Strategic Effort and Organizational Performance: Evidence from a Hospital Reform

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Abstract

Interactions between organizational units may significantly affect resource allocation and efficiency. We study a hospital reform that changed the emergency department's (ED) method for allocating admissions across internal medicine departments from a "first-available-bed" policy, which disproportionately burdened efficient departments, to "equal-load," which distributed admissions evenly. Comparing pre- and post-reform outcomes relative to the prior year, we find a 25% reduction in ED wait times and a 20% decrease in inpatient length of stay, with no change in readmission or mortality rates. A queuing model with strategic departmental effort demonstrates that these improvements are consistent with reduced incentives for free-riding.

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1 Introduction

The importance of firm organization for its performance is long recognized (Laffont and Martimort, 1998; Bloom et al., 2010, 2012; Tsai et al., 2015). Yet despite their potential importance, the effects of strategic interactions between organizational units on workload distribution and performance remain under-explored. Hospitals provide a key example, as the emergency department (ED) plays a crucial role not only in providing urgent care but also in coordinating the routing of patients across inpatient departments. This paper addresses this gap by examining how patient routing across departments impacts hospital performance.

Our study is set in a large Israeli hospital, where admissions from the ED are allocated across multiple internal medicine departments that offer similar services. Splitting workload across multiple similar units, a setup common in Israeli and UK hospitals, among other countries, aims to facilitate resource allocation and management. We show that the rules governing workload allocation can lead to strategic interactions among departments, thereby influencing overall efficiency and care quality. The insights gained extend beyond health-care, offering perspectives on intra-firm strategic interactions within other sectors, such as manufacturing, services, and logistics, where workload distribution is important.[1]

We focus on the impact of admission routing rules and the strategic behaviors they induce. Our analysis leverages a reform that altered the protocol determining how patients are admitted from the ED to different inpatient departments. Initially, patients were assigned to the first department with an open bed. This "first-available-bed" policy created a mechanical relationship between turnover and admissions: departments freeing beds more frequently received more patients. The reform replaced this with a simple "equal load" policy that allocated patients uniformly across departments. This variation in admission rules allows us to examine how routing mechanisms affect multiple dimensions of hospital performance: ED wait times and congestion, department-level length of stay, and clinical outcomes, including readmission rates and mortality.

To elucidate the incentives induced by different patient routing rules, we introduce a theoretical framework that incorporates strategic behavior into a standard queuing theory model. In this model, hospital departments strategically choose their effort levels (service rates) in response to incoming patient flow. The departments' objective function balances the benefits of idle time (e.g., staff rest, training) against the costs of providing higher service rates. The incoming flow rate is determined by the exogenous ED admission rate, admissions routing protocols, and the endogenous effort of other departments. Chosen service

[1] The ED in our setting functions similarly to a central processing unit. Examples of central units that route traffic to other organizational branches can be found in manufacturing assembly lines, retail warehouses, and service industries like banks, restaurants, public transport terminals, and government offices.

rates determine the equilibrium ED visit duration, inpatient length of stay, and hospital bed occupancy.

The model demonstrates that strategic interactions fundamentally alter routing policy impacts. While first-available-bed routing would minimize ED wait times if service rates were fixed, endogenous effort choices reverse this result. Under first-available-bed routing, departments' service rates become strategic substitutes: each department benefits from reducing its discharge speed to shift patient load to others. Equal-load routing eliminates this free-riding incentive, leading to faster discharges. This shift leads to a reduction in the equilibrium levels of ED congestion and the length of hospital admissions.

We proceed with an empirical analysis within a difference-in-differences framework, which identifies the impacts of the patient routing reform by comparing different outcomes around the reform against the same period a year before. We sample all ED visits over these periods, of which a third resulted in an admission to an internal medicine department. We observe rich electronic medical records (EMR) that include patient demographic characteristics, diagnosis codes, ED arrival and exit times, hospital admission and discharge times, and department assignments. Apart from the reform, there were no significant changes in the hospital's activities between the treatment and comparison periods, and falsification analyses show that the incoming cases volume and mix remained unchanged around the reform.

We find that the reform resulted in a substantial decrease of 1.5 hours in the ED visit duration (a 25% reduction relative to the baseline wait time of six hours) and a decrease of one day in the average department length of stay (a 20% reduction from a baseline of five days). These reductions in department processing times align with the theoretical prediction that curbing free-riding via an equal-load policy boosts effort and efficiency, leading to reduced congestion and quicker patient processing. Their magnitude is similar or larger than the reported impacts of other interventions aimed at reducing ED congestion (Morley et al., 2018; Cleveland Clinic, 2019; Gruber et al., 2023), although some of these other interventions, such as increasing bed capacity or extending primary care hours, are substantially more costly than the one evaluated in this study. Importantly, there was no increase in 30-day readmission and 90-day mortality rates post-reform, suggesting that improvements in patient processing times did not adversely affect patient health outcomes.

While the shortening of departmental stays initially reduced internal department occupancy, this temporary dip was offset over time. Within eight weeks, hospital admission rates from the ED increased by 15%, leading to a return to pre-reform occupancy levels. These findings are consistent with dynamics of convergence to a new equilibrium, with faster processing balanced by increased admissions from the ED and stable occupancy after an adaptation period. We find no change in the predicted length of stay of admitted cases, suggesting these dynamics did not impact the mix of patients admitted to the hospital. We also do not find evidence for heterogeneity across departments in the impacts of the reform.

Our analysis reveals that routing rules can profoundly influence hospital performance. Despite the reform being budget-neutral and not altering staffing levels, it significantly shifted flow dynamics, alleviated congestion, and enhanced resource utilization, all without reducing post-discharge outcomes. While an extensive literature analyzes worker-level responses to organizational incentive structures and their effects on the firm's productivity or output, our work explores how organizational incentives affect strategic interactions not at the individual level but across organizational units.[2] Our findings reveal that non-monetary incentives, particularly those induced by rules governing inter-unit interactions within the firm, can affect unit-level strategic behavior. The results highlight the significant role of incentives in fostering coordination among units and enhancing overall firm productivity.

In the context of the healthcare sector, the results highlight an additional important insight. ED congestion is often linked to external load factors or the ED's operational efficiency. However, our study introduces another crucial factor: patient routing. We demonstrate its substantial impact, suggesting that beyond optimizing ED operations, hospital management should strategically design patient routing protocols to align with broader organizational goals.

Our paper adds to the understanding of workload management protocols on productivity. Existing research identifies various drivers of firm performance, including technology and information flows (Acemoglu et al., 2007; Bloom et al., 2014), personnel management (Ichniowski and Shaw, 2003; Lazear and Shaw, 2007), trust (Bloom et al., 2012), management styles (Bandiera et al., 2020), and allocation of authority (Bandiera et al., 2021). This study demonstrates that protocols governing workload allocation can significantly impact productivity.

Our work also contributes to the growing literature examining how operational factors within the emergency department (ED) impact care delivery and patient outcomes. Much recent work has focused on elements influencing processes and performance directly within the ED environment, such as teamwork dynamics (Chan, 2016), wait time targets (Gruber et al., 2023), peer effects (Silver, 2021), and work schedules (Chan, 2018). While this prior research has advanced the understanding of drivers of ED care quality, our study shifts attention to the pivotal role of the ED in coordinating patient routing and flows through the broader hospital.

