Hospital Response to Financial Incentives: Evidence from Emergency Departments in Taiwan

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Abstract

This paper studies a plausibly exogenous policy change in the Taiwanese universal healthcare system and tests hospital responses to financial incentives. A subsidy policy increased diagnostic fee bonuses for night emergency department admissions by 30% in 2010. Using an event study, I find evidence of manipulation—the night admission share increased by 36% among the least urgent patients but not the most urgent ones. The increase implies that hospitals delayed the least urgent admissions in order to increase profits. However, this policy led to insignificant improvements in care provision and health outcomes.

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1 Introduction

Demand for emergency care exceeding its capacity leads to the emergency department (ED) crowding and association with adverse care quality and outcomes (Fee et al. 2007, Kulstad et al. 2010, Cha et al. 2011, Hong et al. 2013, Stang et al. 2015). It is especially challenging for EDs to maintain care quality during nighttime.[1] To improve the ED care provision, National Health Insurance (NHI) in Taiwan imposed a subsidy policy on 24-hour EDs starting in 2010. This policy increased the diagnostic fee bonus of night ED admissions by 30%.[2] This ongoing policy amounted to over five million US dollars in 2010 and is not tied to a specific expenditure. Yet, we do not know whether this policy has brought improvements in emergency care.

In this paper, I examine how EDs respond to the subsidy program at the institutional level. I use Taiwanese administrative data to explore three ways in which hospitals might respond: (1) changes in care capacity (numbers of doctors), (2) changes in treatment intensity (total expenditure), and (3) the possibility of manipulation. Specifically, I test if hospitals moved more patients into the night bonus window to increase profits. I investigate substitution effects between emergency and primary care as well as the impacts on health outcomes in terms of mortality after an emergency department visit. In Appendix C, I test whether hospitals respond differently across ownership types.

I find no effects on care capacity, treatment intensity, and mortality in response to the policy change. I do not observe patients substituting primary care with emergency care. Appendix C shows that hospitals of different ownership types do not respond differently. However, I find patterns consistent with manipulation—the night admission share increased by 36% among the least urgent patients but not the most urgent ones. The results imply that hospitals push more nonurgent admission into the timeframe between 10 pm and 6 am for more profits.

This paper contributes to the literature on how financial incentives cause behavioral changes at the healthcare institutional level. Healthcare providers commonly take two reactive measures in response to financial incentives: increasing care provisions, no matter whether necessary or not (Currie & Gruber 2001, Clemens & Gottlieb 2014, Einav et al. 2018) and upcoding to yield a higher reimbursement from the insurer (Ginsburg & Carter 1986, Steinwald & Dummit 1989, Carter et al. 1990, Cutler 1995, Silverman & Skinner 2004, Dafny 2005). This paper also relates to the literature on policies aiming to improve emergency care quality and outcomes (Berthiaume et al. 2006, Rabin et al. 2012, Morgan

[1] ED wait time is usually longer at night, which can lead to deleterious effects (Goodacre & Webster 2005, Kim 2010).

[2] Night-time bonus window ranges from 10 pm to 6 am.

et al. 2013, Yarmohammadian et al. 2017). I document that the subsidy program untied to specific expenditures does not improve care provision in EDs. Moreover, hospitals react to financial incentives in a novel way other than increasing unnecessary input and upcoding.

A major strength of this paper is the rich administrative data—my final sample includes 3.9 million ED claim records in 2009 and 2010. Data from a healthcare-for-all environment leads to generalizable and policy-relevant findings. To avoid these unintended consequences and improve care provision in EDs, tying the subsidy program to a specific expenditure is one method policymakers can consider.

2 Institutional Background

NHI covers more than 99% of the 23 million Taiwanese residents and affiliates with 93% of medical facilities. The insured choose healthcare providers freely as no gate-keeping system applies. Patients pay out-of-pocket expenses, including co-payments and registration fees, which are regulated depending on hospital status.[3] Importantly, medical facilities are treated equally and face the same payment system across all ownership types. I use this fact along with the fact that the insured also face the same payment scheme across ownership types to study hospital responses to a change in provider financial incentives.

In 2010, NHI increased night diagnostic fees by 30% in teaching hospital EDs in order to maintain and improve the quality of care at night. These hospitals obtain extra bonuses when a patient registers between 10 pm and 6 am, while out-of-pocket expenses patients face did not change. The flow after entering ED is as follows: getting the triage level, registering with an NHI IC card, being diagnosed, and getting treated. Diagnostic fees differ according to triage levels, and the time a patient registers defines the official admission time. Table 1 shows the bonus scheme before and after the policy change according to patients' age.

