The Impact of Increasing Entry Fee on Emergency Department Demand: A Territory-Wide Study

Emergency department (ED) overcrowding is a global health problem. In hopes of reducing patient traffic to mitigate ED overcrowding, several countries have heightened the financial burden for access to ED care by increasing ED entry fees. We perform a territory-wide study of the universal public health system of Hong Kong SAR and empirically investigate the impact of the June 2017 ED entry fee increase from HK$100 (US$13) to HK$180 (US$23) on ED patient visit behavior and the underlying mechanisms. The study data covers all patient visits from 2014 to 2019 at 18 public EDs. Using a difference-in-differences approach, we find that the fee increase persistently reduced overall patient traffic for at least 2.5 years after the intervention. The estimated effect of the 6.3% reduction is larger than the government-reported 4.4%. This is mainly driven by a significant reduction in less-urgent visits, while urgent visits did not decrease. The intervention has been more effective in reducing revisits than initial visits. At the individual patient level, we find a significant reduction in patient ED visit frequency, and this effect is stronger for frequent visitors. We also find that the fee increase has reduced patients who abandoned and did not revisit in the near future. Overall, we provide empirical validation of the financial access hurdle as an effective policy instrument for alleviating healthcare congestion. We also show the policy's effectiveness in limiting inappropriate use of ED services. We highlight the effectiveness and importance of managing *external* demand in addition to improving internal processes.

Key words: Access hurdle; Public policy; Healthcare operations; Emergency department; Abandonment; Behavioral operations

1. Introduction

Overcrowding in emergency departments (EDs) has been exacerbated in recent years. According to the American Hospital Association (2018), the number of patient visits to an ED in the US increased by 50% over the past two decades, while the number of EDs dropped by 10% in the same period. Overcrowding has disrupted EDs' main role as a safety net for the public by providing medical services for urgent patients. To address the issue of overcrowded EDs, prior research in healthcare operations management (OM) has focused on the *internal* levers, such as patient flow management and capacity allocation within an ED system (Keskinocak and Savva 2020), mostly under the assumption that *external* ED demand is somewhat given and uncontrollable. In this paper, we take a different approach and examine an alternative way to mitigate ED overcrowding by managing the 'input' into EDs through access hurdles—a policy intervention which increased the ED entry fee. Several countries recently increased the ED entry fee in their public healthcare system, such as Portugal in 2012 (Ramos and Almeida 2016), South Korea in 2013 (Jung et al. 2014), and Taiwan in 2017 (Chen 2020). While the details of each ED entry fee policy structure vary slightly, the fee increase interventions share a similar goal of encouraging proper use of EDs and reducing attendance to tackle ED overcrowding.

The Hong Kong Special Administrative Region (HK SAR) has actively used the ED entry fee policy in its public healthcare system. Public hospitals serve as the backbone of HK's 'universal' public healthcare system and their EDs are often the only accessible outlet to specialized healthcare service for many patients as specialist out-patient services in the HK public healthcare system are significantly backlogged. The median waiting time for stable new case booking at specialist out-patient clinics ranges from 9 to 82 weeks depending on the region and specialty.[1] As a result, public EDs in HK have been severely overcrowded over the years. For over a century, treatment at public HK EDs was free of charge until the Hospital Authority (HA), the governing body of public hospitals in HK, started charging HK$100 (approximately US$13) for each visit in 2002. The objective of introducing the fee was transparent: "The immediate aim of introducing the new charges at public hospitals is to reduce abuse of the system" (Benitez 2002). 15 years later, in June 2017, the HA decided to increase the fee once more from HK$100 to HK$180 (approximately US$23) with the same goal in mind. In the official press release, the HK government cited "...to encourage appropriate use of services..." as one of the main factors considered in determining the new level of fees (The Government of the Hong Kong Special Administrative Region 2017a). In an earlier press release regarding overcrowding in public hospitals, the government noted a similar message: "We anticipate a longer waiting time today for semi-urgent and non-urgent (triage level 4 and 5) patients and appeal for their understanding and patience. Patients with mild conditions can consider seeking consultation at private doctors or general outpatient clinics" (The Government of the Hong Kong Special Administrative Region 2017b).

In 2020, the Legislative Council of the HK SAR (the unicameral legislature) requested that the HA assess the impact of the 2017 ED entry fee increase (The Government of the Hong Kong Special Administrative Region 2020). The council specifically asked about the effectiveness of raising the

[1] `https://www.ha.org.hk/visitor/ha_visitor_index.asp?Content_ID=214197`

ED entry fee on reducing ED attendances of patients belonging to triage levels 4 (Semi-urgent) and 5 (Non-urgent), the least urgent patients in the five level triage system of HK. The HA reported that the overall number of ED attendances between July 2017 and June 2018, one full year after the fee increase, had decreased by 4.4%, while triage levels 4 and 5 attendances decreased by 6.9% and 17.6%, respectively. However, these results may be misleading without assessing the entire system and identifying the varying impacts of the fee increase on heterogeneous patient groups. Notably, around the same time as the ED fee increase, two other events that could have also affected ED patient traffic occurred. First, in March 2017, a new hospital (Tin Shui Wai Hospital) began accepting patients in its ED.[2] Increased ED capacity may have induced demand, especially in the region. At the same time, traffic to the nearby EDs might be affected by the new ED as existing demand that used to visit other EDs shifts over to the new ED. Second, in July 2017, the HK government expanded the qualified patients for the public assistance program where medical charges (including ED entry fees) are waived.[3] As a countermeasure to the fee increase, the government lowered the access hurdle for vulnerable patients. Since more patients became eligible for the fee waiver, the overall ED traffic from assisted patients might have increased after the expansion. Thus, without properly addressing such potential confounding factors, the assessment of the policy intervention might be biased.

In this paper, we empirically analyze the effectiveness of reducing 'external' ED demand by increasing the ED entry fee at the territory level. Specifically, we first examine the overall effect of the fee increase on ED demand and study the temporal effect as to whether the intervention is a temporary solution for encouraging proper use of EDs with its effect waning over time or is a viable solution that persists. We then seek to answer the following research questions to better understand the underlying mechanisms: (1) By performing a triage-level analysis, we investigate whether increasing ED entry fees is effective in reducing visits from the policy's target group of less urgent patients without hindering access to emergency medical service for urgent patients. (2) By decomposing the overall traffic into initial visits and revisits, we examine the heterogeneity effect of the fee increase across the two types of demand. (3) We track the patients' behavior at the individual level and analyze whether the policy was even more effective in discouraging the "frequent visitors" that frequently present to the ED, which are known to be a cause of ED overcrowding (LaCalle and Rabin 2010). (4) We further explore patient abandonment behavior and examine whether the policy was effective in reducing inappropriate use of ED services.

We study the *entire* public ED system of HK which supports the 7.3 million (in 2022) population and the whole patient visit records. During our six-year study period (January 2014 to December

[2] `https://www.info.gov.hk/gia/general/201703/14/P2017031400473.htm`

[3] `https://www.ha.org.hk/visitor/ha_visitor_index.asp?Parent_ID=10047&Content_ID=259365&Ver=HTML`

2019), the network of 18 public EDs faced, on average, over 2.1 million patient visits per year. In total, we observe over 12 million visits by 4.1 million unique patients. We take advantage of the HK government's public assistance insurance scheme to establish causality between the policy intervention and various outcome measures. Specifically, we identify a control group of patients that were not affected by the fee increase because of their welfare coverage. We use a difference-in-differences (DiD) approach and compare their behavior with that of the treatment group of (fee) "eligible persons" who are subject to the fee increase.

Based on the DiD specifications after addressing potential confounding factors, we find that increasing the ED entry fee reduced the overall ED attendances from fee-paying patients by 6.3%. Our estimate is larger than the government report of a 4.4% reduction across patients. The magnitude of this effect was consistent for the two and a half years after the intervention, supporting the long-term effectiveness. In a more granular triage-level analysis, we find that patients with different urgency responded differently to the fee increase: The fee increase reduced traffic from triage level 4 and 5 patients by 9.8% and 33.6%, respectively, while attendances from triage level 1 to 3 patients did not decrease in the same study period. This indicates that the intervention was effective in reducing less-urgent patient traffic without discouraging urgent patients from visiting an ED. We also find that the intervention is more effective in reducing patients' follow-up visits than initial visits. At the individual patient level, we find the fee increase to successfully reduce visit frequency by 5.5% to 9.8% for infrequent visitors and an additional 7.5% to 15.5% for frequent visitors for various thresholds of categorizing frequent visitors. This suggests that the policy is effective in discouraging the overuse of ED services. Finally, we find another benefit of the fee increase: it reduced patient abandonment, which can mitigate the patients' risk of being in an adverse health condition due to delayed treatment. Interestingly, the abandoned patient visits without subsequent follow-up visits are significantly reduced after the fee increase, indicating that the policy effectively mitigates the potentially inappropriate usage of the service. Overall, our results show that the ED entry fee increase was a successful policy intervention in addressing the overuse of ED services in HK, especially by less-urgent and frequent visitors.

Our paper makes several contributions to both policymakers and the broad literature on ED overcrowding. First, we find that the HK government has significantly under-estimated the effectiveness of the fee increase. With proper control of the two potential confounding factors (the newly opened ED and the fee waiver expansion) occurring around the same time of the ED fee increase, our estimate of the policy effect (6.3%) is larger than the government reported 4.4%. Second, we reaffirm the discussion in the literature on the validity of financial barrier as a policy instrument to moderate ED utilization (Flores-Mateo et al. 2012). Prior studies in the medical literature analyze a subset of EDs (not the entire network) in the short run (a few months pre-and post-intervention) and show that the ED fee increase leads to a higher proportion of urgent patients in ED attendance (Jung et al. 2014, Ramos and Almeida 2016). However, they fail to study how the overall ED demand (i.e., the input to the entire country- or city-wide network of ED systems) is affected in the long run and provide a proper policy evaluation. By performing a territory-wide study of a uniform policy, we find how the general public has responded to a fee increase and identify the nuances of ED utilization by different patient groups under the increased fee. Third, prior research in healthcare OM has focused on how to improve *internal* operations via better patient flow management and capacity allocation within an ED system (Keskinocak and Savva 2020), under the assumption that *external* ED demand is given. We add to this stream of literature by investigating an alternative way to mitigate ED overcrowding, which directly reduces the inputs into the EDs. We hope to bring more attention to the control of external inputs into the ED system in addition to the vast literature on improving internal operations in healthcare OM.

2. Literature Review

In the healthcare OM literature, the access to, cost, and quality of care have been identified as the key outcomes of interest in evaluating healthcare system performances (KC et al. 2020). Please see the review papers in the empirical (KC et al. 2020) and analytical (Keskinocak and Savva 2020) healthcare OM literature.

