time to disposition by 143% and 125%, respectively. Additionally, batching is associated with an increase of 1.36 imaging tests per patient. These findings suggest that when providers have greater discretion, batching is used more liberally, contributing to inefficiencies by increasing imaging volume and delaying result turnaround.

As the ED enters minor overcapacity, batching frequency declines slightly to 13.3%, coinciding with the activation of workflow interventions like the Rapid Medical Assessment (RMA) process (Table A1). However, the adverse effects of batching remain pronounced, with LOS increasing by 143% and time to disposition by 144%, while imaging volume rises even further (+1.47 tests per patient). This suggests that despite operational adaptations, providers continue using batching in a way that exacerbates inefficiencies, likely because these interventions do not directly constrain their ordering behavior.

A notable shift occurs under major overcapacity, where batching drops to 9.9% of encounters, aligning with stricter constraints, such as potential ED diversion and expedited bed assignments. Here, the adverse effects of batching are markedly reduced, with nonsignificant LOS and time to disposition increases. Imaging increases due to batching also decline to 1.16 additional tests per patient. These results suggest that providers use batching more selectively under extreme congestion, likely reserving it for clinically necessary cases rather than as a convenience.

These findings highlight how batching's impact depends on the ED's operational state. When providers have more discretion, batching appears most inefficient, driving up imaging volume and delays. Under severe congestion, however, batching is less frequent and less detrimental, suggesting a more strategic application. From a policy perspective, interventions to curb batching should focus on normal and minor overcapacity settings, where it contributes most to inefficiencies.

⁵ The ED of our other partner hospital (MGH) does not follow these guidelines. Hence, we did not include these analyses in studying the effects of batching at MGH (see Section 4.6 for our analysis using MGH data).

Table 5 Heterogeneous Effects of Batching by ED Capacity Status

	Normal Operations (1)	Minor Overcapacity (2)	Major Overcapacity (3)
Log LOS	0.890** (0.290)	0.888* (0.354)	0.534 (0.602)
Log time to disposition	0.812* (0.341)	0.895* (0.404)	0.742 (0.567)
Number of distinct imaging tests	1.355*** (0.088)	1.474** (0.398)	1.160** (0.357)
72hr return with admission	-0.023 (0.012)	-0.007 (0.032)	0.067 (0.067)
Batch mean	0.158	0.133	0.099
Time FE	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes
Observations	3,742	5,846	1,816

Notes: This table reports two-stage least squares estimates of the impact of batching across different ED capacity levels. ED capacity levels are defined according to internal guidelines in Appendix Table A1. All specifications include time fixed effects and baseline controls.

Robust standard errors clustered at the physician level are reported in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

4.5. Determinants of Image Batching

To investigate the drivers of batching and image ordering behavior, we examine the relationship between physician characteristics and ED crowding and the likelihood of batched testing. We estimate the following regression models:

$$Y_{i,j} = \beta_0 + \beta_1 \mathbf{MD}_j + \gamma Capacity + \alpha \mathbf{X}_i + \epsilon_i \quad (6)$$

Where $Y_{i,j}$ represents our outcome of interest: Batched, a binary measure of whether physician j batched tests for patient i , and the number of images ordered for patient i by physician j . \mathbf{MD}_j is a vector of physician characteristics, including years since residency graduation, whether the physician is male, and the number of hours they are into their shift. $Capacity$ is the current capacity level of the ED, defined in Appendix Table A1. \mathbf{X}_i is the vectors of patient covariates described in the previous section and in Figure 2. We cluster robust standard errors at the physician level. Table 6 presents the results of the regression models.

We find that physician experience has no significant impact on batching behavior, suggesting that more experienced physicians do not tend to be more selective in their batching decisions. Additionally, physician gender shows no significant relationship with batching or overall test volume.