3 Data and Sample Construction

My primary data source is the full count claim data of 2009 and 2010 from the National Health Insurance Research Database (NHIRD) of Taiwan. Personal identifier codes, gender, age, residency, hospital visited, doctor identifier codes, admission dates, ICD-9 codes, co-payments, triage level, diagnostic fees, medical spending, and hospital ownership types are available in the database.

[3]Medical facilities are assigned to one of the four statuses based on their missions, capacities, and the variety of specialty services. The four statuses include major teaching hospitals, minor teaching hospitals, community hospitals, and clinics.

I made three main sample restrictions. First, I exclude patients who face different co-payments and admissions where hospitals are paid differently.[4] Second, I exclude patients admitted for influenza and influenza-like illness because of the H1N1 pandemic in 2009.[5] Figure 1 displays hospital-level monthly visit volume. By doing so, the spike driven by the pandemic in late 2009 was mitigated while the pattern across time persists. Third, I focus on non-holiday admissions. I use the diagnostic fee amount to determine whether a patient was admitted during the night bonus window because the information on the exact admission time is not available. However, the fee scheme does not allow us to distinguish night admissions from holiday admissions before 2010 (see Table 1).[6]

I conduct my analyses at the hospital-week level. I focus on hospitals that experienced the policy change and were constantly providing night-time emergency care in the final sample. This leaves us a balanced panel including 59 non-rural teaching hospitals: 20 public and 39 nonprofit. My final sample contains approximately 3.9 million claim records. Table 2 provides the summary statistics for 2009 and 2010 separately. Note that I subtract diagnostic fees from total expenditure and that I present total expenditure using the NHI point.[7] I do not see significant differences between the pre- and post-policy samples except for one variable: the share of night admission among the least urgent patients increased by almost 10%.

4 Methodology

Using hospital-week-level data from 2009 and 2010, I adopt an event study to investigate the effects over months. There are 24 time periods: 12 months in the pre- and post-policy periods, respectively. I estimate

$$Y_{htw} = \alpha_0 + \sum_{p=-11}^{12} \beta_p \times \mathbf{1}_{t=p} + \alpha_1 NP_h + \tau_h + \tau_m + \epsilon_{htw} \tag{1}$$

where h denotes hospital, t time, w week, and m month. NP is an indicator for nonprofit hospitals. τ_h represents hospital fixed effects and τ_m month fixed effects. ϵ_{htw} represents hospital-specific idiosyncratic shocks that are not observed and assumed to be independent

[4]We exclude patients below age 6 and patients with catastrophic illnesses. See details in Appendix A.

[5]We use ICD-9 codes 480-488 to define influenza and influenza-like illness because there was no specific code for H1N1 at the beginning. I also conduct all analyses without excluding influenza and influenza-like illness and find robust results.

[6]Notably, month-fixed effects do not help with seasonality perfectly because most national holidays, e.g., the lunar new year, follow the lunar calendar. Removing holidays helps account for the seasonality issue.

[7]One NHI point translated to NT$ 0.9419 in 2009 and NT$ 0.9445 in 2010. US$1 is approximately NT$30.

of all observable and unobservable factors. Y denotes my outcomes of interest, including number of doctors at night, treatment expenditure at night, shares of nonurgent visits, shares of night admission, and 7-day and 30-day mortality at night. Estimates are clustered at the hospital level. The coefficient of December 2009 (β_0), the last month in the pre-policy period, is normalized to zero.

The specification requires some assumptions. First, I assume that the admission time of each patient is random in EDs. Second, the randomness of ED admission time should not be affected by any policy changes faced by hospitals.[8] Third, I assume that patients do not choose specific hospitals to visit when an emergency happens. Instead, with random accident locations, patients are admitted to the nearest hospitals. It is worth noticing that this might not hold for nonurgent cases. I consider this possibility in Section 5.2.

5 Results

5.1 Direct Policy Impacts

Care Capacity The capacity of care in the healthcare system is defined as the availability of healthcare providers. Hospitals have the incentive to place or reallocate more doctors at night because night admissions have become more profitable compared to daytime admissions. Using the unique doctor identifiers from the claim records, I calculate the number of doctors available at night. I plot the event-study estimates, β_p, with 95% confidence interval in Figure 2a and find that doctor numbers at night did not change significantly after 2010.

Treatment Intensity Total expenditure, length of stay, numbers of procedures, intensive care unit (ICU) days and in-hospital deaths are common measures of treatment intensity. Total expenditure predicts longer length of stay, more procedures, and more ICU days in ED. However, in this case, the reverse might not be true. In the NHI system, when an ED patient is transferred to another department for hospitalization or surgery, other claims will be filed, and fees will be paid to those other departments. To investigate EDs' local responses, I use total expenditure subtracting diagnostic fees among night admissions as an intensity proxy.[9][10] I examine mortality as policy impacts on health outcomes in Section 5.4. Event-study results in Figure 2b show that total expenditure among night admissions did not respond to the policy change.