Overcrowding in EDs has been well documented in both academia and media. Morley et al. (2018) identify a mismatch between causes of and solutions for ED overcrowding. While the majority of causes are related to 'external' factors such as attending patient type and volume, and timely discharge from the ED, most solutions focus on 'internal' operations, such as improving patient flow within the ED. For example, Saghafian et al. (2015) review analytical advancements in patient flow management in the ED. While interventions for EDs in both the healthcare OM literature (Keskinocak and Savva 2020) and emergency medicine literature (Bittencourt et al. 2020) have focused on *internal* patient flow management (specifically, triage systems), resource allocation, throughput, and output from EDs, managing *external* input into the EDs has not garnered enough attention.

Recent studies have warned of the possibility of ED overuse in the US (Adams 2013) and provided evidence of ED overuse in Chile (Alvial et al. 2021). Others have identified less-urgent visits as one of the main factors contributing to ED overcrowding (Tsai et al. 2010). While there have been several attempts to prevent patients from unnecessary usage of emergency services, there is no universal solution. In the US, mandatory paid sick leave has been associated with a 5.6% reduction in ED visit rate (Ma et al. 2022), but not necessarily with instances of overuse. Under a public healthcare system, several countries have increased the financial barrier of emergency care access in hopes of reducing overall ED patient traffic, especially less-urgent visits: Portugal in 2012 (Ramos and Almeida 2016), South Korea in 2013 (Jung et al. 2014), and Taiwan in 2017 (Chen 2020). Ramos and Almeida (2016) found that increasing co-payments for ED visits did not have an impact on reducing ED utilization. However, their study is limited to three hospitals. Jung et al. (2014) and Chen (2020) study a broader set of hospitals but only the highest tier in the three tiers hospital system in South Korea and Taiwan, respectively. Since EDs operate as a network with patients having a choice to decide which to attend (Park et al. 2022), analyzing a subset of hospitals in a public healthcare system may not provide the whole picture of a nation-wide policy intervention. Specifically, hospitals at the top of the hierarchy serve the most urgent and complicated patients and are less likely to be affected by the intervention, leading to an underestimation of overall policy effectiveness. We study the whole network of EDs in HK's public healthcare system, which allows us to capture the entire demand of ED service in a border-controlled administrative region. Notably, the mean ED visits per year per capita is 0.28 in our study data compared to 0.063 in Chen (2020).

The policy structure in HK also differs from that in South Korea and Taiwan. Since 2002, HK has always implemented a *uniform* pricing policy with a single price for all government ED services regardless of the patient's urgency. The fee increase to HK$180 from HK$100 in 2017 was applied to all fee-paying patients equally. In 2000, South Korea introduced a differential fee of 30,000 KRW (US$23) for level 1 and 2 hospitals and 15,000 KRW (US$12) for level 3 hospitals. In 2013, they raised it to 52,500 KRW (US$40), 27,520 KRW (US$21), and 18,280 KRW (US$14) for level 1, 2, and 3 hospitals, respectively. Taiwan has also implemented a tiered pricing scheme according to the level of hospital in 2005 that ranged from NT$150 (US$5) and NT$300 (US$10) at district and regional hospitals to NT$450 (US$15) at the most advanced medical centers. In 2017, the Taiwanese government further differentiated the pricing at medical centers to restrain ED utilization in medical centers by increasing the fee for non-urgent visits (triage levels 3, 4, and 5) to NT$550 (US$18), while the fee for urgent visits (triage levels 1 and 2) remains unchanged at NT$450. Under differential pricing structures, without fully analyzing the entire patient traffic, it is difficult to derive concluding evidence of the impact of the fee adjustment, as patients may elect to attend the more affordable lower-tier ED and the intervention may shift congestion from higher tier EDs to lower-tier EDs. Our study covers the entirety of a universal public health system serving a market with very limited private emergency medicine services. Compared to prior studies, we provide a deeper understanding of individual patient responses to the fee increase policy by utilizing an anonymized individual patient panel data. We offer a more rigorous approach to estimating the effectiveness of the fee increase as a mechanism of reducing ED patient traffic.

Several papers have recently studied the supply side of the ED process. Chen et al. (2022) study patient flow improvement through early initiation of the admission process based on the prediction of whether a patient would need to be admitted at the triage stage. Li et al. (2021) study the ED decision makers' patient routing behavior and how ED blocking, a process-driven cause of ED overcrowding, affects their decisions. Meng et al. (2021) study facility layout and nurse behavior in EDs. Soltani et al. (2022) study the impact of physician workload on post-ED care use. Song et al. (2018) show that publicly disclosing relative performance feedback leads to improved ED physician productivity. The demand side of ED systems has been studied mainly from a network coordination perspective. Dong et al. (2019) and Park et al. (2022) study waiting time announcements and delay sensitive patients' ED choice behavior in ED network settings. Deo and Gurvich (2011) also study ambulance diversion policies from a network perspective. These studies are based on a given total patient demand and routing the patients within a network of EDs. In contrast, we study a policy that controls the volume of total demand for the entire network via access hurdle.

3. Study Setting, Data Description, and Identification Strategy

We first discuss the study setting with an overview of the healthcare system and ED network in HK. Then, we discuss the policy intervention of increasing the ED entry fee by the HK government, followed by the data description and identification strategy.

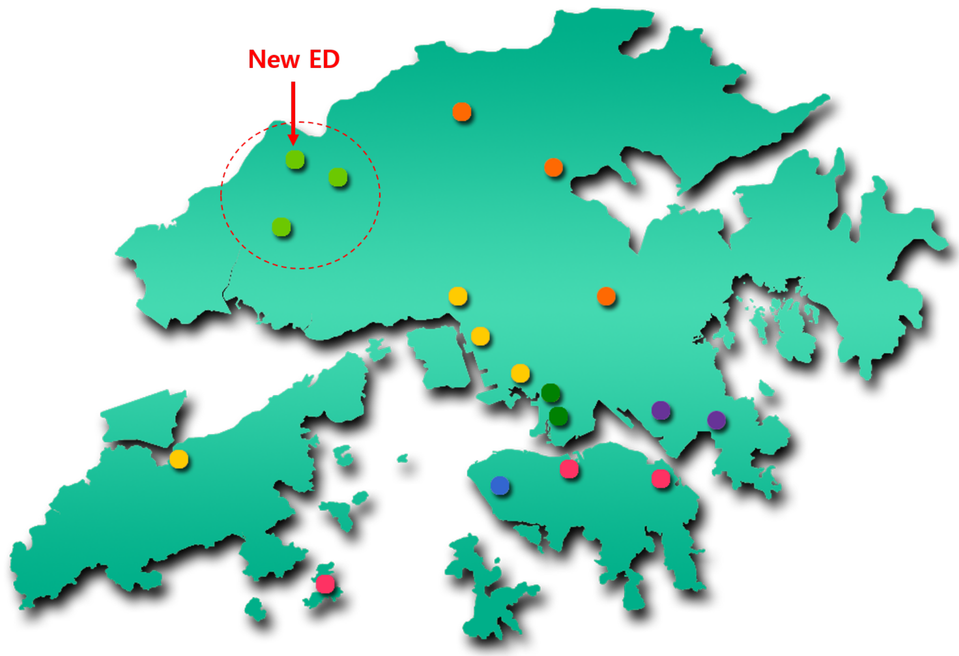
3.1. Study Setting

3.1.1. Healthcare System and EDs in HK. Healthcare in the Hong Kong SAR is largely supported by a 'universal' public health system with a limited private sector. While there are private hospital operators in the city, they target a certain group of patients, typically holding self-paid private health insurance. The public health system is operated by the Hospital Authority (HA), the governing body of 43 public hospitals and institutions, including 17 (+1)[4] tier one hospitals that serve as the backbone of health support for the general public in HK. All tier one hospitals in HK provide Accident and Emergency (A&E) department service, the equivalent of ED in other countries. Figure 1 illustrates the locations of the 18 EDs in HK.

All 18 public HK EDs implement a triage system where patients are categorized into five priority groups based on the emergency of their medical condition. Regarding the patient flow, patients first register and pay the entry fee upon arrival. This is the first timestamp we capture in the data as the registration time, which we use to identify which ED and when they attended. Patients are quickly called into the triage station where experienced nursing staffs assess the patient and sort them into triage categories: triage level 1 (Critical), 2 (Emergency), 3 (Urgent), 4 (Semi-urgent),

[4] A new ED opened in March 2017 during our study period.

Figure 1 Location of Emergency Departments in Hong Kong SAR



Note. Each dot indicates an ED. Color codes represent the Hospital Authority's public hospital cluster system. The circled area indicates the new ED that opened in March 2017 and the cluster to which it belongs.

and 5 (Non-urgent). Patients then wait in the waiting area until their name is called to be seen by the next available physician. We observe patients leaving the ED either before they see a physician or after consulting with a physician and without consent from the ED staff. We capture the first type of behavior as patient abandonment and study how it has been affected by the fee increase. Table 1 provides the distribution of patient visits across triage categories between 2014 and 2019. We note that while 64.5% of ED visits were classified as less-urgent patients (triage levels 4 and 5) pre-intervention, it drops to 60.5% post-intervention, showing preliminary evidence of improved proper ED usage.