[2] Incentive structures discussed by the literature include pay schemes (Lazear, 2000; Amodio and Martinez-Carrasco, 2023; Bandiera et al., 2005; Larkin, 2014; Oyer, 1998; Chan et al., 2014), worker monitoring or visibility within the organization (Bandiera et al., 2005; Chan, 2016), social pressures or preferences (Ashraf and Bandiera, 2018; Bandiera et al., 2005, 2010; Mas and Moretti, 2009) and work schedules (Chan, 2018).

Another related line of research has examined the optimal design of queues and routing protocols for service providers. For instance, Wang and Zhou (2018) shows that supermarket cashiers operate more efficiently in dedicated queues rather than in pooled queues serving multiple cashiers. Similarly, Song et al. (2015) finds that pooled queues for providers within emergency departments lead to longer wait times and lengths of stay compared to segregated queues. While this prior work has focused on the impact of queue design on individual service providers' performance, our study explores an analogous mechanism at the inter-departmental level, revealing how different routing protocols induce strategic behaviors among organizational units. Our results highlight that just as pooled queues can reduce effort among individual providers, routing protocols can trigger similar free-riding dynamics at the organizational unit level.

The remainder of the paper is organized as follows. Section 2 discusses the institutional details. Section 3 presents our conceptual framework that analyzes the impact of various patient routing rules on the effort exerted by hospital departments and on patient waiting times. Section 4 describes the data and empirical approach. Section 5 presents our main results. Section 6 concludes.

2 Institutional Background

Our study examines the interaction between the hospital's emergency and internal medicine departments at Emek Medical Center ("Emek" hereafter), a large general hospital in northern Israel. With 500 beds, Emek represents the median among Israel's large general hospitals, ranking 14 out of 31. Emek is owned by Clalit Health Services, Israel's largest HMO. It admits all Israeli residents regardless of their coverage. For admissions to the internal departments, which are at the core of this study, Emek is reimbursed on a per diem basis, according to a fixed fee schedule. Physicians and staff are salaried employees.

Israel's hospital system operates under significant capacity constraints. Hospital bed availability (3.0 per 1,000 people) is lower than the OECD average of 4.4 (OECD, 2023), with even lower rates in the northern periphery served by Emek. Despite these constraints, Israeli hospitals maintain discharge rates comparable to OECD averages (144 versus 130 per 1,000 population) and higher ED visit rates (33 versus 27). This throughput is achieved through shorter hospital stays (6 versus OECD 7.7 days) and exceptionally high occupancy rates (89% versus 70% OECD average), creating persistent strain on ED admissions and resulting in long wait times for ED visits.

The ED. The ED serves as the hospital's primary entry point, handling approximately 110,000 unscheduled patients annually. Upon arrival, patients are triaged to one of four specialized ED units: internal medicine, surgical, pediatric, or trauma. These ED units assess each case, provide initial treatment, and decide whether to admit the patient to the hospital.[3] We focus on the internal medicine ED (henceforth, "the ED"), which receives about 22 percent of all ED visits and admits patients to the hospital's internal medicine departments.

The Internal Medicine Departments. Emek operates five internal medicine departments (henceforth "the departments") with a total of 184 beds. As is common in Israeli hospitals (as well as in other countries, such as the UK), these departments provide the same services but operate independently. Each department is headed by a senior physician responsible for its medical and administrative management. This structure of dividing patient volumes enables better resource allocation and monitoring within each department and facilitates comparisons and learning across departments.

Assignment of ED Admissions. ED admissions account for about 93% of all internal department admissions, reflecting the close integration between ED and department operations. A key element of the transfer process is the routing rules—centrally set protocols determining how ED admits are assigned across departments. Before the reform, patient allocation was based on bed availability: when an ED physician admitted a patient, the ED routed them to the department with the lowest occupancy. If no beds were available, the patient waited in the ED until the first department freed a bed. Under this rule, departments that discharged patients more quickly received a greater share of new admissions.

The Reform in Patient Routing. In response to concerns about discharge incentives, Emek implemented a routing reform that allocated ED admissions to departments according to a predetermined sequence, implemented by computer software, based on bed capacity rather than current occupancy. Under this new policy, departments could receive patients even when at full occupancy. In these cases, patients were physically placed in a different department but remained under the care of their assigned department's staff. According to hospital management (Linder, 2019), the reform aimed to enhance both fairness and efficiency through improved discharge incentives.

The reform, announced on October 3 and implemented on October 6, 2019, focused on

[3] In severe and urgent cases, patients may be admitted immediately after the initial triage, e.g., to the Intensive Care Unit.

the assignment of patients from the ED to internal departments. While it was accompanied by minor updates to certain clinical procedures—stress echocardiograms, angioplasties, specialist consultations in the ED, and transfers to long-term care facilities—these changes affected only a small subset of cases and are unlikely to drive our results. The reform involved no substantial changes to hospital operations, budgets, staffing levels, or departmental structure. No other major reforms or policy changes were implemented during our sample period.

3 Wait Times with Strategic Department Effort

This section introduces a stylized model to elucidate the impact of various patient routing rules on the effort exerted by hospital departments and on patient waiting times. The model aims to clarify the strategic interactions and incentives involved in different routing rules and embed the specific reform we discuss in a more general framework suitable for understanding similar scenarios in other organizations and contexts.

To study the relationship between case arrivals, service rates, and wait times, we rely on classic queuing theory models, the M/M/1 (single server) and M/M/m (multi-server) models (Erlang, 1917; Kendall, 1953).[4] These models represent queues as Markovian systems with Poisson arrivals and exponentially distributed service times. We make one key modification—we treat service rate as endogenous choice strategically determined in equilibrium.[5]

We analyze the reform as a shift from one type of queuing system to another. Before the reform, patient assignment was based on bed availability, resembling a shared queue served by multiple servers ("pooled load"). After the reform, patients were assigned to internal departments based on a preset order, akin to dividing the patient flow into separate, single-server queues ("equal load").

Setup. Consider a hospital with patients admitted from the ED at an exogenous Poisson rate λ into two internal medicine departments, each choosing its service rate μ_i (for $i = 1, 2$). Department i's payoff is:

$$U(\mu_i, \mu_{-i}) = r(\mu_i, \mu_{-i}, \lambda) - c(\mu_i) \tag{1}$$

where r denotes the average idle time (namely, the time with no patients or low-maintenance patients, which can be used for staff rest, training, etc.), derived below from arrival rate and

[4]The M/M/m notation refers to a system with m identical servers fed by a single queue, with exponentially distributed inter-arrival and service times (Kendall, 1953).

[5]Gopalakrishnan et al. (2016) also study strategic effort with multiple servers.

service times based on classical queueing theory results, and c denotes the cost (staffing, management, equipment, etc.) of providing the service rate, given by $c(\mu) = \alpha\mu^2$. That is, (1) frames the choice of service rate as striking a tradeoff between the benefits of idle time—a compact term capturing the benefits of reduced occupancy (such as more time for staff development and rest)—and the convex effort costs of doing so.

We compare two routing protocols that correspond to the post- and pre-reform rules: equal load and pooled load. The equal load case involves evenly distributing patient admissions across departments, which means department effort decisions are not strategically affecting each other's load. Conversely, in the pooled load case, patients are admitted to the first available department, inducing strategic interaction between departments.