[8] Besides the subsidy for diagnostic fees, Taiwan Triage and Acuity Scale (TTAS) went from four to five levels in 2010. I discuss how this reform had no impact on my findings in Appendix B.

[9] We use "points" assigned in the NHI guideline rather than the nominal value of total charges to proxy expenditure.

[10] Diagnostic fees are subtracted because the fees increased by 30% after the policy change.

5.2 Substitution Effects: Emergency Department and Primary Care Utilization

Since the policy change increased resources given to EDs, patients might substitute primary care with emergency care to receive better quality care. Using outpatient claim records from all levels of medical facilities, Figure 3 shows that primary care utilization has remained stable between 2008 and 2011. I see no discontinuity following the subsidy policy. To statistically test the substitution effects, I estimate Equation 1 using the share of nonurgent admissions in EDs as the outcome.[11] In Figure 4, I look at both all-day and night-only admissions and do not detect substitution effects.

5.3 Impacts on Night Admissions

Overall Responses The 30% increase in night diagnostic fees provided financial incentives for hospitals to admit more patients during the night bonus windows. Therefore, I estimate Equation 1 using the share of night admissions as the outcome. My event-study results in Figure 5 report no effects on night admission shares. Note that I observe seasonality at the beginning of the year possibly due to the lunar new year.

Heterogeneity: The Least Urgent Patients Previous literature has found that hospitals react to financial incentives by upcoding or manipulation. Delaying admitting nonurgent patients is one way for hospitals to increase profits without hurting patients. I thus test whether the policy change affects the share of night admissions among patients in the bottom triage level. The estimation in Figure 6 shows that, among the least urgent patients, the share of night admission increased significantly after the policy change. To precisely quantify the effect sizes, I adopt a difference-in-differences (DID) approach estimating Equation 2. $POST_y$ is an indicator for year 2010; γ_1 is the coefficient of interest. Results in Table 3 report a 9.1 p.p. (36%) increase.[12] My findings suggest a pattern consistent with manipulation. Note that patients do not necessarily wait longer. It is likely that, after patients got assigned to the least urgent triage level, hospitals registered these

[11] We apply the ED admission categories classified by the NYU Center for Health and Public Service Research to determine nonurgent admissions. The description of each category can be found here. I define claim records with ICD-9 codes assigned at least 80% probability of being category non-emergent as "nonurgent" admissions. Note that only 0.8% of ED admissions defined as 100% nonurgent in the full count claim data.

[12] Some studies find that hospitals of different ownership types respond to financial incentives differently (Duggan 2000, Dafny 2005, Silverman & Skinner 2004). However, I do not detect significant differences when I consider hospital ownership types in all specifications for all outcomes.

patients later to fit these records in the night bonus windows.

$$Y_{hyw} = \gamma_0 + \gamma_1 POST_y + \gamma_2 NP_h + \tau_h + \tau_m + \epsilon_{hyw} \tag{2}$$

Heterogeneity: Acute Myocardial Infarction (AMI) Patients One might wonder if admitting significantly more nonurgent patients around the time transitioning into the night bonus window would crowd out urgent patients who arrived at a similar time. In the same fashion, I examine the policy impact on shares of night admission among AMI patients, the most urgent cases.[13] In Figure 7, I see no effects among this group, which is plausible given that delaying treating these patients might lead to larger costs for hospitals.

5.4 Impacts on Health Outcomes

There are two mechanisms by which increasing diagnostic fees can affect health outcomes. First, hospitals may increase medical inputs and thus improve health outcomes. Second, admitting more least urgent patients at night might crowd out resources for urgent patients who were admitted right after 10 pm and leads to adverse health outcomes. Although I find no evidence of these mechanisms, I still wonder if this policy could improve health outcomes through some unobserved channels. For instance, hospitals might invest in ED equipment using the subsidy. Thus, I examine the 7-day and 30-day mortality rates among patients who were admitted within the night bonus windows. The estimation in Figure 8 shows that the policy change has imprecise impacts on mortality rates.

6 Conclusion

I show that providing EDs with financial incentives does not necessarily lead to better care quality or outcomes. In response to a 30% increase in diagnostic fees, I find that hospitals did not increase the care provision. The overall inflow to EDs did not change following the new policy. However, I find evidence consistent with manipulation—to increase profits, hospitals delay admitting the least urgent patients. Meanwhile, the most urgent cases, AMI patients, were not delayed as a result of the policy change. Lastly, I find no effects on mortality.