Within the public HK health system, patients are classified into one of seven payment schemes (noted as paycode in the HA system): Eligible People (EP), Public Assistance (PA), Government Servant (GS), Hospital Authority (HA), Non-eligible People (NEP), Others (OTH), and Unclear (UNC). Table 2 shows the patient distribution over payment schemes. Almost 70% of patients are under the EP scheme. These are the general public supported by government subsidies in the form of universal health insurance who pay the nominal ED entry fee; hence, they are subject to the fee increase. The second-largest payment group is PA. The PA scheme provides further government support to socioeconomically disadvantaged patients. PA patients receive a broad assistance from

Table 1 Patient visit distribution over triage categories

Triage Category	Before fee increase		After fee increase		Total	
	Frequency	Percent	Frequency	Percent	Frequency	Percent
1 (Critical)	69,264	0.9%	56,470	1.1%	125,734	1.0%
2 (Emergency)	154,505	2.1%	133,722	2.5%	288,227	2.2%
3 (Urgent)	2,431,292	32.3%	1,906,188	35.7%	4,337,480	33.7%
4 (Semi-urgent)	4,441,167	59.0%	3,029,832	56.7%	7,470,999	58.0%
5 (Non-urgnet)	414,011	5.5%	202,946	3.8%	616,957	4.8%
Missing	23,427	0.3%	12,739	0.2%	36,166	0.3%
Total	7,533,666		5,341,897		12,875,563	

Table 2 Patient distribution by payment scheme: Raw data

Paycode	Visits						Unique patients			
	Before fee increase		After fee increase		Total		Before fee increase		After fee increase	
	Frequency	Percent	Frequency	Percent	Frequency	Percent	Frequency	Percent	Frequency	Percent
Eligible Person (EP)	5,502,714	73.0%	3,499,861	65.5%	9,002,575	69.9%	2,427,349	81.2%	1,843,534	76.0%
Public Assistance (PA)	1,180,514	15.7%	1,214,974	22.7%	2,395,488	18.6%	288,153	9.6%	361,610	14.9%
Government Servant (GS)	466,801	6.2%	341,794	6.4%	808,595	6.3%	193,278	6.5%	163,134	6.7%
Hospital Authority (HA)	227,305	3.0%	179,287	3.4%	406,592	3.2%	71,718	2.4%	65,694	2.7%
Non-eligible Person (NEP)	106,212	1.4%	72,330	1.4%	178,542	1.4%	73,398	2.5%	49,927	2.1%
Others (OTH)	49,898	0.7%	33,555	0.6%	83,453	0.6%	42,815	1.4%	29,321	1.2%
Unclear (UNC)	222	0.0%	96	0.0%	318	0.0%	197	0.0%	89	0.0%
Total	7,533,666		5,341,897		12,875,563		2,989,991		2,426,771	

Note. Patients may visit an ED multiple times with different paycodes. Hence, the percentage of unique patients adds up to more than 100%. Before fee-increase period: January 1, 2014 to June 17, 2017. After fee-increase period: June 18, 2017 to December 31, 2019.

the HK government and medical fee waivers, including ED services. Therefore, they are not affected by the fee increase. This social support scheme allows us to use PA patients as the control group against the treatment group of EP patients in our identification strategy. However, the distribution of unique EP and PA patients changed significantly post-intervention: 5.2% decrease for EP and 5.3% increase for PA. This is due to the expansion of the public assistance program which we explain in more detail in Section 3.2. GS and HA employees are both public servants employed by the HK government. NEP are patients without a valid visa (e.g., tourists) and do not receive the universal public insurance benefit that residents receive as EP. They have to pay a higher fee for all medical services at government hospitals, including the ED at HK$1,230 per visit. OTH and UNC are patients without identified residential status and pay the same rate as NEP patients.

3.1.2. ED Entry Fee Increase. For over a century, treatments at public hospital EDs in HK were free of charge until the HA started charging HK$100 (US$13) for each visit in 2002. The fee would cover all tests performed during the visit and the medicines prescribed. The immediate goal of implementing an ED fee was to reduce system abuse (Benitez 2002). Fifteen years later, on June 18, 2017, the HA raised the ED visit fee by 80% to HK$180 (US$23) citing a similar reason of "encourage appropriate use of services" (The Government of the Hong Kong Special Administrative Region 2017a).

In 2020, the Legislative Council of Hong Kong requested that the HA assess the effectiveness of increasing the ED attending fee (The Government of the Hong Kong Special Administrative Region 2020). The HA was asked whether the policy intervention reduced visits from less urgent patients. The HA reported a decrease of 6.9% and 17.6%, respectively, in triage levels 4 (Semi-urgent) and 5 (Non-urgent) attendances and a slight increase in triage levels 1 (Critical), 2 (Emergency), and 3 (Urgent) of 1.3% in the first year after the fee increase. These calculations, however, are based on a comparison of simple averages before and after the fee increase, which overlooked some important confounding factors occurring at a similar time of the policy intervention. First, in March 2017, a new hospital (Tin Shui Wai Hospital) started to accept patient visits to its ED. Second, the government assured that access to healthcare by the public especially patients in need would not be hindered due to the fee increase. In July 2017, the government extended the medical fee waiver to cover more patients through the Comprehensive Social Security Assistance (CSSA) program (Hong Kong Hospital Authority 2017). We disentangle these two potential confounding factors from the fee increase and focus on the effect of the fee increase only as explained in the next section.

3.2. Data Description

The main data contains every single ED visit record to a public ED in HK between January 2014 and December 2019. Specifically, the records include (1) patient information, such as anonymized patient ID, age, gender, residential district, and payment scheme; (2) visit information, such as triage level and time of registration; and (3) ED information, such as name and district. We supplement the patient-visit data with two additional data sets[5]: (1) daily weather reports, which includes average humidity, precipitation, temperature, and wind speed; and (2) district-level demographic information, such as median household income, population, median household size, and the number of establishments in each industry sector. The original individual visit level data set contains over 12 million patient-visits to the 18 EDs in HK made by over 4.1 million unique patients. Given that the HK population is approximately 7.3 million (in 2022[6]), about 56% of the HK population has used the ED during the study period.[7] Also, 144,132 (i.e., 3.5% of total patients) unique patients had visited the ED more than twice a year on average (i.e., total number of visits ≥ 12 over the six year study period). These observations potentially indicate a significant overuse of EDs in HK.

[5] Both from the HK government data archive at https://data.gov.hk/en/

[6] https://www.censtatd.gov.hk/en/web_table.html?id=1A

[7] Since people moved to and from HK over the years, this is not an exact calculation but an upper limit.

Table 3 Patient distribution by payment scheme: Final study data

Paycode	Visits						Unique patients			
	Before fee increase		After fee increase		Total		Before fee increase		After fee increase	
	Frequency	Percent	Frequency	Percent	Frequency	Percent	Frequency	Percent	Frequency	Percent
Eligible Person (EP)	3,148,786	75.6%	2,135,445	75.2%	5,284,231	75.5%	1,523,939	82.6%	1,191,354	81.7%
Public Assistance (PA)	458,784	11.0%	308,059	10.8%	766,843	10.9%	117,216	6.4%	89,603	6.1%
Government Servant (GS)	285,446	6.9%	204,904	7.2%	490,350	7.0%	127,083	6.9%	105,453	7.2%
Hospital Authority (HA)	166,601	4.0%	121,206	4.3%	287,807	4.1%	51,479	2.8%	46,054	3.2%
Non-eligible Person (NEP)	63,948	1.5%	44,130	1.6%	108,078	1.5%	47,686	2.6%	32,354	2.2%
Others (OTH)	38,793	0.9%	26,897	0.9%	65,690	0.9%	33,231	1.8%	23,483	1.6%
Unclear (UNC)	123	0.0%	42	0.0%	165	0.0%	117	0.0%	40	0.0%
Total	4,162,481		2,840,683		7,003,164		1,845,202		1,457,978	

Note. Patients may visit an ED multiple times with a different paycode. Hence, the percentage of unique patients adds up to more than 100%.

We construct the final study data set (Table 3) by excluding visit records according to several criteria. First, a new ED (Tin Shui Wai Hospital) opened in March 2017, increasing the total number of EDs available for patients in HK. The newly opened ED might have absorbed some patient-visits from adjacent EDs and/or generate more traffic by increasing accessibility for nearby patients. As ED-level patient traffic can be affected by the new ED opening, we exclude the new ED and two nearby EDs belonging to the same HA cluster, as highlighted in Figure 1. Second, in July 2017, the HA expanded the fee waiver policy for patients aged 75 years or older. For elderly patients ($Age \geq 75$), the number of patient visits under the PA scheme account for 30.6% before vs. 65.7% after the fee increase. For patients under 75 years old, the patient visits under the PA scheme account for 12.2% before vs. 11.7% after the fee increase. The fee waiver expansion is likely to have affected patients in the opposite direction from the fee increase in encouraging patients to visit public hospital EDs more easily with a lower financial burden. Thus, we exclude all patients older than 75 years from our analysis. Third, we further limit our analysis to the general adult ED patients by excluding children ($Age < 18$) from our patient sample. Prior literature finds mixed results regarding younger patient's price-elasticity of demand for medical service (Colle and Grossman 1979, Becker et al. 2013). Our final study data set includes over 7 million patient-visits across the 15 EDs in HK made by 2.2 million unique patients. We focus on patients under the payment scheme of EP (treatment group) and PA (control group). In our main analyses, we aggregate the patient-visit level data into the ED-day level. Demand rate is a measure that is important at the hospital level. Hence, we use the day level to allow enough granularity while aggregated enough to remove noise that may arise with shorter time frames.

Our data set has several advantages in exploring our research questions. First, during the study period, we have a clear treatment group who are directly affected by the fee increase, and a control group who are not influenced by the policy change at all. Second, our data set covers every single

ED visit in HK during the study period across all public EDs in the territory. In other words, we have the “population” of HK ED patient visit records. The total number of visits in our data matches the numbers in the 2020 government assessment of the fee increase (The Government of the Hong Kong Special Administrative Region 2020). Most prior studies that examined a similar ED entry fee increase policy rely on a sample, not the entire population, which may lead to selection bias. For example, Ramos and Almeida (2016) utilized aggregated patient visits for only three different EDs.

3.3. Identification Strategy

3.3.1. Difference-in-Differences. Given our study setting, we adopt a difference-in-differences (DiD) estimation framework, which has been used widely on quasi-experimental or natural experimental data (Angrist and Pischke 2009). This methodology has been extensively used in many OM studies (e.g., Bell et al. 2018, Lee et al. 2021a) to investigate the effect of a new policy (e.g., Levine and Toffel 2010, Lee et al. 2021b). Our objective is to examine the effect of the policy intervention, where the ED entry fee increased from HK\$100 to HK\$180, on ED-day-level traffic (and patient-level ED visit behavior). As aforementioned, EP patients are all subject to the fee increase whereas PA patients are not affected by the fee increase due to their medical fee waiver benefit. Naturally we use the former as a treatment group and the latter as a control group.

We provide our DiD specification for the ED-day-level analysis as follows:

$$Y_{ijd} = \beta_1 Treat_j + \beta_2 After_d + \beta_3 Treat_j \times After_d + ED_i + T_d + \mathbf{X_{id}} + \varepsilon_{ijd}, \tag{1}$$

where the subscripts i, j, and d denote the ED, payment type of the patient-group (EP or PA), and day, respectively. Y_{ijd} represents the total number of visits by patient group j on day d to ED i. The binary variable $Treat_j$ is the treatment group indicator: $=1$ for the patient group covered by the EP payment scheme (treatment group) and $=0$ for the patient group under the PA payment scheme (control group). It captures the difference in traffic volume between the treatment and control group patients. The binary variable $After_d = 1$ if day d is after the fee increase and 0 otherwise. Our key parameter of interest is the interaction term of the two (β_3), which measures the impact of the policy intervention on EP patient traffic. Our preferred specification includes ED fixed effects (ED_i) to capture ED-specific and time-invariant factors, as well as temporal controls (T_d)—monthly and day-of-week fixed effects—to capture time-specific and ED-invariant factors.