Equal load. Each department considers its own queue with an arrival rate $\lambda_i = \lambda/2$, which reflects a fixed (in this case, half) of the total arrival rate. We consider idleness and payoffs in the steady state. Let $p_k(t)$ denote the (time-dependent) probability that there are k patients in the system—waiting or being treated—at time t. Classical results for this model (referred to as M/M/1) show that when the service rate exceeds the arrival rate ($\mu_i > \lambda_i$), the system has a steady-state distribution characterized by the probabilities: $p_0 = 1 - \rho$, and $p_k = \rho^k p_0$, where $\rho = \frac{\lambda_i}{\mu_i}$ (Kendall, 1953). The factor ρ equals $1 - p_0$, the proportion of time the department is occupied, and must be smaller than one for the steady state to exist (otherwise, the system diverges). Under equal load, the expected idle time r, which equals p_0 by definition, depends on the arrival rate λ and the department's effort μ_i, as follows:

$$r_i(\mu_i, \lambda_i) = 1 - \frac{\lambda}{2\mu_i}. \tag{2}$$

That is, with equal load, r only depends on the department's own service rate and not on the other department's effort μ_{-i}. The optimal μ_i maximizes (1) given (2). An internal solution must satisfy the first-order condition: $\frac{\partial c}{\partial \mu_i} = \frac{\partial r}{\partial \mu_i}$, and is therefore given by:

$$\mu_i^{\text{equal-load}} = \sqrt[3]{\lambda/4\alpha}. \tag{3}$$

A steady-state solution exists as long as the effort cost is sufficiently low ($\alpha \leq \frac{4}{\lambda^2}$).

Pooled load. In this scenario, both departments handle patient arrivals jointly (in what is known as the M/M/2 model), with a pooled arrival rate of λ. Departmental payoffs now depend on the other department's service rate. Following Kalai et al. (1992), we denote: p_0: the steady-state probability that there are no patients in the system. p_{10}: the steady-state probability that department 1 is busy and department 2 is idle. p_{01}: the steady-state probability that department 1 is idle and department 2 is busy.[6] By definition, in this case $r_1 = p_0 + p_{01}$ and $r_2 = p_0 + p_{10}$.

The expected idle time of department i in steady state depends on the service rates of both departments:

$$r_i(\mu_i, \mu_{-i}, \lambda) = \frac{\mu_i(\mu_i + \mu_{-i} - \lambda)(\lambda + 2\mu_{-i})}{2\mu_i\mu_{-i}(\mu_i + \mu_{-i}) + \lambda(\mu_i^2 + \mu_{-i}^2)}. \quad (4)$$

When $\mu_{-i} = 0$, then $r_i = 1 - \frac{\lambda}{\mu_i}$. Namely, if the other department does not serve any patients, the idle time with pooled load reduces to the idle time equal-load case (with twice the load).

Considering the symmetric Nash equilibrium, where the common effort denoted $\mu_i^{\text{pooled}} = \mu$, the equilibrium level of effort satisfies (see Appendix for the calculation details):

$$\mu^3 + \frac{\lambda}{2}\mu^2 - \frac{\lambda}{4\alpha} = 0, \quad (5)$$

which has one real root, implying the solution is unique. A steady-state solution exists ($\lambda < 2\mu$) if the effort cost is sufficiently low ($\alpha < \frac{1}{\lambda^2}$).

Comparison and Implications. When the effort cost is sufficiently low for a steady-state solution to exist, pooled load induces strictly lower effort than equal load because the departments' effort levels are strategic substitutes. This situation is illustrated in Figure 1 for the case when $\lambda = 1$ and $\alpha = 1/2$. The figure shows that the pooled load equilibrium results in lower effort levels because each department strategically sets its effort in response to the other. In contrast, under equal load, where "free riding" incentives are eliminated, the effort levels are higher.

Strategic behavior is essential for this result. Under non-strategic behavior, where departments maintain the same service rates regardless of load distribution, pooled load always results in shorter expected wait times compared to equal load (see appendix). This is a classic result in queuing theory: a single queue feeding multiple servers reduces idle server time compared to separate queues because it minimizes instances of one server being idle while

[6] When the system load $\rho = \frac{\lambda}{\mu_1 + \mu_2}$ (redefined here for the pooled load case with some abuse of notation) is smaller than one, a steady state exists, and the above probabilities are given by (Rubinovitch, 1985):

$$p_0 = \frac{1 - \rho}{1 - \rho + \frac{\lambda(\mu_1 + \mu_2)}{2\mu_1\mu_2}},$$

$$p_{10} = \frac{\lambda p_0}{2\mu_1}, \quad p_{01} = \frac{\lambda p_0}{2\mu_2}.$$

Note that $p_0 + p_{01} + p_{10} < 1$, as there are also states when both departments are busy.

customers wait in another line. However, this advantage of pooled load does not generally hold when departments strategically adjust their service rates, as departments serve patients at a lower rate under pooled load than under equal load.

Assuming strategic behavior by departments, this stylized model yields three testable predictions in the context of the ED reform, which represents a shift from a pooled to an equal load protocol. First, the reform should increase departments' equilibrium service rates, manifesting as shorter inpatient lengths of stay. This effect operates through the elimination of free-riding behavior, as departments can no longer shift their burden to other departments. Second, holding arrival rates constant, these higher departmental service rates should reduce congestion in the emergency department, resulting in decreased ED wait times and shorter overall ED visit durations. Third, holding arrival rates constant, the shorter inpatient lengths of stay should lead to lower average bed occupancy rates, providing an additional empirical test of the model's predictions.

4 Empirical Approach

4.1 Identification and Estimation

To identify the effect of the Emek reform in the assignment of admissions from the ED to the hospital departments, we use a difference-in-differences (DD) framework and compare outcomes before and after the reform, which switched from a pooled load to an equal load policy, against the same period in the previous year, during which the initial, pooled load policy was in place. We set the observation window to span twenty weeks before and twenty weeks after the reform implementation date (the "treatment year"), and compare it with the equivalent forty-week period in the previous year (the "comparison year"), to capture any seasonal trends in outcomes. This observation period is set to end just before the COVID-19 pandemic.[7]

The key identification assumption is that, in the absence of the reform, trends in the hospital's activity during the treatment year would have been parallel to those in the comparison year. To support this, we examine the trends in outcomes before the reform. There are two types of remaining identification concerns. The first concern is that other changes to hospital procedures or operations may have occurred simultaneously with the reform. However, apart from limited protocol changes, there were no major changes in the hospital policy, budget, or staffing at the time of the reform. The second concern is that around the time

[7] While the WHO issued travel notice advising travelers to avoid non-essential travel to China on January 28, 2020, the first identified COVID case in Israel was only on 21 February 2020. A public health emergency was announced a month later.

of the reform, there may have been a change in the mix of patients visiting the emergency department. We explore this concern by performing auxiliary falsification analyses described below (Section 5.3).

We use a standard DD specification for estimating the reform's impacts:

$$Y_{jt} = \beta \text{Reform}_j \cdot \text{Post}_t + \mu \text{Reform}_j + \eta \text{Post}_t + X_{jt}\delta + u_{jt}, \tag{6}$$

where j index patients; t index the time the patient first arrives at the ED; Y_{jt} is any one of the outcomes we measure; $Reform_j$ is the treatment indicator, with the value one in the treatment year and zero in the comparison year; $Post_t$ is an indicator for $t \geq 0$, where 0 is the week of October 6 in each of the years; and X_{jt} denotes a vector of visit-level controls. We estimate specifications with and without controls, to check for robustness. The key parameter of interest is β, capturing the impact of the reform on the outcome.