The amount of money involved in this policy in a single year might be small—it amounted to five million US dollars in 2010. Thus, the manipulation has not hurt the system on a noticeable level (yet). However, if this five million US dollars reflect the average annual program expense in the past 12 years, it becomes considerable. It takes a

[13] We classify patients as AMI admissions using ICD-9 codes 410-414.

lot to sustain a universal healthcare system. My results suggest the need to tie subsidy policies to a specific expenditure.

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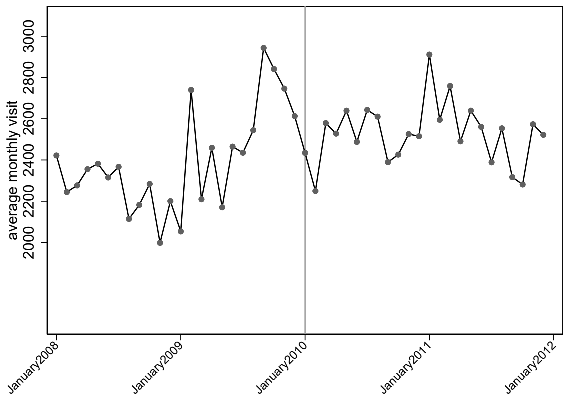
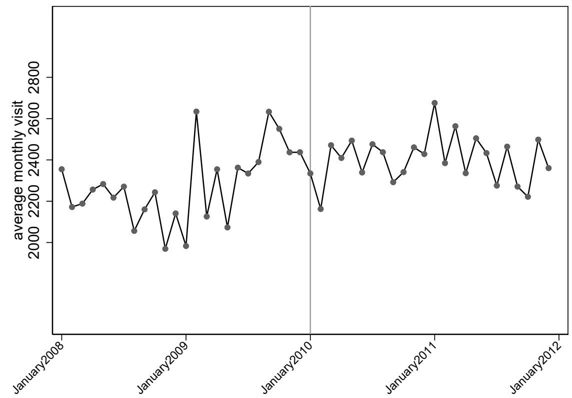
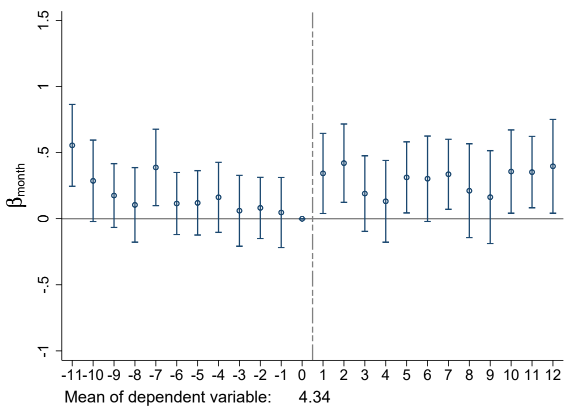