Table 6 Determinants of Test Ordering Behavior

	Batched (1)	Number of Imaging Tests (2)
<i>Panel A. Physician Characteristics</i>		
Physician experience	-0.000 (0.002)	-0.003 (0.002)
Physician male	0.001 (0.029)	0.004 (0.041)
Hours into shift	-0.004* (0.002)	-0.001 (0.003)
<i>Panel B. ED Conditions</i>		
Capacity Level: Minor overcapacity	-0.017 (0.010)	-0.009 (0.013)
Capacity Level: Major overcapacity	-0.047* (0.017)	-0.025 (0.024)
Time FE	Yes	Yes
Baseline controls	Yes	Yes
Observations	11,404	11,404
R ²	0.044	0.093

Notes: This table reports OLS estimates of the relationship between physician/ED characteristics and test ordering behavior. All specifications control for patient characteristics and time fixed effects. Robust standard errors clustered at the physician level are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

However, the timing within a physician's shift significantly influences batching decisions. Specifically, for each additional hour into the physician's shift, the likelihood of batching tests decreases by 0.3 percentage points ($p < 0.05$). Because the Mayo Clinic ED features very few handoffs, and physicians tend to stay with their patients until disposition, this decline in batching as shifts progress may reflect physicians adopting different testing strategies to ensure they can complete their work before their shift ends.

ED capacity conditions also show interesting relationships with test ordering patterns. Under major overcapacity conditions, we observe a small but significant decrease in batching. This selective reduction in testing during periods of high ED occupancy contrasts with previous literature, suggesting that ED crowding prompts less discernment in the use of diagnostic resources (Pines 2009).

4.6. Generalizability of Results Across EDs

To assess the generalizability of our findings beyond the Mayo Clinic ED, we replicated our analysis using data from the MGH ED, one of the busiest emergency departments in the United States. The

MGH dataset comprises 129,489 patient encounters from November 10, 2021, through December 10, 2022. This extensive dataset provides a robust sample to validate the external applicability of our results.

Unlike the Mayo Clinic ED, where patients are randomly assigned to physicians upon arrival through a rotational system, the MGH ED employs a different patient assignment mechanism. At MGH, patients are triaged into different care areas (e.g., urgent care, fast track, observation) based on acuity and presenting complaints, then assigned to physicians based on availability within those areas rather than through random rotation. To address this non-random assignment and potential selection bias, we adjust our instrumental variable strategy to account for these differences by including additional covariates for care area assignment, acuity level, and presenting complaints in both stages of our 2SLS and instrument construction, thereby accounting for the sorting of patients into different ED zones. While this approach cannot guarantee the same level of causal identification as Mayo's randomized system, it provides a more robust comparison of the effects of batching on patient outcomes across different ED settings.

After adjusting for institutional differences and using the same exclusion criteria we used with Mayo, we find strong evidence that our key findings generalize to the MGH setting. The 2SLS results in Table 7 suggest that batching leads to a 44.3% increase in length of stay and approximately 1.8 additional imaging tests per patient. To formally assess whether the estimated effects differ significantly across the two ED settings, we conduct a Z-test comparing the 2SLS coefficients from MGH and Mayo by estimating:

$$Z = \frac{\hat{\beta}_{\text{MGH}} - \hat{\beta}_{\text{Mayo}}}{\sqrt{SE_{\text{MGH}}^2 + SE_{\text{Mayo}}^2}}$$

As reported in Column 4, the Z-statistics for each outcome indicate no statistically significant differences in the estimated effects between the two settings. This suggests that the impact of batching is mainly consistent across hospitals despite differences in patient assignment mechanisms and operational structures. Overall, these results reinforce the external validity of our findings and provide further evidence that the observed effects of batching are not merely an artifact of a single institutions workflow but a systematic consequence of batching in high-volume emergency care settings.