We control for additional factors in the vector $\mathbf{X_{id}}$. First, we account for demand-side factors using census data at the district level.[8] Prior literature (e.g., Fisher et al. 2020) used similar

[8] The granularity of districts in HK is similar to that of postal codes in other countries.

approaches to characterize demand factors of a particular location. We include (a) median household income (*HHIncome*), (b) population (*Population*), and (c) median household size (*HHSize*) at the ED-year level (census information is collected yearly) in our model specification. We map each ED to the corresponding district in the census data. Second, we control for weather, as it is known to impact traffic (Martínez-de Albéniz and Belkaid 2021). We include daily average humidity (*Humidity*), precipitation (*Rain*), temperature (*Temp*) and its square (to capture the non-linearity), and wind speed (*WindSpeed*) at the ED-day-level by mapping each ED to the nearest weather collection point. Third, we include the percentage of establishments in manual labor-oriented industries (e.g., manufacturing, mining, and construction) (*IndComp*), as ED traffic may be associated with the number of workers involved in heavy physical activities. The information is available at the district-month level, and we map each ED to the corresponding district to construct an ED-month level control.

Finally, the disturbance term (ε_{ijd}) captures unobservable determinants of the total traffic at the ED-patient group-day level. Overall patient visits within the same ED are unlikely to be independent, as each ED faces similar local economic and industrial labor market conditions day by day. We account for this effect by clustering standard errors at the ED level.

Table 4 provides the descriptive statistics of the variables, and Table 5 reports Pearson correlation coefficients among all variables used in our analysis, excluding fixed effects.

3.3.2. Parallel Trend Assumption. The key assumption for the DiD approach is the existence of a *parallel trend*. It does not require the control and treatment groups to be *a priori* the same in all aspects but requires that the two groups follow the same trend in the absence of the treatment, while the levels may differ due to differences in characteristics.[9] To test violation of the parallel trend assumption, we follow the literature (e.g., Fisher et al. 2019, 2020, Lee et al. 2022, Li et al. 2022) and compare the trends in the total ED patient traffic between the treatment and control groups by estimating the following model using observations from the pre-intervention period only:

$$Y_{ijd} = \gamma_1 Treat_j + \gamma_2 Trend_d + \gamma_3 Treat_j \times Trend_d + ED_i + T_d + \mathbf{X_{id}} + \varepsilon_{ijd}, \tag{2}$$

where $Trend_d$ denotes the number of days since the start of the observation period (January 1, 2014). As shown in Column (2) in Table 6, the coefficient of $Treat_j \times Trend_d$ is close to zero and statistically insignificant, suggesting that there does not exist a statistically significant difference in pre-intervention traffic trend between the treatment and control groups. Therefore, we do not find evidence of violating the parallel trend assumption and rule out the possibility that different pre-trends drive the results of our DiD estimation.

[9] "*Threats to the internal validity of the DD estimator cannot come from either permanent differences between the treatment and control groups, or shared trends*" (Roberts and Whited 2013, p. 525).

Table 4 **Descriptive statistics of ED day level aggregated data ($N = 63,831$)**

ED Day level	Mean	SD	Min	Max
Traffic	92.82	77.81	0	289
Tri1Traffic	0.74	1.16	0	12
Tri2Traffic	1.78	2.27	0	19
Tri3Traffic	27.33	26.76	0	150
Tri4Traffic	57.98	51.09	0	223
Tri5Traffic	4.97	5.88	0	60
Population	543,657	239,014	144,500	1,000,300
HHSize	2.85	.11	2.6	3.1
HHIncome (HK$)	27,264	4,732	18,000	38,300
IndComp (%)	6.6	2.9	2.1	16.3
Humidity (%)	78.2	11.5	16	100
Rain (mm)	6.25	19.50	0	369
Temp ($^{\circ}C$)	23.7	5.2	3.7	34
WindSpeed (km/h)	9.9	5.2	0	86.9

Table 5 **Pearson correlation coefficients**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) *Traffic*	1.00													
(2) *Tri1Traffic*	**0.51**	1.00												
(3) *Tri2Traffic*	**0.65**	**0.47**	1.00											
(4) *Tri3Traffic*	**0.86**	**0.59**	**0.67**	1.00										
(5) *Tri4Traffic*	**0.96**	**0.39**	**0.56**	**0.69**	1.00									
(6) *Tri5Traffic*	**0.61**	**0.27**	**0.26**	**0.43**	**0.57**	1.00								
(7) *Population*	**0.14**	**0.24**	**0.24**	**0.23**	**0.07**	**0.05**	1.00							
(8) *HHSize*	**0.10**	**-0.02**	**0.04**	**0.04**	**0.12**	**0.01**	**0.10**	1.00						
(9) *HHIncome*	**-0.10**	**-0.14**	**-0.06**	**-0.18**	**-0.02**	**-0.26**	0.00	**0.16**	1.00					
(10) *IndComp*	**-0.07**	**-0.12**	**-0.06**	**-0.05**	**-0.06**	**-0.04**	**-0.48**	**-0.11**	**-0.15**	1.00				
(11) *Humidity*	-0.01	**-0.01**	-0.01	-0.00	**-0.01**	**0.01**	**0.03**	**0.03**	**0.01**	**-0.04**	1.00			
(12) *Rain*	-0.00	-0.01	-0.00	-0.00	-0.00	**-0.02**	**0.02**	0.00	0.00	**-0.01**	**0.32**	1.00		
(13) *Temp*	**0.02**	**-0.03**	-0.00	**0.01**	**0.02**	**-0.03**	-0.00	**-0.04**	-0.00	**0.01**	**0.26**	**0.11**	1.00	
(14) *WindSpeed*	**-0.14**	**-0.09**	**-0.14**	**-0.18**	**-0.10**	**-0.03**	**-0.18**	**-0.35**	**0.06**	**0.10**	**-0.05**	**0.04**	**-0.09**	1.00

Note. Bold denotes statistical significance at the 1% level.

4. Effectiveness of Increasing ED Entry Fee in Reducing Demand

In this section, we present the results of the main ED-day-level analysis for overall patient traffic, temporal analysis of the intervention effectiveness, and further analyses to check the validity of our results, including placebo tests and addressing potential serial correlations in the error.

4.1. Overall Effect

We estimate Equation 1 to examine the impact of increasing the ED entry fee on overall ED traffic. In Column (1) of Table 6, we observe a significant impact of the policy intervention on

Table 6 Impact of increasing ED entry fee on overall ED traffic

Dependent variable:	*Traffic* (daily ED-level patient visit count)				
	(1) Main	(2) Parallel trend	(3) Placebo 1 (June 18, 2016)	(4) Placebo 2 (June 18, 2015)	(5) Yearly Effect
Sample period:	All	Pre-intervention only			All
$Treat \times After$	-10.43***				
	(2.367)				
$Treat$	143.0***	140.0***	141.6***	142.2***	143.0***
	(10.06)	(10.43)	(10.10)	(10.03)	(10.06)
$After$	-2.111				
	(1.966)				
$Treat \times Trend$		0.00478			
		(0.00348)			
$Trend$		-0.00878**			
		(0.00286)			
$Treat \times After(placebo)$			2.546	2.856	
			(2.225)	(1.737)	
$After(placebo)$			-2.682	-3.037	
			(1.526)	(1.937)	
$Treat \times After2017$					-11.41***
					(1.711)
$Treat \times After2018$					-10.97***
					(2.274)
$Treat \times After2019$					-9.355**
					(2.954)
$After2017$					-0.861
					(1.387)
$After2018$					-2.279
					(2.004)
$After2019$					-4.011
					(2.575)
Demand factors	Yes	Yes	Yes	Yes	Yes
Weather	Yes	Yes	Yes	Yes	Yes
Industry composition	Yes	Yes	Yes	Yes	Yes
ED FEs	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes	Yes
Day-of-week FEs	Yes	Yes	Yes	Yes	Yes
Observations	63,831	36,821	36,821	36,821	63,831
Adjusted R^2	0.911	0.913	0.913	0.913	0.912

Note. Standard errors clustered by ED are in parentheses. Demand factors: Population, HHsize, HHincome; Weather: Humidity, rain, average temperature and its square, and wind speed; Industry composition: Percentage of firms in manual labor industries.

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

overall ED traffic. The estimated coefficient of $Treat \times After$ is negative and statistically significant ($\beta_3 = -10.43$, $p < 0.001$), indicating that, on average, 10.43 fewer fee-paying patients visited an ED per day after the ED entry fee increased. This difference is substantial, as the average daily traffic of EP patients in the pre-intervention period is 166.1 patients per ED.[10] Approximately, the increased entry fee has driven a 6.3% ($= -10.43/166.1 \times 100$) decrease in fee-paying ED traffic per day. The magnitude of the estimated intervention effect is larger than the HK government's reported 4.4% policy effectiveness.

4.2. Placebo Test

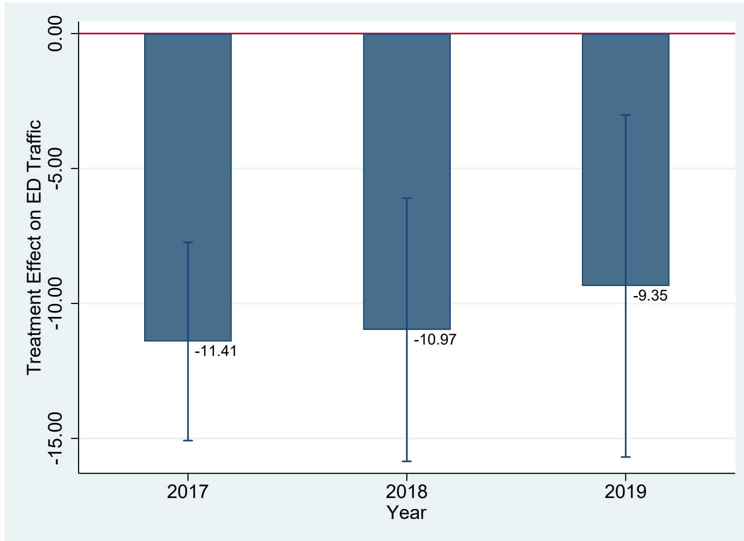
We consider the possibility of the estimated results being driven by unobserved external shocks.We perform a set of *placebo tests* to ensure that the observed impact on ED traffic for the treatment patient group is attributable to the policy intervention. We repeat the DiD estimation in Equation 1 on the pre-intervention period observations only with two alternative intervention dates as fake shocks. Specifically, during this pre-intervention period, we falsely assume that the onset of intervention occurs (1) one year before (June 18, 2016) or (2) two years before (June 18, 2015) the actual date. If there was an unobservable event during this period that affected EP patients' ED utilization behavior differently than that of PA patients, then the estimated coefficient of $Treat \times After(placebo)$ should recognize it with statistical significance. As seen in Columns (3) and (4) of Table 6, the estimated treatment effects ($Treat \times After(placebo)$) are statistically indistinguishable from zero. This ensures that the observed change is more likely due to the policy intervention, as opposed to some alternative unobserved events.