(a) Including Influenza Related

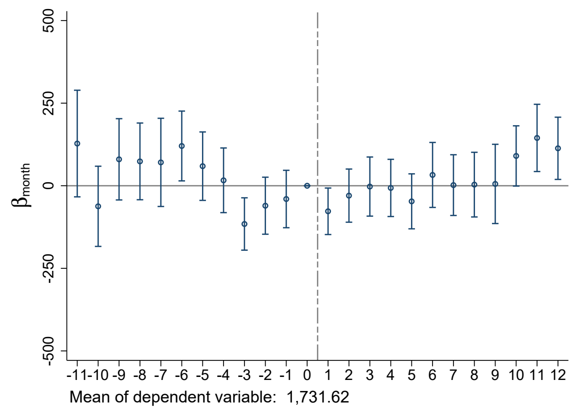


(b) Excluding Influenza Related

Figure 1: Hospital-Level Monthly Visit Volume



(a) Numbers of ED Doctors at Night



(b) Treatment Expenditure at Night

Figure 2: Direct Impacts on Inputs

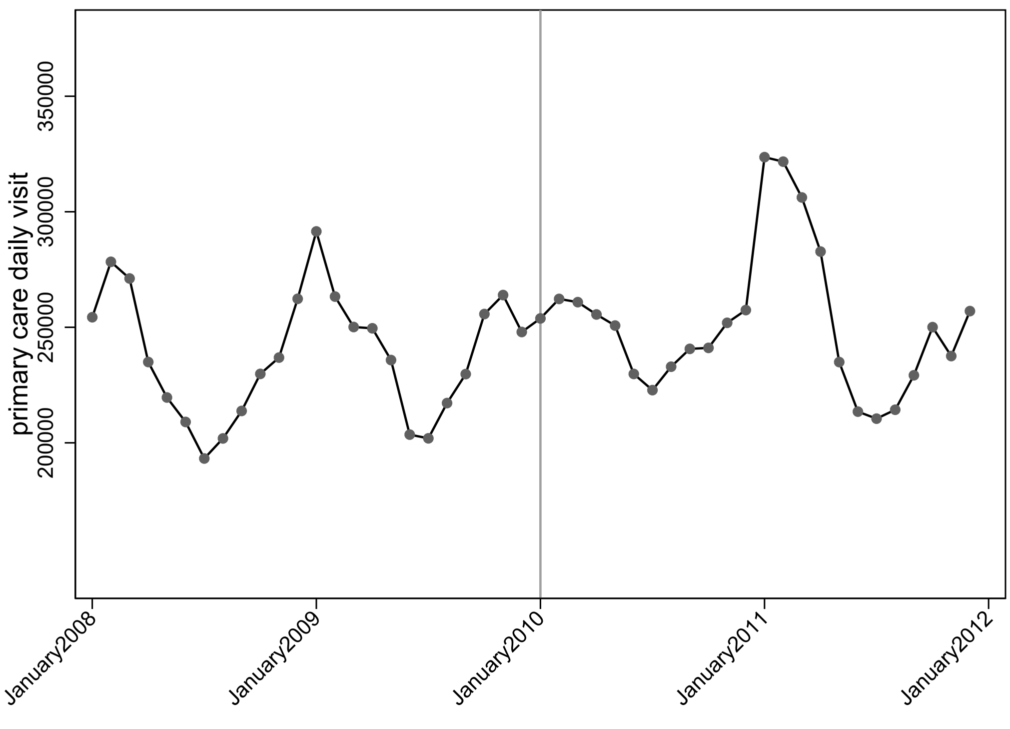
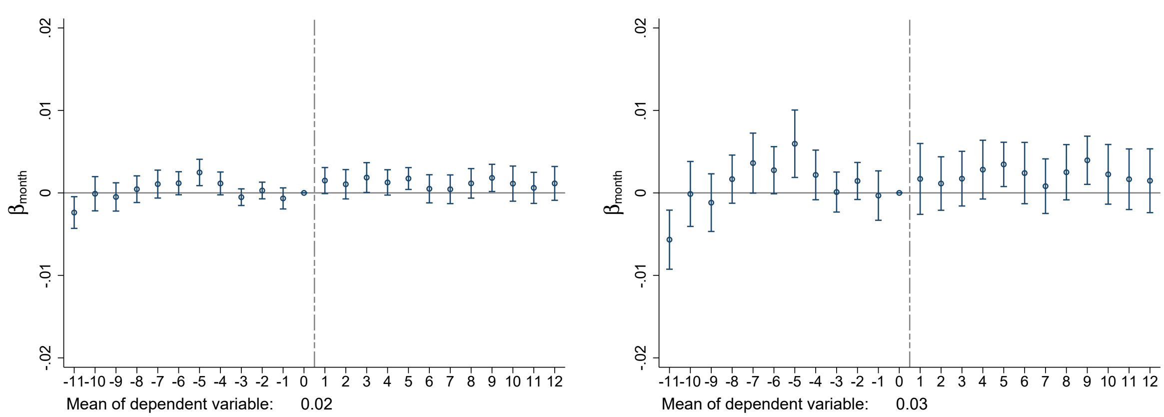


Figure 3: Primary Care Daily Visit

Notes: For data consistency, I only include non-holiday visits of patients above age 6 without catastrophic illness. The fluctuation is driven by seasonality, and thus the volumes always peak in winter.