4.7. Managerial Implications

Our findings have important implications for the management of ED operations. First, while potentially appealing as a workflow efficiency strategy, batch ordering of imaging tests can significantly

Table 7 Comparison of Effects of Batching Across Hospital Settings

	Sequenced Mean (SD) (1)	OLS (2)	2SLS (3)	Z-Statistic (4)
Log LOS	6.42 (0.847)	0.21*** (0.010)	0.34 (0.450)	-0.907
Number of distinct imaging tests	1.34 (0.563)	0.780*** (0.009)	1.835*** (0.320)	1.23
72hr return with admission	0.0123 (0.110)	-0.0048*** (0.001)	0.0158 (0.038)	0.617
Time FE	—	Yes	Yes	—
Baseline controls	—	Yes	Yes	—
Observations	—	42,085	42,085	—

Notes: This table reports OLS and two-stage least squares estimates from the MGH dataset. All specifications include time fixed effects, baseline controls, and care area fixed effects. Robust standard errors clustered at the physician level are reported in parentheses. Column 1 reports the mean and standard deviation for non-batched patients (sequenced). Column 4 reports the Z-statistic from a formal test comparing the 2SLS coefficient in Column 3 to the 2SLS coefficient in Column 5 of Table 4. Significance levels: *** $p < 0.001$

increase ED LOS and resource utilization without corresponding improvements in patient outcomes. The substantial magnitude of these effects—an 130% increase in LOS for batched patients—suggests that ED managers should carefully evaluate policies around physician test ordering discretion. As our mediation analysis reveals, these delays arise primarily through increased diagnostic intensity rather than the batching process itself, indicating that sequential ordering may serve as a natural filter against unnecessary testing.

The significant variation we observe in batching behavior across physicians treating similar patients suggests an opportunity for standardization. ED managers might consider implementing decision support systems that encourage sequential ordering, particularly for conditions where the information gained from initial tests frequently eliminates the need for additional imaging. However, our heterogeneity analysis indicates that such policies should be flexible to ED conditions—the reduced impact of batching on test ordering during periods of major overcapacity suggests that different strategies may be optimal under varying capacity constraints. This would specifically be the case if, for example, ED physicians consciously or subconsciously avoid over-testing when they know resources are significantly limited.

The substantial cost implications of batch ordering—both in terms of operational efficiency and resource utilization—suggest that EDs could benefit from more structured approaches to test ordering. While preserving physician autonomy in clinical decision-making is crucial, our results

indicate that completely unfettered discretion in test ordering timing may lead to suboptimal system performance. Simple interventions like providing feedback to physicians about their batching rates relative to peers or implementing “nudge” systems that suggest sequential ordering pathways could help reduce unnecessary testing while maintaining the quality of care.

Finally, our findings have implications beyond individual EDs, as increased admission rates from batch ordering create spillover effects throughout the hospital system. Hospital administrators should consider these downstream impacts when developing imaging protocols and resource allocation strategies. Batching leads to increased testing and higher admission rates, suggesting that policies aimed at reducing unnecessary batch ordering could yield benefits across multiple dimensions of hospital operations.

4.8. Robustness Checks

While our research design leverages the random assignment of patients to physicians to identify causal effects, several limitations warrant discussion. A primary concern is that physicians’ tendency to batch order tests may correlate with other unobserved practice patterns that affect our outcomes of interest. Although we found no significant associations between observable physician characteristics (such as experience, gender, or training) and batch ordering tendency, unobserved characteristics could influence both the tendency to batch and other aspects of patient care. For instance, physicians who tend to batch order tests might also have different approaches to patient assessment, documentation practices, or consultation patterns that independently affect the LOS and disposition decisions. Removing such unobserved factors’ potential impact might require running a fully randomized experiment. However, the consistency and magnitude of our findings across (a) both OLS and 2SLS specifications and (b) two different hospitals with different practice settings provide strong evidence behind our findings. In particular, unobserved physician characteristics would need to be substantial to invalidate our core finding that batching increases both test utilization and processing times.