4.3. Temporal Treatment Effect

The estimate (β_3) presented in Column (1) of Table 6 represents the long-term average treatment effect over the entire post-intervention period of 2.5 years. We follow the literature on the time-varying treatment effect (Wang and Goldfarb 2017, Fisher et al. 2019) to examine the dynamics of the treatment effect over time. That is, we investigate whether the treatment effect persists, strengthens, or fades over time. We generate a sequence of dummy variables $After2017$, $After2018$, and $After2019$ that correspond to each year after the fee increase ($After2017$ only contains time periods after the policy intervention on June 18, 2017). We estimate Equation 1 after replacing $After$ with the three dummy variables. The coefficient estimates for each of the interaction terms can be interpreted as the average treatment effect observed over the corresponding interval in the post-intervention period. Column (5) of Table 6 shows the average treatment effect for each year

[10] The average daily per ED traffic (across both EP and PA) is 92.82 (Table 4) and the average *before* the entry fee increase is 95.92 patients per ED per day. The pre-intervention average daily EP patient traffic per ED is 166.1, which we use as the baseline for percentage-wise reduction effectiveness calculation.

Figure 2 **Persistent impact of increasing ED entry fee on overall ED traffic over time**



Note. This figure is based on Column (5) in Table 6. Bars represent the 95% confidence interval.

after the treatment, and Figure 2 provides a graphical representation of these estimates along with their 95% confidence intervals. We find that the effect of the entry fee increase on overall ED traffic persists over time. The average treatment effect is statistically significant in all three years. However, the effect does not strengthen or fade away, in the 2.5 years in the post-intervention period. The effects in 2017, 2018, and 2019 are *not* statistically different from each other ($p > 0.1$).

We further investigate the treatment effect by exploring different lengths of the pre- and post-intervention periods. Specifically, we consider the study periods of (1) one month, (2) three months, (3) six months, (4) one year, and (5) two years before and after the intervention. As shown in Column (1) of Table A.1 in the Appendix, we still find a significant impact of the fee increase on overall ED traffic ($-7.051, p < 0.001$) when we only consider the two months around the intervention (May 18 to July 18 in 2017). This indicates that the fee increase was immediately effective. For longer periods, from three months to two years before and after the intervention, we still find consistent results. This ensures that our main findings are not limited to the available study period.

4.4. Robustness Check: Serial Correlation

In the main analysis, we cluster the standard error at the ED level to account for the possibility of overestimating the t-statistics and significance levels due to potential serial correlation in the error term. Bertrand et al. (2004) claim that the DiD approach can possibly suffer from high false positives in the presence of serial correlation. For instance, they find a 67.5% false positive rate when the first-order auto-correlation coefficient is 0.51. To mitigate this concern, they suggested an alternative approach: taking a simple average of the data before and after the intervention, and then running a regression with a panel of length of 2. This method substantially reduces the sample size. In our setting, we only have 60 observations (i.e., 15 EDs, before vs. after, and EP vs. PA). As shown in Table A.2 in the Appendix, even with low statistical power (due to the small sample size), we obtain similar results, indicating that the significance of our main results is not driven by serial correlation.

5. Mechanisms of ED Entry Fee Increase Effect

As previously mentioned, the HK government's main purpose in increasing ED entry fees was to reduce system abuse (Benitez 2002) and encourage appropriate use of ED services (The Government of the Hong Kong Special Administrative Region 2017a). We perform additional analyses to better understand the underlying mechanisms of the intervention's impact and to check whether HA has achieved its goal. First, we examine whether the entry fee increase discouraged less-urgent patients from visiting an ED while not discouraging urgent patients. Second, we decompose overall ED patient visits into two categories: (1) initial visits (patients who had *not* visited an ED in the past 3, 7, or 30 days) and (2) revisits (patients who had visited an ED in the past 3, 7, or 30 days). We investigate whether the fee increase was more effective in reducing patients' follow-up visits than their initial visits (or vice versa). Third, we test whether frequent visitors, who are known to be major drivers of ED overcrowding, are more affected by the fee increase than less-frequent visitors. Lastly, we study another important aspect of patient behavior, yet overlooked by the HA: patient abandonment. Prior research in healthcare OM has studied it in ED settings (e.g., Batt and Terwiesch 2015, Bolandifar et al. 2019). We examine the impact of a higher financial burden on patients' ED abandonment behavior and their subsequent revisits after abandonment.

5.1. Impact of Fee Increase by Patient Urgency: Triage-level Analysis

We first investigate whether the policy intervention discouraged less-urgent patients' ED visits without hindering urgent patients' access to ED care. We examine the impact of increasing ED entry fee on patient traffic for varying urgency levels. Urgent patients are less likely to be affected by the fee increase, while less-urgent patients are more likely to be affected. That is, less-urgent patients would be hesitant to visit an ED for their minor symptoms due to higher entry fees. We estimate Equation 1 at the individual triage level by replacing the dependent variable of overall ED traffic with each triage-level traffic. Table 7 provides the average treatment effects for triage levels 1 to 5 (Column (1) to (Column (5)), respectively. The estimated coefficients of $Treat \times After$ are *positive* and statistically significant for urgent patients (triage levels 1, 2, and 3), while they are *negative* and significant for less-urgent patients (triage levels 4 and 5). To be specific, the fee increase reduced triage level 4 and 5 visits by 9.8% ($= -10.57/107.49 \times 100$) and 33.6% ($= -3.36/10.00 \times 100$)[11],

[11] The pre-intervention average daily EP patient traffic per ED is 107.49 and 10.00 patients for triage levels 4 and 5, respectively.

Table 7 Impact of increasing ED entry fee on triage-level ED traffic

Dependent variable:	*Traffic* (daily ED-triage level patient visit count)				
	(1)	(2)	(3)	(4)	(5)
	Triage 1	Triage 2	Triage 3	Triage 4	Triage 5
$Treat \times After$	0.148^{***}	0.565^{***}	2.792^{*}	-10.57^{***}	-3.360^{***}
	(0.0302)	(0.106)	(1.139)	(2.505)	(0.478)
$Treat$	0.878^{***}	2.169^{***}	36.85^{***}	95.10^{***}	8.038^{***}
	(0.171)	(0.397)	(5.238)	(6.868)	(0.911)
$After$	-0.0198	-0.189^{*}	-1.361^{*}	-1.211	0.671^{**}
	(0.0177)	(0.0649)	(0.566)	(1.971)	(0.197)
Other controls	Yes	Yes	Yes	Yes	Yes
Observations	63,831	63,831	63,831	63,831	63,831
Adjusted R^2	0.365	0.516	0.801	0.894	0.601

Note. Standard errors clustered by ED are in parentheses. The same set of control variables (demand factors, weather, industry composition, ED FEs, Month FEs, and Day-of-week FEs) from Table 6 are used.
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

respectively, compared to their pre-intervention averages. Thus, we find that the significant drop in overall ED traffic after the entry fee increase was mainly driven by fewer visits from less-urgent patients as intended by the HK government.

Alternatively, we follow Jung et al. (2014) and Ramos and Almeida (2016) to examine the impact of the fee increase on the relative urgency of each patient visit (captured by the assigned triage level of each patient-visit). Based on the results from Table 7, we expect results consistent with the literature: more urgent/severe patient-visits after the policy intervention. To test this argument, we use the (non-aggregated) original patient-visit level data and generate an indicator variable, *High-severity visit* $= 1$, if the patient-visit is classified as triage level 1 or 2, and $= 0$ if the patient-visit is categorized as triage level 3, 4, or 5. We use *High-severity visit* as the dependent variable and adopt a DiD specification with EP patients as the treatment group. We test a set of control groups. We initially consider all patients under any payment scheme other than EP as the control group (Column (1) in Table A.3), and then keep PA patients only as the control (Columns (2)-(4)). In Column (3), we further limit our analysis to the general adult ED patients by excluding visits from children ($Age < 18$). In Columns (1) to (3) we use a linear probability model, while in Column (4), we use a logit model to address the binary nature of the dependent variable. For this analysis at the individual patient-visit level, we include additional control variables to account for patient factors such as gender, age, and whether the patient visits an ED via ambulance. As shown in Table A.3 in the Appendix, the estimated coefficients of $Treat \times After$ are *positive* and statistically significant across models, indicating that patients tend to visit the ED for more urgent

Table 8 Impact of ED entry fee increase on initial visits vs. revisits

Dependent variable:	*Traffic* (daily ED-level patient visit count)					
Revisit window:	3 days		7 days		30 days	
	(1) Initial visit	(2) Revisit	(3) Initial visit	(4) Revisit	(5) Initial visit	(6) Revisit
$Treat \times After$	-9.562***	-0.866***	-8.428**	-2.000***	-7.046**	-3.382***
	(2.268)	(0.197)	(2.176)	(0.369)	(2.058)	(0.552)
$Treat$	138.2***	4.850***	132.4***	10.65***	122.3***	20.69***
	(9.694)	(0.465)	(9.379)	(1.016)	(8.752)	(1.796)
$After$	-2.052	-0.0597	-1.895	-0.216	-1.150	-0.961*
	(1.888)	(0.180)	(1.823)	(0.271)	(1.646)	(0.439)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	63,831	63,831	63,831	63,831	63,831	63,831
Adjusted R^2	0.911	0.583	0.910	0.707	0.908	0.786

Note. Standard errors clustered by ED are in parentheses. The same set of control variables (demand factors, weather, industry composition, ED FEs, Month FEs, and Day-of-week FEs) from Table 6 are used.
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

issues rather than mild symptoms since the fee increase. The results are consistent with the HA's intention to encourage proper ED usage.