(a) All Day

(b) Night Only

Figure 4: Substitution Effects between EDs and Primary Care

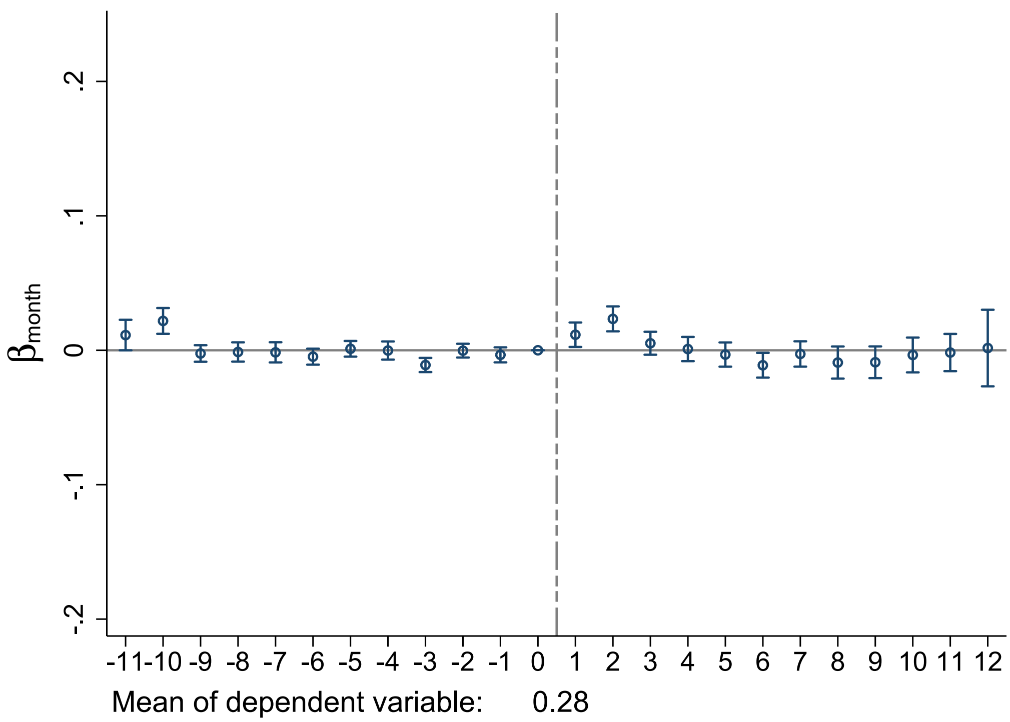


Figure 5: Impacts on Shares of Night Admissions

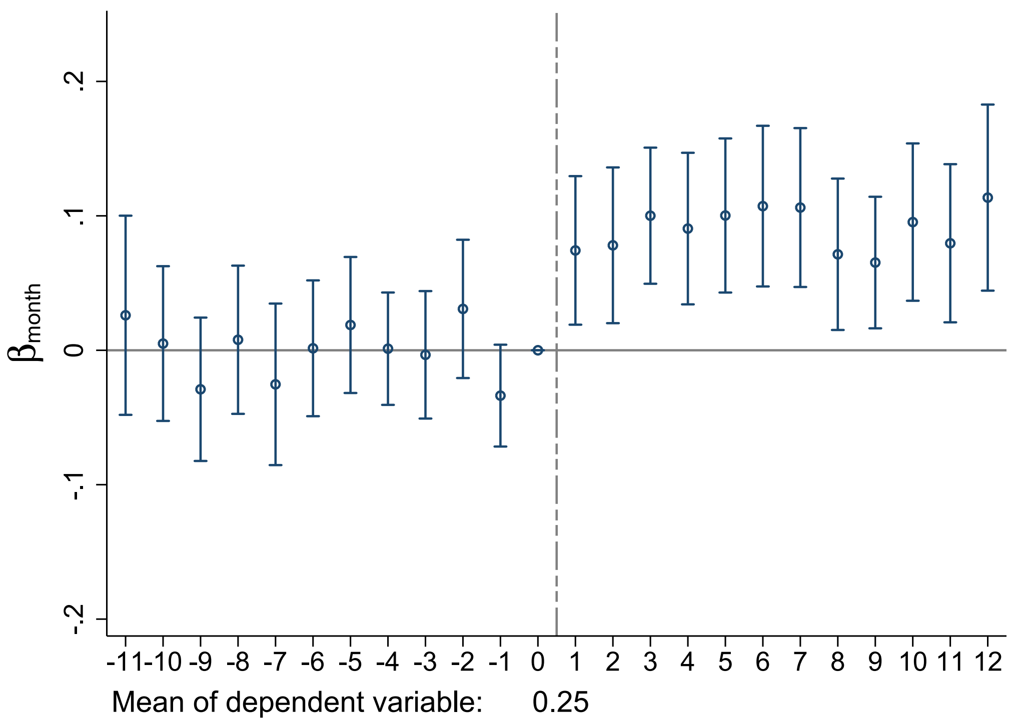


Figure 6: Impacts on Shares of Night Admissions Among the Least Urgent

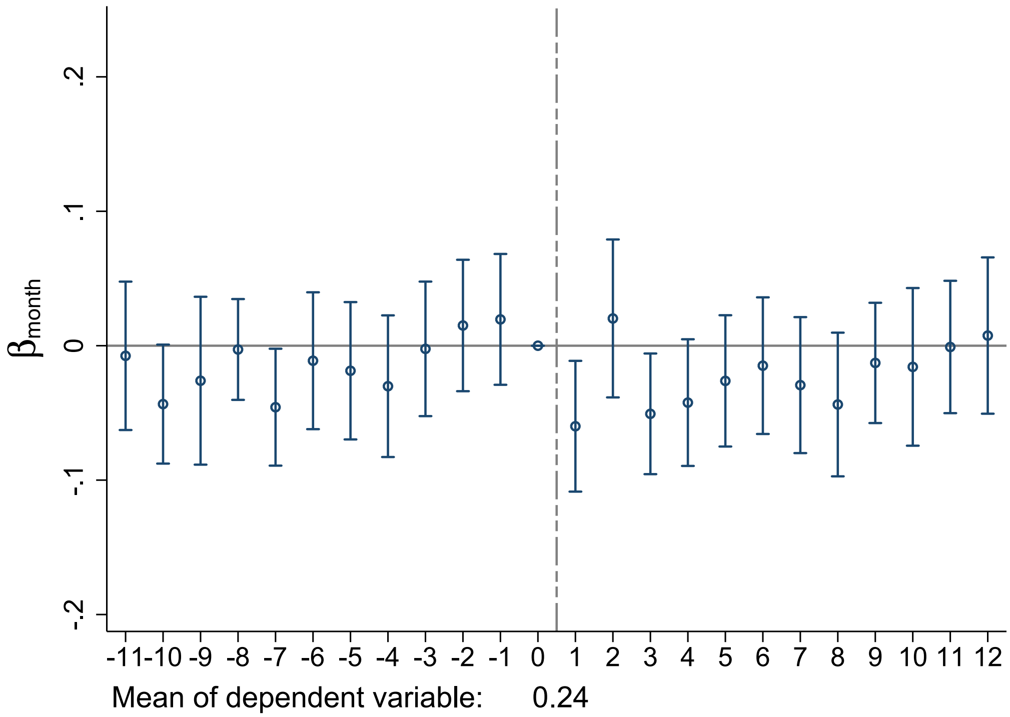
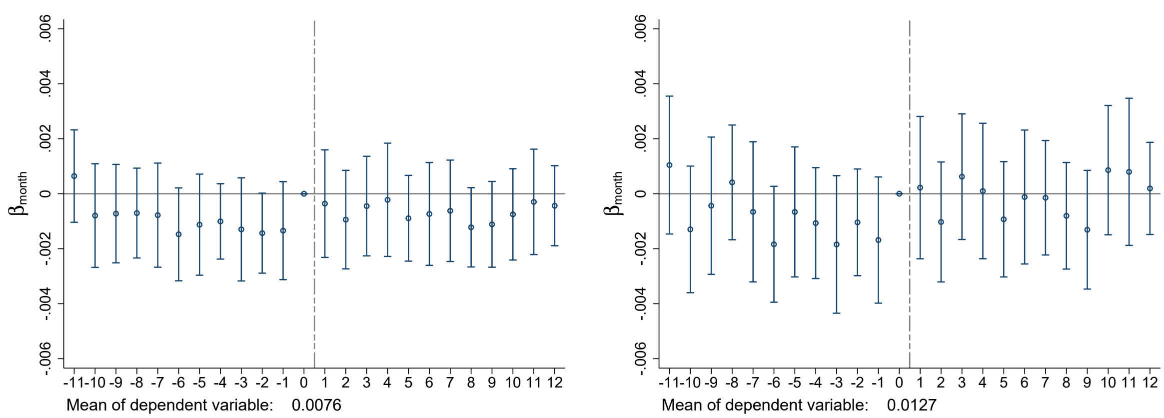


Figure 7: Impacts on Shares of Night Admissions Among AMI Patients



(a) 7-Day Mortality

(b) 30-Day Mortality

Figure 8: Impacts on Mortality at Night

Table 1: Diagnostic Fee Bonus Scheme Of Non-Rural Hospitals

	bonus before 2010			bonus after 2010		
age	day	holiday	night	day	holiday	night
0 to 6m	100%	120%	120%	100%	120%	150%
6m to 2yrs	30%	50%	50%	30%	50%	80%
2 to 6yrs	20%	40%	40%	20%	40%	70%
6yrs and above	0%	20%	20%	0%	20%	50%

Notes: Holidays include weekends and national holidays. A hospital gets only the night bonus when a patient is admitted during holiday nights.