4.2 Data

Sample construction. Our study sample includes all visits to the internal medicine ED twenty weeks before and after October 6 (the date of the reform in the treatment year) in both the treatment and comparison years. The sample includes a total of 38,848 visits, of which 12,950 were admitted to one of the internal medicine departments; the rest were discharged without admission.

Panel A of Table 1 describe the characteristics of ED visits in our sample. Just under half (48%) of all ED visit started after hours (between 6 PM and 8 AM); 74% of visits started during weekdays (Sunday through Thursday, in Israel). Nearly half (47%) of the visits are by minority patients, defined as those residing in localities where the majority of the population is non-Jewish, such as Arab or Druze localities, which are common in the hospital catchment area. The average age of patients was 59 years. The gender split was roughly equal, with women making up 47% of the sample. Visit-level characteristics serve as controls in robustness analyses, and for placebo tests for assessing potential changes in the incoming case mix around the reform.

Outcome variables. Our first outcomes of interest are ED visit duration and inpatient admission length of stay. Duration measurements are based on electronic medical record ("EMR") timestamps. ED visit duration is defined as the time from the patient's arrival in the ED to either discharge from the ED or admission to the hospital. Additionally, for patients admitted to the hospital we measure inpatient length of stay (LOS), defined as the time from admission to discharge or death.

In addition, we measure the share of ED admissions and hospital bed occupancy levels. Admissions are observed for each ED visit, and we record an indicator for whether the patient was admitted to the hospital. The daily count of occupied beds in each department is calculated based on admission timestamps by tracking the incoming and outgoing patient flows over time. Specifically, for each day, we start with the previous day's occupied bed count, add the new hospitalizations, and subtract the discharges.[8] We then calculate the occupancy level for each of the 2,800 department-day observations across the treatment and comparison years.

To evaluate the reform's impact on admitted patients' health, we consider 30-day hospital readmission and 90-day mortality rates for all admitted patients. The 30-day readmission variable is coded as a binary indicator for whether a patient was readmitted to the same hospital within 30 days. We observe mortality from official vital statistics and code an indicator for all-cause mortality within 90 days of admission. This covers mortality regardless of location, including at home or in other hospitals. Panel B of Table 1 provides the summary statistics of our main outcomes. The average ED visit duration is 6.13 hours. For the third of the patients admitted from the ED, the average inpatient length of stay at the hospital was 5.05 days. Of all admitted patients, 12.8% were readmitted to the hospital within 30 days, and 14.4% died within 90 days.

Control variables. In our analysis, we control for the following visit-level characteristics: patient gender, age, minority ethnicity (based on place of residence), and an indicator for whether the hospital visit occurred during holidays affecting hospital staffing levels (according to the Jewish lunar calendar of each year).

5 Results

5.1 The Reform's Impact on Hospital Congestion and Operations

To assess potential pretrends in outcomes, we plotted the raw means of each outcome around the reform date and the corresponding date in the previous year (henceforth, we refer to them jointly as "the reform date"). Figure 2 shows these plots. In the 20 weeks leading up to the reform date, the trajectories of all outcomes are very similar between the treatment and comparison years. In contrast, after the reform date, there is a discernible divergence in key outcomes.

[8] We begin this series with an initial condition of zero occupied beds, employing a 45-day runoff period before the start of each sample period. As over 99% of observed hospital stays are shorter than 45 days, the likelihood of missing admissions is negligible.

Panels A and B of Figure 2 show the trajectories of the ED visit duration and inpatient length of stay. Prior to the reform, both groups exhibited a similar average ED visit duration of about six hours and a similar inpatient length of stay of about five days. In the post-reform period, we observe a significant and sharp reduction in the average ED visit duration by approximately one hour in the treatment relative to the comparison year. Similarly, inpatient length of stay decreased markedly following the reform, with the treatment group showing an average reduction of about one day compared to the comparison year.

Quantifying the reform's impact on ED visit duration and inpatient length of stay, Columns 1–4 of Table 2 show the DD estimates of (6), with and without controls. These estimates suggest that the reform has reduced ED visit duration by an average of 1.5 hours and inpatient length of stay by slightly less than one day and they are robust to including controls for patient and period characteristics. These findings are both statistically and economically significant. The reduction in ED length of stay reflects a 25% decrease from the pre-reform baseline of 6.2 hours; the reduction in length of stay reflects a 20% reduction from the baseline of 5.15 days.

These substantial reductions in ED visit duration and inpatient LOS are consistent with the model's prediction that shifting from a pooled load equilibrium to a separate load equilibrium will incentivize departments to increase their effort to expedite service. I.e., eliminate the incentive to free ride across firm units.

Panel C of Figure 2 and columns 5–6 of Table 2 show the trajectories and estimated impacts on the rate of admissions from the ED. In the first three months after the reform date, the trends in hospitalization rates remain indistinguishable (a common uptrend may reflect seasonality in respiratory complications characteristic of winter months). All else being equal, a significant decrease in the average inpatient length of stay should lead to a reduction in average bed occupancy. This is precisely what we observe. Panel D of Figure 2 shows that, after the reform, bed occupancy—which was similar between the years in the period before the reform—exhibited a notable decline in the treatment year. Columns 7–8 of Table 2 show that bed occupancy decreased by approximately seven percent.

Over time, from the fourth month until the end of our study period, ED admission rates increased in the treatment relative to the comparison year (Panel C of Figure 2). Such an increase may reflect an endogenous response of the hospital admission decisions to the persistent decrease in bed occupancy following the reform. Results suggest that the initial effect on occupancy reduction is offset, at least to some extent, by this later rise in admission rates.[9] They also raise the question of whether this change was associated with a change in

[9]This outcome is in line with Currie and Slusky (2020) that show that monetary incentives can influence a physician's decision to admit the marginal patient.

the mix of admitted patients, which we return to below.

To explore potential heterogeneity in the reform's effects, we estimate a model that interacts the main effect with department size. This approach is informed by well-established literature highlighting the potential for misallocation when productivity varies across establishments or plants (Syverson, 2011). Our results indicate no significant heterogeneity in the reform's impact along this dimension (Appendix Table A1). Nonetheless, it is important to note that if department productivity is heterogeneous, a uniform allocation induced by an equal-load policy may result in suboptimal outcomes.

5.2 Impacts on Patient Health

The documented sharp operational changes at the hospital, particularly the marked decrease in the average length of inpatient stay, raise the question of how care quality was impacted. While shorter hospital stays could indicate a reduction in unnecessary admission days, there is a concern about the risk of premature discharges. To address this, we examined the reform's effects on hospital readmissions and patient mortality, as premature discharges can lead to readmissions or, in severe cases, mortality.

Panels A and B of Figure 2 show the trends in 30-day readmission and 90-day mortality around the reform date for the treatment and comparison years. There are no apparent changes in patient outcomes in the treatment group relative to the comparison group following the reform. Estimates in Table 3 show no significant changes in readmission or mortality rates.[10] Importantly, these findings suggest that the changes in hospital operations, reflected in reduced ED visits and hospitalization durations, did not adversely affect care quality, at least not in a manner detectable by commonly used patient outcome metrics.