5.2. Initial Visit vs. Revisit

Next, we explore whether the entry fee increase has a varying impact on patient's revisit behavior compared to non-revisit—initial—visits. We divide the total patient traffic into initial visit traffic and revisit traffic. To determine whether each focal visit is an initial visit or a follow-up, we consider three time windows for revisits: within (1) three, (2) seven, or (3) 30 days from the initial visit. Using the three windows, we define a focal visit as *revisit* (*initial visit*) if a patient had (did not have) a prior visit during the time window. We then estimate Equation 1 after replacing the dependent variable with the daily ED revisits or initial visits. Table 8 provides the average treatment effect for initial visits (Columns (1), (3), and (5)) and revisits (Columns (2), (4), and (6)) across the three revisit windows, respectively. Although the estimated coefficients of $Treat \times After$ are *negative* and statistically significant across all models, regardless of its visit type, the magnitude of the treatment effect is (more than twice) larger for revisits than initial visits. Specifically, the entry fee increase reduced initial visits by 6.0% ($= -9.562/159.4 \times 100$) for three days, 5.5% ($= -8.428/151.9 \times 100$) for seven days, and 5.1% ($= -7.046/137.3 \times 100$) for 30 days window, respectively, with respect to their pre-intervention averages. Revisits decreased by 13.1% ($= -0.866/6.6 \times 100$) for three days, 14.2% ($= -2.000/14.1 \times 100$) for seven days, and 11.8%

($= -3.382/28.8 \times 100$) 30-days, respectively.[12] One plausible explanation of this result is a sunk cost effect (Arkes and Blumer 1985). As patients must pay a higher entry fee for each ED visit after the fee increase, they are likely to be more reluctant to make a follow-up visit after paying fees for a prior visit, although payment for the prior visit (i.e., sunk cost) should not influence the patients' revisit decision. Consistent with the sunk cost effect argument, while the entry fee increase leads to fewer initial visits, it is much more effective in reducing revisits.

5.3. Frequent Visitors: Individual Patient-level Analysis

Since we have identified the varying impact of entry fee increases on revisit behavior at the aggregate level, we turn our focus to individual patients' visit behavior. The result in Section 5.2 that the impact of the entry fee increase on follow-up visit reduction was more than twice in magnitude than that on the initial visit implies that the fee increase could be effective in reducing ED visits from patients who frequently visit an ED. The emergency medicine literature identifies these "frequent visitors" as one of the causes of ED overcrowding (LaCalle and Rabin 2010).

For individual patient-level analysis, we use a sub-sample of patients satisfying the following two conditions: (1) patients who visited an ED both before and after the intervention and (2) patients who were under the same payment scheme for all of their visits, of either EP or PA only. The first condition is to ensure that the patients were present in HK in both the pre- and post-intervention periods so that we can examine the change in individual patients' visit frequency. For example, we cannot examine the impact of the fee increase on patients' ED visit frequency if a patient visited the ED only once during the study period. We exclude such patients in our analysis. More specifically, we condition on patients who visited at least once in 2014 and 2019 each to build a patient group that was likely present in HK for the entire study period. The second condition allows us to cleanly maintain our treatment and control group selections. Some rare patients have multiple payment schemes (e.g., the first three visits are under EP while the remaining two are under PA). We drop such patients to avoid misclassification between the treatment and control groups. We identify 162,768 patients satisfying the two conditions. Among these patients, we further define "frequent visitors" ($Frequent = 1$) as patients who had visited EDs most frequently in the top 10th percentile (5th, or 1st percentile). We collapse the patient-visit level raw data into individual patient-period levels with two observations per patient, one each for pre- and post-intervention periods. Each observation contains the average number of visits per year for the corresponding period and visit-specific patient characteristics, such as gender, age group, ambulance arrival, medical specialty, residential district (since patients can move over time), and triage level, that are averaged out over

[12] The pre-intervention average daily initial visit traffic per ED is 159.4, 151.9, and 137.3 patients for three-, seven-, and 30-day windows, respectively. The pre-intervention average daily revisit traffic per ED is 6.6, 14.1, and 28.8 patients for three-, seven-, and 30-day windows, respectively.

Table 9 Impact of ED entry fee increase on individual patient-level visit frequency: Frequent vs infrequent visitors

Dependent variable:	*Log (Visits per year)*		
	(1)	(2)	(3)
Frequent visitor cutoff percentile:	90%	95%	99%
Cutoff no. of visits per year:	>= 1.4	>= 2.0	>= 3.8
After	0.755***	0.519***	0.282***
	(0.011)	(0.010)	(0.011)
Treat	-0.050***	-0.083***	-0.163***
	(0.004)	(0.004)	(0.005)
$Treat \times After$	-0.098***	-0.086***	-0.055***
	(0.008)	(0.008)	(0.007)
Frequent	1.110***	1.112***	1.329***
	(0.008)	(0.009)	(0.013)
$After \times Frequent$	-0.643***	-0.569***	-0.537***
	(0.013)	(0.015)	(0.022)
$Treat \times Frequent$	-0.173***	-0.105***	-0.013
	(0.008)	(0.009)	(0.014)
$Treat \times After \times Frequent$	-0.013	-0.075***	-0.155***
	(0.014)	(0.016)	(0.025)
Other controls	Yes	Yes	Yes
Observations	325,536	325,536	325,536
Adjusted R^2	0.672	0.662	0.617

Note. Standard errors clustered by ED are in parentheses. Other controls include (1) Individual patient factors (gender, age, ambulance arrival, residential district, medical specialty, triage level), (2) Patient's residential district factors (population, household size, and household income), (3) Weather (humidity, rain, average temperature, and wind speed), (4) Industrial composition (percentage of firms in manual labor industries), and (5) fixed effects (ED FEs, year FEs, month FEs, day-of-week FEs, and hour-of-day FEs). $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

the period. For example, a patient who visited an ED once by ambulance and walked in twice before the fee increase will have the ambulance arrival control variable averaged out to $\frac{1}{3}$ in the pre-intervention observation. Control variables similar to those in Table 6 are collapsed as well.

Then, we augment Equation 1 by including a moderating factor, *Frequent*, and interact it with the treatment effect. The dependent variable is replaced with the log-transformed number of visits per year by each patient. At the individual-patient level, we compare the visit frequency between patients covered by EP only (treatment) and PA only (control) for the entire six-year study period. The model is a triple-difference specification (Cui et al. 2020) that examines whether the intervention effect varies between frequent visitors and infrequent visitors by considering pre-intervention visit frequency as a moderating factor.

Table 9 provides estimation results of the triple-difference specification based on the three thresholds of $Frequent$. We find that the coefficient estimates for $Treat \times After$ are all negative and statistically significant, indicating that infrequent patients reduce their number of visits per year by 5.5% to 9.8% (note that the definition of infrequent patients varies across models). More importantly, the coefficient estimates for $Treat \times After \times Frequent$ are negative and statistically significant in Columns (2) and (3). This indicates that, when defining frequent-visitors as the top 5% (Column (2)) or top 1% (Column (3)) visitors with respect to the number of visits per year, frequent-visitors further reduce their visit frequency by an additional 7.5% to 15.5% compared to infrequent visitors. These results suggest that increasing ED entry fees is a viable solution for further limiting visit frequency by the population who overuses ED the most. This is again consistent with the HA's intention under the fee increase to reduce ED abuse (Benitez 2002).

5.4. Patient Abandonment

Lastly, we examine the impact of the entry fee increase on patients' abandonment behavior (also known as reneging in queueing literature) in the ED. ED abandonment is typically considered an undesirable outcome, as it can potentially lead to the risk of a patient suffering adverse health consequences due to treatment delays (e.g., Hunt et al. 2006, Batt and Terwiesch 2015). Reducing patient abandonment can mitigate such risk and thus can be considered a beneficial outcome of the policy intervention. If patients pay a higher fee for entering an ED, they are likely to have a higher tolerance for waiting. We investigate this argument using the (non-aggregated) original patient-visit level data also used in Table A.3. We generate an indicator variable, *Abandonment*, $= 1$ when the patient leaves the waiting area (after registering with the entry fee payment) without being seen by a physician, and 0 otherwise. We use *Abandonment* as the dependent variable and perform a DiD at the individual patient-visit level. For this analysis, we additionally include triage dummies as control variables. Similar to the previous analysis at the patient-visit level, we consider all payment schemes as the control group (Column (1)), only PA (Column (2)), only adult PA patients (Column (3)), and logit specification (Column (4)). As shown in Table 10, across the different models, the coefficient estimates for $Treat \times After$ are all negative and statistically significant. Given the average EP patient pre-intervention abandonment rate of 1.49%, a reduction of 1.09 percentage point (Column (3)) is a significant effect, representing a 73.15% drop in abandonment rate post-fee increase.

We repeat the analysis for patient-visits by each triage level separately. The average abandonment rate is 0%, 0.02%, 0.12%, 2.00%, and 2.66% for patients in triage level 1, 2, 3, 4, and 5, respectively. As expected, no patient abandoned under a critical condition (triage level 1) while patients under a mild condition (triage levels 4 and 5) were more likely to abandon. As seen in Table A.4 in the

Table 10 Impact of ED entry fee increase on patient abandonment

Dependent variable:	*Abandonment (=1 if abandon; =0 otherwise)*			
Control group:	All other insurance	Only PA		
	(1)	(2)	(3) sub-sample of $Age \geq 18$	(4) logit
$Treat \times After$	-0.00891***	-0.0105**	-0.0109**	-0.295***
	(0.00183)	(0.00290)	(0.00274)	(0.0660)
$Treat$	-0.00543***	-0.00544***	-0.00774***	-0.443***
	(0.00101)	(0.00110)	(0.00139)	(0.0733)
$After$	-0.00151	0.000714	0.00163	-0.479***
	(0.00457)	(0.00494)	(0.00463)	(0.139)
Other controls	Yes	Yes	Yes	Yes
Observations	8,326,920	7,247,342	5,924,741	5,924,741
Adjusted R^2	0.0388	0.0386	0.0354	0.1764 (pseudo)

Note. Standard errors clustered by ED are in parentheses. Other controls include (1) Patient factors (Gender, Age, Ambulance;), (2) Demand factors (Population, HHSize, HHIncome;), (3) Weather (Humidity, Rain, Average temperature and its square, and Wind speed), (4) Industry composition (Percentage of firms in manual labor industries), and (5) Fixed effects (ED FEs, month FEs, day-of-week FEs, and hour-of-day FEs).
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Appendix, the significant drop in abandonment is mainly from less-urgent patients (triage levels 4 and 5), whereas abandonment of urgent patients (triage levels 1, 2, and 3) is unaffected by the fee increase.

Some abandoned patients may return to an ED in the near future while others do not revisit. The focal visit of patients who do not revisit after abandonment (or at least a subset of them) can be seen as an "inappropriate" use of the service who did not need to visit an ED in the first place. We further analyze whether the fee increase led to a decrease in such inappropriate use of EDs. We define *Abandonment_no_revisit* as 1 if a patient abandoned and did not make subsequent follow-up visit in the next three, seven, or 30 days, and 0 otherwise. We use *Abandonment_no_revisit* as the dependent variable and perform a DiD at the individual patient-visit level. Similar to the analysis in Section 5.2, we consider three revisit windows: (1) three, (2) seven, and (3) 30 days *after* the focal visit. We note that while we applied revisit windows for *pre*-visit periods in Section 5.2, here, we use the windows for *post*-visit periods. For this analysis, we adopt a logit specification. As shown in Table 11, regardless of the revisit windows, the coefficient estimates for $Treat \times After$ are all negative and statistically significant. That is, the fee increase substantially reduced the potential inappropriate use of ED services.