Nevertheless, the validity of our results largely depends on our identification strategy (Section 3.3). Thus, we performed several robustness checks (see Appendix D) to gain further confidence about the validity of our results. To provide robustness checks related to potential exclusion restriction violations, we adjusted for observable margins of care that may be correlated with the tendency to batch, namely the decision to admit patients to the hospital and the testing tendency of the physician (Appendix Table D2). Additionally, we provide a placebo test where we check whether the instrument has a positive first stage for a placebo outcome, namely the number of laboratory tests ordered. Furthermore, we investigate whether the reduced-form effects observed in Section 4.1 are due to differences in batch ordering rates across physicians or due to other provider differences correlated with batch tendency. We examine this by studying reduced-form effects among

patients with conditions that rarely require multiple imaging tests as a falsification check. Finally, to address monotonicity, we follow approaches of Dobbie et al. (2018) and Bhuller et al. (2020) and construct physician-complaint-specific leniency instruments, and check whether our instrument has a positive first stage across key complaint, severity, capacity, and demographic-related subsamples (Appendix Figure D1). Across all robustness checks and main outcomes, we found that the magnitudes of our estimates remain fairly unchanged, and the implications of our results remain consistent. Our robustness checks, thus, give us further confidence about the validity of our main findings. However, we acknowledge that a randomized experiment might ultimately be needed to verify the results obtained from our observational data.

5. Conclusion

Although prior literature examines task ordering from the perspective of centralized protocols, frontline physicians often have discretion over how and when they order diagnostic tests, especially in high-pressure environments like EDs. In practice, due to system design or individual choice, this delegation of decision-making results in physicians self-managing their test-ordering strategies. Given the limited research on the operational implications of test ordering, little is known about how healthcare managers should guide these practices when such discretion exists. Understanding when and how physicians exercise this discretion informs decisions about system design, how to encourage optimal use of discretion, and how to adjust policies to account for the behaviors of frontline clinicians.

We explore this underexamined area by analyzing the drivers and consequences of batch ordering imaging tests in the ED. Utilizing detailed operational data from two large U.S. EDs, one with random patient-physician assignment, we find that physicians are more likely to batch order imaging tests earlier in their shifts and when the ED is less crowded. This suggests that time pressure and occupancy levels significantly influence the decision to batch, consistent with the notion that physicians may adjust their ordering behavior based on their workload and the operational demands of the ED.

Our results indicate that batch ordering imaging tests significantly increase the number of imaging studies performed per patient encounter, confirming that batching contributes to higher resource utilization. However, we do not find evidence that batching reduces patient LOS in the ED or impacts the likelihood of a 72-hour return with admission. On the contrary, batching dramatically increases the time spent in the ED and the time to disposition, suggesting that significant inefficiencies from initiating multiple diagnostic imaging processes simultaneously exist. This result aligns with previous research emphasizing the importance of diagnostic pathways in achieving optimal health outcomes and operational efficacy (Carpenter et al. 2015, Masic et al. (2008), Singh and

Graber (2015)). This is consistent with the information gain advantage of sequential test ordering, where the results of one test may eliminate the need for another. Our findings suggest that discretion allows physicians to tailor their test ordering to specific situations. However, it may also lead to resource-intensive practices that do not benefit patients or the ED system.

Moreover, excess testing in EDs is not a benign phenomenon. It is associated with increased risks, including patient exposure to unnecessary radiation and the resultant psychological and physical burden from incidental findings (Müskens et al. 2022). Moreover, the economic implications are substantial, with the overuse of diagnostic tests contributing significantly to the escalating costs of healthcare (Atkinson and Saghafian 2023). As such, our results suggest the need to examine the practice of batching across different clinical conditions and in other clinical settings beyond the ED while also considering its consequences across a variety of metrics that affect hospitals' publicly reported outcomes (Saghafian and Hopp 2020, Saghafian and Hopp (2019)).

Our study underscores the importance of developing evidence-based guidelines to inform physicians' test ordering strategies. By understanding how batching impacts patient outcomes and ED operations, healthcare managers can design interventions to optimize test ordering practices. This may include providing decision support tools, adjusting policies to encourage sequential ordering when appropriate, or offering feedback to physicians on their ordering patterns and associated outcomes. By aligning physician test ordering strategies more closely with patient needs (Atkinson and Saghafian 2023), EDs may enhance patient satisfaction and outcomes while improving operational efficiency.

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