5.3 Case Mix

The interpretation of our results as reflecting a change in medical staff's behavior presumes no sharp change in the rate and characteristics of incoming ED visits. An important consideration is whether the reform influenced the mix of patients admitted through the ED. It is conceivable that the enhanced operational efficiency led to the admission of patients with lower complexity. This section examines both of these issues.

[10]The 90-day mortality measurement for cases admitted toward the end of our treatment period partially overlaps with the onset of the COVID-19 public health emergency. However, significant COVID-19-related mortality in Israel only occurred after our measurement period, specifically in late 2020. Further, if COVID-19 had influenced our mortality estimates, it would likely have introduced an upward bias.

Incoming ED Visit Volume and Characteristics. We examined the reform's association on incoming ED visit volume and characteristics by estimating equation (6) with predetermined visit characteristics, serving as negative controls for falsification tests (Danieli et al., 2023). Table 4, Columns 1–6, provides these estimates. Column 1 indicates no significant change in the daily number of ED visits around the time of the reform. Columns 2–4 show results for the reform's association with incoming ED case characteristics, yielding estimates that are fairly precise zeros; this indicates no significant change in the patient mix at the ED following the reform. Columns 5 and 6 investigate changes in the timing of visits, finding no significant impacts. Appendix Figure A1 depicts the time trends for these variables. In line with the DD estimates, there are no marked shifts in any of the examined variables around the reform date, with the treatment and comparison trends closely aligned. Given that the case mix remained stable, any observed changes in hospital costs or resource utilization can be more confidently attributed to the reform itself rather than to a shift in the patient mix.

Inpatient Admission Complexity. In an auxiliary analysis, we investigated whether the reform, which resulted in changes to ED visit duration and hospital inpatient admission lengths, also changed the average complexity of cases admitted to the hospital. This analysis focuses on admitted cases and proceeds in two steps. First, we predict the length of stay based on all case characteristics observed at admission, using data from before the beginning of the treatment period. Second, we use the predicted length of stay as a proxy for case complexity and estimate whether it was impacted by the reform. For predicting length of stay, we trained a standard random forest model on data from the baseline period leading up to the reform. Model calibration is illustrated in Panel A of Appendix Figure A2. Results, shown in Panel B of Appendix Figure A2, indicate no significant change in the predicted inpatient length of stay around the time of the reform, suggesting no surge in the average complexity of cases admitted post-reform.

Returning to the noticeable rise in admission rates starting in the fourth month after the reform, Appendix Figure A2 shows no indication that it was accompanied by a change in the predicted inpatient length of stay. This finding is consistent with the marginally admitted patient post-reform being similar, on observable characteristics, to the average admitted patient pre-reform, which may be the case when, due to congestion, high demand for hospital services was not fully served pre-reform. This situation is plausible in the context of the heavily constrained Israeli healthcare system (see discussion in Section 2), suggesting that such admissions may have a net positive value.

6 Conclusion

This study analyzed a reform in a large Israeli hospital that modified the rules regulating patient routing between the ED and internal medicine departments, moving from a "first-available-bed" assignment policy to an "equal-load" rule. Using a difference-in-differences approach and leveraging detailed electronic medical record data on the timing of events, we found that the reform led to a 25% reduction in the average duration of ED visits and a 20% shortening of hospital length of stay. Importantly, these improvements occurred without an increase in 30-day readmission rates or 90-day mortality rates, suggesting that the quality of care was maintained.

These findings are consistent with the predictions of our queuing theory model, which demonstrates how a "first-available-bed" policy can induce free-riding among departments, leading to reduced effort and efficiency. In contrast, an "equal-load" policy eliminates these perverse incentives, resulting in improved performance. The empirical results align with the model's predictions, highlighting the importance of routing protocols in driving hospital-wide performance.

Our study underscores the importance of considering the strategic interactions between hospital units when designing operational policies. By carefully crafting these protocols to align departmental incentives, hospitals can unlock significant efficiency gains without additional resource investments. More broadly, our findings suggest that workload allocation rules can be a powerful tool for enhancing productivity and performance in organizations with multiple interacting units.

The insights from this study extend beyond healthcare to other service-oriented sectors where central intake points coordinate work allocation across specialized units. In settings such as manufacturing, logistics, and customer service, routing protocols can similarly influence the strategic behavior of organizational units and overall efficiency. Managers should carefully consider the incentives created by these protocols and design them to foster cooperation and optimize system-wide performance.

Future research could explore the design of optimal workload allocation policies in various organizational contexts, considering factors such as the degree of specialization across units and the constraints on allocation specific to other contexts. Additionally, studies could examine how other organizational structure aspects interact with workload allocation policies to shape performance. As this study demonstrates, a deeper understanding of the strategic dynamics within organizations can yield valuable insights for enhancing efficiency and productivity.

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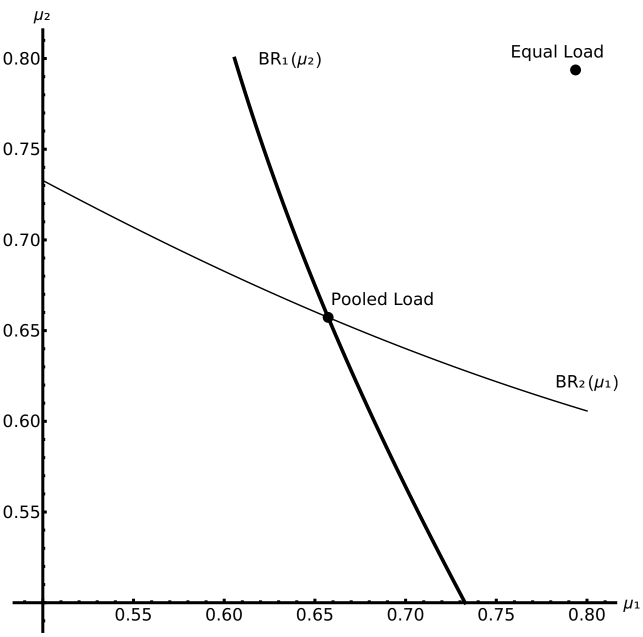
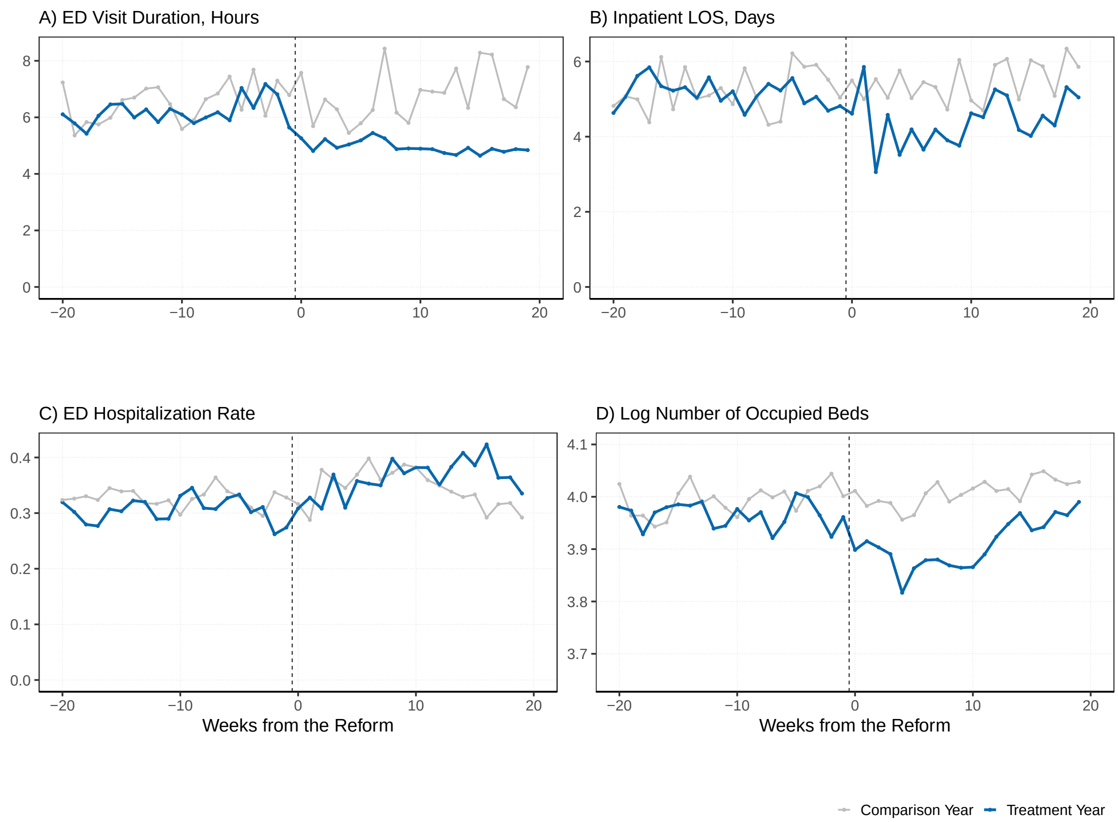
Figure 1: Illustration: Equal-Load Versus Pooled-Load Levels of Effort