To sum up, we find that the ED entry fee increase did reduce abuse of ED services in HK as the government intended. After the intervention, less-urgent patients significantly reduced their visits to the ED, opening up possible resource availability for urgent patients, while urgent patients did

Table 11 Impact of ED entry fee increase on patient abandonment with no follow-up visits (logit)

Dependent variable:	*Abandonment_no_revisit* (0/1)		
	(1)	(2)	(3)
Revisit window:	3 days	7 days	30 days
$Treat \times After$	-0.213*	-0.206**	-0.199**
	(0.0838)	(0.0790)	(0.0741)
$Treat$	-0.244**	-0.144*	0.0548
	(0.0746)	(0.0702)	(0.0664)
$After$	-0.213***	-0.529***	-0.527***
	(0.115)	(0.115)	(0.119)
Other controls	Yes	Yes	Yes
Observations	5,877,668	5,877,668	5,877,668
Pseudo R^2	0.193	0.192	0.191

Note. Standard errors clustered by ED are in parentheses. *Abandonment_no_revisit* is 1 if a patient abandoned and did not make a follow-up visit in the subsequent 3, 7, or 30 days, and 0 otherwise. Other controls include (1) Patient factors (Gender, Age, Ambulance;), (2) Demand factors (Population, HHSize, HHIncome;), (3) Weather (Humidity, Rain, Average temperature and its square, and Wind speed), (4) Industry composition (Percentage of firms in manual labor industries), and (5) Fixed effects (ED FEs, month FEs, day-of-week FEs, and hour-of-day FEs). $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

not reduce their visits to the ED. Although the ED entry fee increase reduces both initial visits and subsequent revisits, the effect is more than twice as strong for revisits than initial visits. The intervention effect is also much stronger for frequent visitors than infrequent visitors. Finally, we find an unintended benefit of the fee increase in reducing patient abandonment. Patients are more likely to wait and see a physician after paying a higher entrance fee. This can potentially reduce the risk of encountering an adverse health condition due to delayed treatment. Moreover, we find that the number of patients who abandoned and did not revisit in the near future (i.e., a proxy for improper usage of the ED service) is significantly reduced after the fee increase. Overall, HK's first ED entry fee increase in 15 years was a successful intervention that achieved its goal by affecting patient behavior from various angles. These findings are in-line with the policy's reported purpose.

6. Implications and Conclusion

ED overcrowding is a prevalent issue in many countries, causing social and economic hardships for public health and the healthcare system. In order to mitigate ED overcrowding, several countries have heightened the access hurdle to ED care by increasing ED entry fees. We examine the effectiveness of a territory-wide policy intervention to emergency healthcare access. Specifically, we analyze HK SAR's universal public healthcare system and the general public's response to the ED entry fee increase from HK$100 to HK$180 in 2017. Using several data structures and difference-in-differences approaches, we find that an ED entry fee increase is an effective solution for mitigating overcrowding in HK's public hospital EDs. The effect persists, at least for 2.5 years after the intervention, which supports the viability of financial access hurdle as a long-term solution to ED overcrowding. We further study the underlying mechanisms of the intervention's effectiveness: (1) Entry fee increase was effective in discouraging less-urgent visits (triage levels 4 and 5) while attendances of patients with urgent conditions (triage levels 1 to 3) did not decrease. (2) The intervention was more effective in reducing revisits than initial visits. (3) At the individual patient level, frequent visitors were more strongly affected by the fee increase when compared to infrequent visitors, showing the intervention's effectiveness in addressing overuse of ED services. (4) Increasing the financial hurdle for ED access reduced patient abandonment as well as potential improper visits (i.e., abandoned patient visits without follow-up visits).

Our findings contribute to both healthcare policymakers and the broad literature on ED overcrowding in healthcare OM. First, we provide empirical validation for increasing the financial burden (entry fee or copayments in other healthcare settings) to access care as an effective policy instrument for alleviating congestion in a healthcare system. Financial barrier has been discussed as a policy instrument to moderate ED utilization (Flores-Mateo et al. 2012); however, prior studies in the medical literature analyze only a subset of EDs (not the entire network) in the short run (a few months before and after the intervention), thus failing to study the long-term effectiveness of the policy intervention on overall ED demand and provide proper policy evaluation. Our territory-wide study allows us to examine the general public response to a fee increase and to identify the underlying mechanisms.

Second, while prior studies have focused on a tiered fee policy differentiated by patient severity level (e.g., Taiwan) or hospital tier (e.g., South Korea and Taiwan), we find that a *uniform* fee increase does not discourage urgent patients who need timely care and should not be sensitive to price change. The fee increase seems to have a natural price discrimination effect among the heterogeneous patient group, as urgent patients will value the medical service more than their less-urgent counterparts with a lower valuation of the service for the same price. Hence, only the less-urgent patients are discouraged from attending an ED at a higher price.

Third, we find that a higher price for service leads to fewer abandonments. This helps to reduce the risk that individual patients are exposed to, and also leads to improved patient flow with fewer revisits. While prior studies in healthcare OM examining patient abandonment in the ED have focused on internal operations such as patient response to visual queue elements inside the ED (Batt and Terwiesch 2015, Bolandifar et al. 2019), we find evidence of an *exogenous* demand control policy also improving the internal patient flow.

Fourth, prior research in healthcare OM has focused on how to improve *internal* operations via better patient flow management and capacity allocation within an ED system (Keskinocak and Savva 2020), under the assumption that the *external* ED demand is given and uncontrollable. We add to this stream of literature by investigating an alternative way to mitigate ED overcrowding, which directly reduces the 'inputs' into the EDs through access hurdle.

Finally, while our work contributes to the vast stream of literature on emergency department operations, it also elucidates important policy implications for HK policymakers. Our estimate of the treatment effect is much cleaner as we decouple two potential confounding factors: (1) new ED opening and (2) an expansion of the public assistance program that offers a medical fee waiver. The true effect of increasing ED entry fees is stronger (6.3%) than what the HK government has reported (4.4%). Moreover, we show several empirical evidence supporting the HK government's reported intention underlying the policy intervention: to reduce system abuse (Benitez 2002) and encourage appropriate use of ED services (The Government of the Hong Kong Special Administrative Region 2017a).

Our study is not free of limitations, which suggests avenues for future research. First, although we include district-level socioeconomic factors such as household income, our data set does not provide patient-level information. The impact of increasing ED entry fees might be stronger for vulnerable populations (e.g., with low purchasing power and socioeconomic disadvantages). Future research may extend our study by incorporating patient-level socioeconomic status information and examining potential heterogeneous intervention effects. Second, our work is based on patients' ED visit information in HK SAR. As cultural differences may affect patient response to the fee increase, validating our findings using data from other countries and comparing multiple countries can be a fruitful avenue for future research. Lastly, we hope our study can shed light on demand control via access hurdles in service settings in general and bring more attention from OM scholars to study various methods of managing 'inputs' into the ED system.

References

Adams JG (2013) Emergency department overuse: Perceptions and solutions. *JAMA* 309(11):1173–1174.

Alvial X, Rojas A, Carrasco R, Durán C, Fernández-Campusano C (2021) Overuse of health care in the emergency services in chile. *International Journal of Environmental Research and Public Health* 18(6):3082.

American Hospital Association (2018) Trends affecting hospitals and health systems. URL `https://www.aha.org/system/files/2018-07/2018-aha-chartbook.pdf`, accessed: 2023-01-26.

Angrist J, Pischke JS (2009) *Mostly Harmless Econometrics: An Empiricist's Companion* (Princeton University Press).

Arkes HR, Blumer C (1985) The psychology of sunk cost. *Organizational Behavior and Human Decision Processes* 35(1):124–140.

Batt RJ, Terwiesch C (2015) Waiting patiently: An empirical study of queue abandonment in an emergency department. *Management Science* 61(1):39–59.

Becker D, Blackburn J, Morrisey M, Sen B, Kilgore M, Caldwell C, Menachemi N (2013) Co-payments and the use of emergency department services in the children's health insurance program. *Medical Care Research and Review* 70:514–530.

Bell D, Gallino S, Moreno A (2018) Offline showrooms in omnichannel retail: Demand and operational benefits. *Management Science* 64(4):1477–1973.

Benitez MA (2002) Hong kong tackles health-service overload by charging emergency fee. *The Lancet* 360(9347):1757.

Bertrand M, Duflo E, Mullainathan S (2004) How much should we trust differences-in-differences estimates? *The Quarterly Journal of Economics* 119(1):249–275.

Bittencourt RJ, Stevanato AdM, Bragança CTN, Gottems LBD, O'Dwyer G (2020) Interventions in overcrowding of emergency departments: an overview of systematic reviews. *Revista de Saúde Pública* 54.

Bolandifar E, DeHoratius N, Olsen T, Wiler J (2019) An empirical study of the behavior of patients who leave the emergency department without being seen. *Journal of Operations Management* 65:430–446.

Chen W, Argon NT, Bohrmann T, Linthicum B, Lopiano K, Mehrotra A, Travers D, Ziya S (2022) Using hospital admission predictions at triage for improving patient length of stay in emergency departments. *Operations Research* .

Chen WY (2020) The welfare effect of co-payment adjustments on emergency department visits in medical centers: Evidence from Taiwan. *Health Policy* 124(11):1192–1199.

Colle AD, Grossman M (1979) Determinants of pediatric care utilization. Technical report, National Bureau of Economic Research.

Cui R, Li M, Li Q (2020) Value of high-quality logistics: Evidence from a clash between sf express and alibaba. *Management Science* 66(9):3879–3902.

Deo S, Gurvich I (2011) Centralized vs. decentralized ambulance diversion: A network perspective. *Management Science* 57(7):1300–1319.

Dong J, Yom-Tov E, Yom-Tov GB (2019) The impact of delay announcements on hospital network coordination and waiting times. *Management Science* 65(5):1969–1994.

Fisher M, Gallino S, Netessine S (2020) Does online training work in retail? *Manufacturing & Service Operations Management* 23(4):876–894.

Fisher ML, Gallino S, Xu JJ (2019) The value of rapid delivery in omnichannel retailing. *Journal of Marketing Research* 56(5):732–748.