The figure demonstrates the model predictions for the equilibrium effort under pooled load and the optimal effort under equal load. The plot shows numeric results calculated using the model developed in Section 3 with an overall arrival rate $\lambda = 1$ and an effort cost parameter $\alpha = 1/2$. The axes show the effort levels of two departments, denoted by subscripts 1 and 2. In the equal-load scenario, each department determines its level of effort when facing exactly half of all arrivals ($\lambda_i = 1/2$, for $i = 1, 2$). In this case, each department's effort is determined independently of the other's effort. The point in the northeast of the plot ($\mu_1 = \mu_2 = 0.79$) marks the optimal effort levels in this case. With pooled load, each department's effort is the best response to the other's effort level, $\mu_1 = BR_1(\mu_2)$ and $\mu_2 = BR_2(\mu_1)$. The resulting steady-state equilibrium (marked by the labeled dot in the intersection of the BR curves, with coordinates $\mu_1 = \mu_2 = 0.65$) involves lower effort than the equal-load case because department efforts are strategic substitutes.

Figure 2: Characteristics of ED Visits and Hospitalizations Around the Reform



The figure describes the evolution of our outcomes of interest around the time of reform. The different panels show the average weekly outcomes around the time of the reform (treatment year) and around the same time a year earlier (comparison year). The x-axis shows event time in weeks relative to week zero—the week starting with the reform's enactment date or the same calendar date in the previous year (a dashed vertical line marks week -1). The y-axis shows mean outcomes. All panels are based on patient-level data, except for Panel D, which is based on department-level data. ED Length of Stay is the duration from ED arrival to departure (either discharge or admission to the hospital). Inpatient Length of Stay is the time from hospital admission from the ED to hospital discharge for any reason. ED Rate of admission is the share of ED cases admitted to the hospital from the ED. Bed Occupancy Rate is the share of occupied hospital department beds out of total bed capacity, calculated at the weekly level. Panels A and C are based on a sample of all ED arrivals. Panels B and D are based on the sample of all admissions from the ED (with panel occupancy rates calculated at the department-week level and aggregated to the hospital level). See Section 4.2 for additional details on the sample construction and variable definitions.

Figure 3: Patient Outcomes

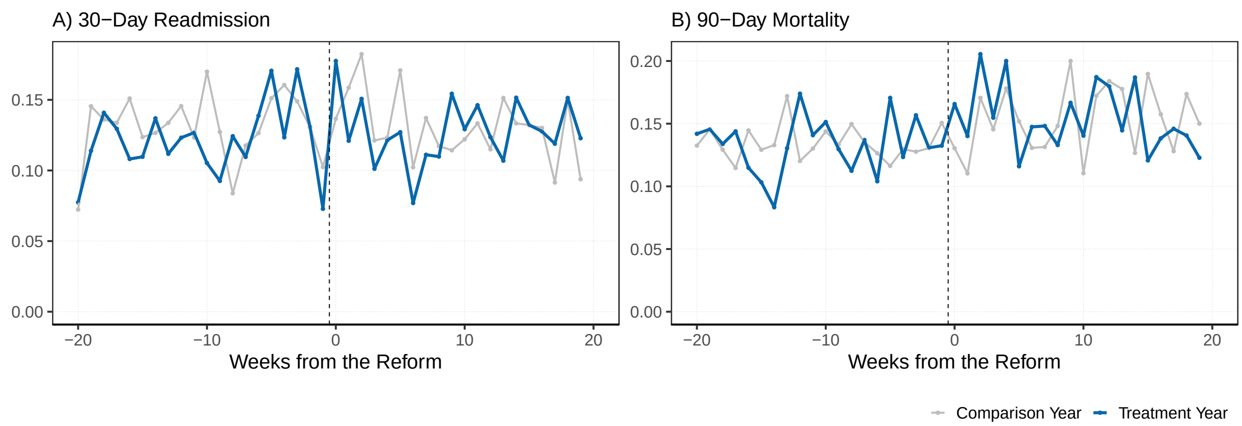


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Table 1: Descriptive Statistics for the Main Study Sample

	Mean (1)	S.D. (2)
A. Characteristics of ED Visits		
After-Hours visit Share	0.49	
Weekday Visit	0.74	
Minority Patient	0.47	
Patient Age	58.81	20.11
Female Patient	0.47	
Number Of ED Visits	69.25	12.25
B. ED Visit and Hospital Admission Outcomes		
ED Visit Duration (Hours)	6.13	5.03
Inpatient Admission from the ED	0.33	
Inpatient Length of Stay (Days)	5.05	6.36
30-Day Readmission	0.13	
90-Day All-Cause Mortality Rate	0.14	

Notes: This table shows summary statistics for the main study variables. The sample includes 38,848 ED visits. Statistics on inpatient hospital admissions, specifically Department Length of Stay (LOS), 30-day readmission rate, and 90-Day All-Cause Mortality Rate, refers to a subset of 12,950 ED visits resulting in an admission to the hospital. Standard deviations (Column 2) are reported only for continuous variables. All other variables represent proportions. See Section 4.2 for sample construction and variable definitions.