Flores-Mateo G, Violan-Fors C, Carrillo-Santisteve P, Peiró S, Argimon JM (2012) Effectiveness of organizational interventions to reduce emergency department utilization: a systematic review. *PloS one* 7(5):e35903.

Hong Kong Hospital Authority (2017) Waiving of medical charges (for eligible persons). URL `https://www.ha.org.hk/haho/ho/cs/v3/serviceguide_feewaving_en.htm`, accessed: 2022-10-06.

Hunt K, Weber E, Shoastack D (2006) Characteristics of frequent users of ed. annals of emergency medicine. *Annals of Emergency Medicine* 48(1):1–10.

Jung H, Do YK, Kim Y, Ro J (2014) The impact of an emergency fee increase on the composition of patients visiting emergency departments. *Journal of Preventive Medicine and Public Health* 47(6):309.

KC DS, Scholtes S, Terwiesch C (2020) Empirical research in healthcare operations: Past research, present understanding, and future opportunities. *Manufacturing & Service Operations Management* 22(1):73–83.

Keskinocak P, Savva N (2020) A review of the healthcare-management (modeling) literature published in manufacturing & service operations management. *Manufacturing & Service Operations Management* 22(1):59–72.

LaCalle E, Rabin E (2010) Frequent users of emergency departments: the myths, the data, and the policy implications. *Annals of Emergency Medicine* 56(1):42–48.

Lee HS, Kesavan S, Deshpande V (2021a) Managing the impact of fitting-room traffic on retail sales: Using labor to reduce phantom stockouts. *Manufacturing & Service Operations Management* 23(6):1580–1596.

Lee HS, Kesavan S, Kuhnen C (2022) When do group incentives for retail store managers work? *Production and Operations Management* 31(8):3077–3095.

Lee J, Lee HS, Shin H, Vish K (2021b) Alleviating drug shortages: The role of mandated reporting induced operational transparency. *Management Science* 67(4):2326–2339.

Levine D, Toffel M (2010) Quality management and job quality: How the iso 9001 standard for quality management systems affects employees and employers. *Management Science* 56(6):978–996.

Li S, Lu LX, Lu SF, Huang S (2022) Estimating the stockout-based demand sipplover effect in a fashion retail setting. *Manufacturing & Service Operations Management* .

Li W, Sun Z, Hong LJ (2021) Who is next: Patient prioritization under emergency department blocking. *Operations Research* .

Ma Y, Johnston KJ, Yu H, Wharam JF, Wen H (2022) State mandatory paid sick leave associated with a decline in emergency department use in the us, 2011–19: Study examines the association between state mandatory paid sick leave and emergency department use. *Health Affairs* 41(8):1169–1175.

Martínez-de Albéniz V, Belkaid A (2021) Here comes the sun: Fashion goods retailing under weather fluctuations. *European Journal of Operational Research* 294(3):820–830.

Meng L, Batt RJ, Terwiesch C (2021) The impact of facility layout on service worker behavior: An empirical study of nurses in the emergency department. *Manufacturing & Service Operations Management* 23(4):819–834.

Morley C, Unwin M, Peterson GM, Stankovich J, Kinsman L (2018) Emergency department crowding: a systematic review of causes, consequences and solutions. *PloS one* 13(8):e0203316.

Park E, Ouyang H, Wang J, Savin S, Leung SC, Rainer T (2022) Patient sensitivity to emergency department waiting time announcements. *Available at SSRN 4047005* .

Ramos P, Almeida A (2016) The impact of an increase in user costs on the demand for emergency services: the case of portuguese hospitals. *Health Economics* 25(11):1372–1388.

Roberts MR, Whited TM (2013) Endogeneity in empirical corporate finance. Constantinides G, Harris M, Stulz R, eds., *Handbook of the Economics of Finance*, volume 2, 493–572 (Elsevier).

Saghafian S, Austin G, Traub SJ (2015) Operations research/management contributions to emergency department patient flow optimization: Review and research prospects. *IIE Transactions on Healthcare Systems Engineering* 5(2):101–123.

Soltani M, Batt RJ, Bavafa H, Patterson BW (2022) Does what happens in the ED stay in the ED? The effects of emergency department physician workload on post-ED care use. *Manufacturing & Service Operations Management* 24(6):3079–3098.

Song H, Tucker AL, Murrell KL, Vinson DR (2018) Closing the productivity gap: Improving worker productivity through public relative performance feedback and validation of best practices. *Management Science* 64(6):2628–2649.

The Government of the Hong Kong Special Administrative Region (2017a) Fees and charges at public hospitals to be revised next month. URL `https://www.info.gov.hk/gia/general/201705/22/P2017052200538.htm`, accessed: 2022-10-06.

The Government of the Hong Kong Special Administrative Region (2017b) Hospital authority anticipates overcrowding in medical wards. URL `https://www.info.gov.hk/gia/general/201703/06/P2017030600242.htm`, accessed: 2022-10-06.

The Government of the Hong Kong Special Administrative Region (2020) Lcq14: Services of the accident and emergency departments of public hospitals. URL `https://www.info.gov.hk/gia/general/202001/15/P2020011400653.htm`, accessed: 2022-10-06.

Tsai JCH, Liang YW, Pearson WS (2010) Utilization of emergency department in patients with non-urgent medical problems: patient preference and emergency department convenience. *Journal of the Formosan Medical Association* 109(7):533–542.

Wang K, Goldfarb A (2017) Can offline stores drive online sales? *Journal of Marketing Research* 54(5):706–719.

Appendix

Table A.1 Robustness analysis: Short-term impact of increasing ED entry fee on overall ED traffic

Dependent variable:	*Traffic* (daily ED-level patient visit count)				
	(1)	(2)	(3)	(4)	(5)
Sample period:	One month	Three months	Six months	One year	Two years
	before and after the intervention (June 18, 2017)				
$Treat \times After$	-7.051***	-16.68***	-12.16***	-13.78***	-11.18***
	(0.994)	(1.220)	(1.140)	(1.534)	(1.814)
$Treat$	150.3***	150.5***	144.3***	145.1***	144.1***
	(10.59)	(9.914)	(9.652)	(10.21)	(10.12)
$After$	1.205	5.160***	3.224**	0.856	-1.144
	(0.830)	(0.817)	(0.825)	(1.204)	(0.915)
Other controls	Yes	Yes	Yes	Yes	Yes
Observations	1,819	5,449	10,783	21,478	42,628
Adjusted R^2	0.918	0.919	0.917	0.915	0.914

Note. Standard errors clustered by ED are in parentheses. The same set of control variables (demand factors, weather, industry composition, ED FEs, monthly FEs, and day-of-week FEs) in Table 6 are used. $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A.2 Robustness check: DiD with a panel of length of two periods (pre- vs. post-intervention)

Dependent variable:	*Traffic* (daily ED-level patient visit count)					
	(1)	(2)	(3)	(4)	(5)	(6)
	Overall	Triage 1	Triage 2	Triage 3	Triage 4	Triage 5
$Treat \times After$	-9.871**	0.146***	0.563***	3.019*	-10.04**	-3.558***
	(2.998)	(0.0289)	(0.123)	(1.384)	(3.024)	(0.491)
$Treat$	141.4***	0.856***	2.122***	36.11***	94.15***	8.131***
	(12.48)	(0.190)	(0.447)	(6.014)	(8.363)	(0.963)
$After$	10.99	0.325	0.635	12.91	1.501	-4.379*
	(14.53)	(0.366)	(0.584)	(10.98)	(10.24)	(1.718)
Demand factors	Yes	Yes	Yes	Yes	Yes	Yes
Weather	Yes	Yes	Yes	Yes	Yes	Yes
Industry composition	Yes	Yes	Yes	Yes	Yes	Yes
Observations	60	60	60	60	60	60
Adjusted R^2	0.855	0.545	0.557	0.644	0.838	0.660

Note. Standard errors clustered by ED are in parentheses. Demand factors: Population, HHsize, HHincome; Weather: Humidity, rain, average temperature and its square, and wind speed; Industry composition: Percentage of firms in manual labor industries.
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A.3 Impact of increasing ED entry fee on the high-severity visits/low-severity visits ratio

Dependent variable:	*High-severity visit*			
Control group:	All other insurance	Only PA		
	(1)	(2)	(3) sub-sample of $Age \geq 18$	(4) logit
$Treat \times After$	0.00137***	0.00151**	0.00149*	0.0853***
	(0.000284)	(0.000494)	(0.000573)	(0.0172)
$Treat$	0.00288***	0.00240**	0.00399***	0.146***
	(0.000579)	(0.000743)	(0.000843)	(0.0167)
$After$	0.000411	0.000218	0.000206	-0.0239
	(0.000526)	(0.000700)	(0.000795)	(0.0287)
Other controls	Yes	Yes	Yes	Yes
Observations	8,326,920	7,247,342	5,924,741	5,924,741
Adjusted R^2	0.0380	0.0393	0.0402	0.1321 (pseudo)

Note. Standard errors clustered by ED are in parentheses. Other controls include (1) Patient factors (Gender, Age, Ambulance;), (2) Demand factors (Population, HHSize, HHIncome;), (3) Weather (Humidity, rain, average temperature and its square, and wind speed), (4) Industry composition (percentage of firms in manual labor industries), and (5) fixed effects (ED FEs, monthly FEs, day-of-week FEs, and hour-of-day FEs).
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A.4 Impact of increasing ED entry fee on patient abandonment: By triage level

Dependent variable:	*Abandonment (=1 if abandon; =0 otherwise)*				
	(1) Triage 1	(2) Triage 2	(3) Triage 3	(4) Triage 4	(5) Triage 5
$Treat \times After$	.	0.000116	-0.00231	-0.0186***	-0.0424*
	.	(0.000183)	(0.000383)	(0.00425)	(0.0157)
$Treat$	.	-0.000160	-0.000671**	-0.00935***	-0.0249***
	.	(0.000173)	(0.000224)	(0.00189)	(0.00453)
$After$	.	-0.000510+	-0.000301	0.00656	0.0267+
	.	(0.000270)	(0.000628)	(0.00707)	(0.0144)
Other controls	.	Yes	Yes	Yes	Yes
Observations	47,073	113,863	1,744,776	3,701,253	317,776
Adjusted R^2	.	0.0002	0.0031	0.0372	0.0652

Note. Standard errors clustered by ED are in parentheses. Other controls include (1) Patient factors (Gender, Age, Ambulance;), (2) Demand factors (Population, HHSize, HHIncome;), (3) Weather (Humidity, rain, average temperature and its square, and wind speed), (4) Industry composition (percentage of firms in manual labor industries), and (5) fixed effects (ED FEs, month FEs, day-of-week FEs, and hour-of-day FEs). Note that there is no patient abandoned at triage 1.
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.