Table 2: The Impacts of the Reform on Admissions and Hospitalization

	ED Visit Duration (Hours)		Inpatient Length of Stay (Days)		Inpatient Admission from the ED		Log Occupancy	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post×Treatment	-1.529	-1.560	-0.972	-0.957	0.040	0.047	-0.070	-0.077
	(0.101)	(0.100)	(0.222)	(0.222)	(0.010)	(0.009)	(0.010)	(0.010)
Post	0.310	0.277	0.250	0.204	0.015	-0.002	0.014	0.016
	(0.082)	(0.081)	(0.161)	(0.161)	(0.007)	(0.006)	(0.007)	(0.007)
Treatment	-0.360	-0.316	-0.058	-0.046	-0.022	-0.019	-0.029	-0.023
	(0.073)	(0.072)	(0.148)	(0.147)	(0.007)	(0.006)	(0.007)	(0.007)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
N	38,848	38,848	12,950	12,950	38,848	38,848	2,800	2,800
Mean Dep. Var	6.174	6.174	5.152	5.152	0.305	0.305	3.965	3.965

Notes: This table presents the DD estimates of the average effect of the reform (Equation (6)) for the main outcomes of interest. The controls, added in the even columns, include patient age, gender, minority group status, and an indicator for holidays affecting hospital staffing. In the department-day level analysis of bed occupancy, the same controls were included in terms of their department-day rates. The mean dependent variable is for the comparison year. Robust standard errors appear in parentheses.

Table 3: The Impacts of the Reform on Patient Outcomes

	30-Day Readmission		90-Day All-Cause Mortality	
	(1)	(2)	(3)	(4)
Post×Treatment	0.0072	0.0080	0.0022	0.0044
	(0.0117)	(0.0118)	(0.0123)	(0.0121)
Post	0.0005	-0.0014	0.0190	0.0143
	(0.0084)	(0.0084)	(0.0087)	(0.0086)
Treatment	-0.0093	-0.0085	-0.0025	-0.0008
	(0.0084)	(0.0084)	(0.0086)	(0.0085)
Controls	No	Yes	No	Yes
N	12,950	12,950	12,950	12,950
Mean Dep. Var	0.1208	0.1208	0.1322	0.1322

Notes: This table presents the DD estimates of the average effect of the reform (Equation (6)) for the patient outcomes of interest. The controls, added in the even columns, include patient age, gender, minority group status, and an indicator for holidays affecting hospital staffing. The mean dependent variable is for the comparison year. Robust standard errors appear in parentheses.

Table 4: The Association of the Reform with the Rate and Characteristics of Incoming ED Visits

	Number of ED Visits	Patient Age	Minority Patient	Female Patient	After-Hours Visit	Weekday Visit	Predicted LOS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post×Treatment	-2.435	-0.674	-0.002	0.012	0.006	-0.019	-0.051
	(2.053)	(0.408)	(0.010)	(0.010)	(0.010)	(0.009)	(0.112)
Post	-2.129	2.097	-0.018	-0.007	-0.042	0.010	0.042
	(1.475)	(0.289)	(0.007)	(0.007)	(0.007)	(0.006)	(0.077)
Treatment	1.093	-0.238	-0.012	0.003	0.008	0.001	0.024
	(1.478)	(0.287)	(0.007)	(0.007)	(0.007)	(0.006)	(0.080)
N	561	38,848	38,848	38,848	38,848	38,848	12,828
Mean Dep. Var	71.471	57.827	0.474	0.475	0.511	0.740	5.482

Notes: This table presents the DD estimates of the average effect of the reform (Equation (6)) for selected covariates that should not have been affected by the reform. The mean dependent variable is calculated during the comparison year. Robust standard errors appear in parentheses.

Appendix A The Pooled Load Equilibrium

The department solves for the optimal μ_i to maximize its payoff given μ_{-i}. The first-order condition is $\frac{\partial c}{\partial \mu_i} = \frac{\partial r_i}{\partial \mu_i}$, where:

$$\frac{\partial r_i}{\partial \mu_i} = \frac{\partial p_0}{\partial \mu_i} \cdot (1 + \frac{\lambda}{2\mu_{-i}}),$$

with:

$$\frac{\partial p_0}{\partial \mu_i} = \frac{2\lambda\mu_{-i}(\mu_i + \mu_{-i})\big(\mu_{-i}(\mu_i + \mu_{-i}) - \lambda(\mu_{-i} - \mu_i)\big)}{\big(2\mu_i\mu_{-i}(\mu_i + \mu_{-i}) + \lambda(\mu_i^2 + \mu_{-i}^2)\big)^2}.$$

The sign of the RHS term is determined by: $\mu_{-i}(\mu_i + \mu_{-i}) - \lambda(\mu_{-i} - \mu_i)$, which is always positive as long as $\mu_i + \mu_{-i} > \lambda$ (i.e., a steady state exists and hence idle time r increases in additional effort).

In the symmetric Nash equilibrium (i.e., $\mu_i = \mu_{-i} = \mu$) with the quadratic cost $c(\mu_i) = \alpha\mu_i^2$, simplifying the first-order condition for the equilibrium level of effort gives $2\alpha\mu = \dfrac{\lambda}{\lambda\mu + 2\mu^2}$. Rearranging yields:

$$\mu^3 + \frac{\lambda}{2}\mu^2 - \frac{\lambda}{4\alpha} = 0,$$

which has a unique solution on the interval $\mu > 0$.

Expected Wait Times in Steady State

Let $\bar{N}$ denote the expected number of patients in the system in steady state. It is given by:

$$\bar{N}^{\text{equal}} = \frac{\rho}{1 - \rho}$$

for equal load (where $\rho = \lambda/(2\mu_i^{\text{equal}})$), and by

$$\bar{N}^{\text{pooled}} = \frac{2\rho}{1 - \rho^2}$$

for pooled load (where $\rho = \lambda/(\mu_1^{\text{pooled}} + \mu_2^{\text{pooled}})$). By Little's Law (Little, 1961), the expected wait times are the expected number of patients divided by the rate of arrival, i.e.:

$$\bar{W}^{\text{equal}} = \frac{2\rho}{\lambda(1 - \rho)}$$

for equal load (where each department rate is $\lambda/2$), and:

$$\bar{W}^{\text{pooled}} = \frac{2\rho}{\lambda(1-\rho^2)}$$

for pooled load (where the pooled rate is λ). Hence, if departments were non-strategic, serving patients at the same rate under pooled load as under equal load ($\mu^{\text{pooled}} = \mu^{\text{equal}}$), then ρ would be equal in both scenarios and hence also expected wait time would always be shorter under (non-strategic) pooled load than under equal load. However, this is not generally true if $\mu^{\text{pooled}} < \mu^{\text{equal}}$.

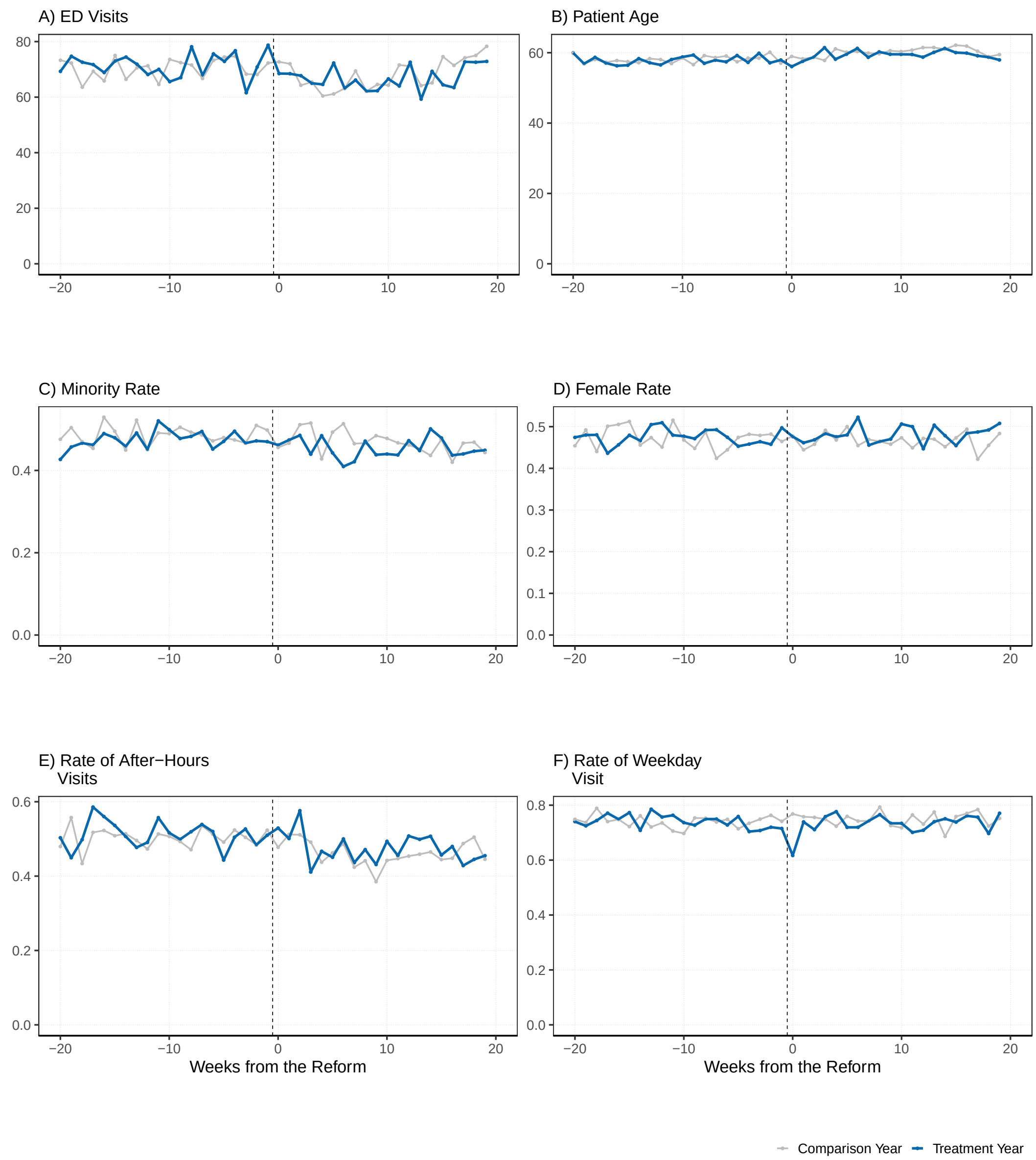
Appendix B Predicting Length of Stay

This section outlines the construction of the predicted inpatient length of stay variable, which we use in examining the inpatient admission profiles as detailed in Section 5.3. To enhance the statistical power of our prediction exercise, we included all visits to the internal medicine ED resulting in hospitalization from March 1, 2018, to May 12, 2019, just before the beginning of the treatment period. The sample includes a total of 9,943 admissions, each containing information about the patient characteristics and the diagnoses and diagnoses made at the time of reception to the ED.[11]

We divided the data into training and testing sets in a 70-30 random split and developed a random forest model to estimate the patient's department length of stay (LOS). Panel A of Appendix Figure A2 displays the model's calibration plot, applying a third-degree polynomial correction and utilizing only the test set. The figure plots the means of predicted department LOS, in five percent bins, against the actual department LOS. The proximity of these points to the 45-degree line suggests that the model is effective in accurately predicting department LOS.

[11]The data include diagnoses from various stages of the admission: in reception, during hospitalization, in the family, during discharge, psychiatric, and background. However, we only include diagnoses in reception to best represent the patient's condition at arrival.

Appendix Figure A1: Placebo: Case Characteristics Around the Reform



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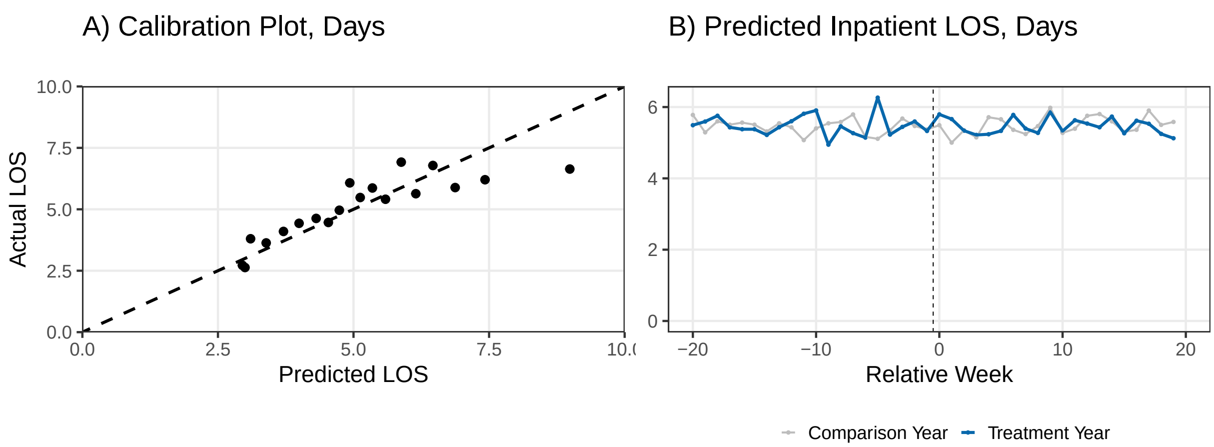
Appendix Figure A2: Predicted Inpatient LOS



The figure describes the evolution of our outcomes of interest around the time of reform. The different panels show the average weekly outcomes around the time of the reform (treatment year) and around the same time a year earlier (comparison year). The x-axis shows event time in weeks relative to week zero—the week starting with the reform's enactment date or the same calendar date in the previous year (a dashed vertical line marks week -1). The y-axis shows mean outcomes. the length of stay for admitted

Appendix Table A1: Heterogeneity in the Impacts of the Reform on Inpatient Length of Stay

	Inpatient Length of Stay (Days)	
	(1)	(2)
Post×Treatment×Large	-0.688	-0.768
	(0.449)	(0.448)
Post×Treatment	-0.662	-0.609
	(0.290)	(0.289)
Post×Large	0.463	0.463
	(0.326)	(0.326)
Treatment×Large	0.421	0.443
	(0.297)	(0.296)
Post	0.042	-0.005
	(0.210)	(0.209)
Treatment	-0.248	-0.248
	(0.200)	(0.200)
Large	-0.148	-0.094
	(0.215)	(0.216)
Controls	No	Yes
N	12,950	12,950
Mean Dep. Var	5.152	5.152

Notes: This table presents triple-difference estimates of the reform's average effect on inpatient length of stay (in days), disaggregated by department size (Large indicates above-median bed capacity). Post indicates the post period, and Treat indicates the reform year. Column (2) includes controls for patient characteristics (age, gender, minority group status) and hospital staffing conditions (holiday indicator). The mean dependent variable is calculated for the pre-reform comparison year. Robust standard errors are shown in parentheses. The sample includes all cases admitted from the ED to one of the internal medicine departments during the study period.