Table 2: Summary Statistics for the Final Sample

	2009		2010	
	Mean	S.D.	Mean	S.D.
# of Claims	1,937,099		1,937,895	
Patient-Level Characteristics				
Male	0.52	0.50	0.51	0.50
Age	43.73	22.98	45.31	22.77
Above Age 85	0.04	0.18	0.04	0.20
Visited Nonprofit Hospitals	0.65	0.48	0.66	0.48
Hospital-Week-Level				
# of Doctors Night	4.26	3.43	4.42	3.46
Total Expenditure at Night (NIH poin)	1730.45	722.65	1732.84	697.74
Shares among All Admissions				
Nonurgent Admissions	0.02	0.01	0.02	0.01
Night Admissions	0.29	0.05	0.28	0.06
Shares of Night Admissions among				
Nonurgent Admissions	0.03	0.02	0.03	0.02
Least Urgent Admissions	0.20	0.26	0.29	0.23
AMI Admissions	0.25	0.26	0.24	0.25
Mortality				
7-Day	0.0105	0.0060	0.0110	0.0062
30-Day	0.0195	0.0107	0.0209	0.0105
7-Day; Night	0.0075	0.0085	0.0076	0.0087
30-Day; Night	0.0124	0.0112	0.0130	0.0117

Notes: Age is capped at 85. Night admissions are patients registered between 10 pm and 6 am. I subtract diagnostic fees from the total expenditure because diagnostic fee bonuses increased in 2010 by the policy, while all expenditures are recorded in the unit of the NHI point. I classify patients as AMI admissions using ICD-9 codes 410-414. I define an admission as the least urgent when a patient is assigned to the bottom triage level.

Table 3: DID: Impact on Night Admission Shares among Least Urgent Patients

	(1)	(2)
Post 2010	0.099***	0.091***
	(0.017)	(0.017)
Nonprofit	0.073**	0.144***
	(0.021)	(0.004)
Hospital FE	No	Yes
Month FE	No	Yes
Mean of dep var	0.247	0.247
Adjusted R^2	0.054	0.135
Observations	4,064	4,064

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Night admissions are patients registered between 10 pm and 6 am. I define an admission as the least urgent when a patient is assigned to the bottom triage level.

Online Appendices

A Sample Restrictions

I include only non-holiday claim records in my sample because the diagnostic fee scheme does not allow us to distinguish night admissions from holiday admissions before 2010 (see Table 1). Given that the information on admission time is not available, the differences in diagnostic fees are the only source to determine if a patient is admitted during the night bonus window. Besides this, I made some sample restrictions from both patients' and hospitals' sides.

Patients' Side First, I exclude patients below age six because (1) the diagnostic fee bonus scheme varies across age below six (see Table 1) and (2) they may pay different co-payments based on cities. Second, I exclude patients with catastrophic illness because hospitals are paid more (by the NHI) for treating them. In the full-count claim records, patients with catastrophic illness make up around 5% of the sample. Third, I exclude patients who visited the ED for influenza and influenza-like illness because of the H1N1 pandemic in late 2009.

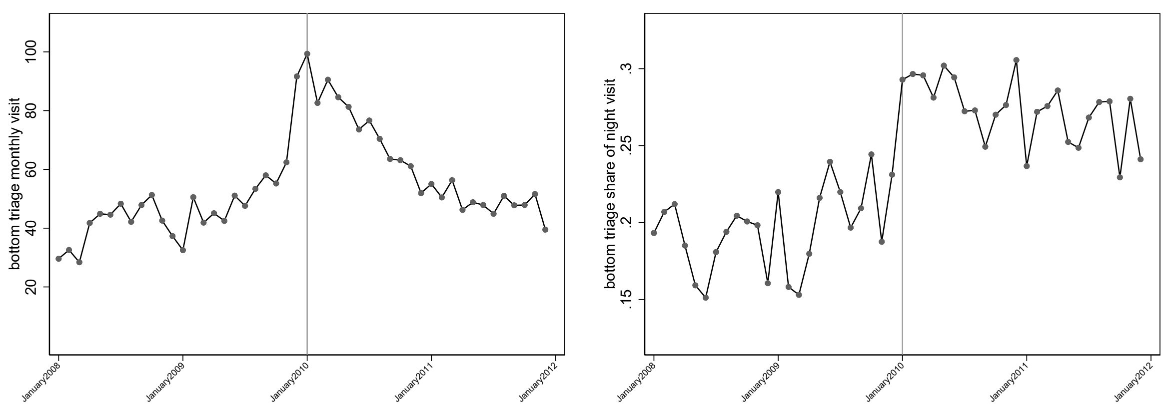
Hospitals' Side Only major and minor teaching hospitals with 24-hour EDs were treated by the subsidy policy. Among teaching hospitals, I first exclude hospitals that did not constantly provide 24-hour emergency care in 2009 and 2010. Second, I exclude rural hospitals because they face other subsidy programs at the same time, and their patients have particular characteristics. Third, I exclude for-profit hospitals because there are only five for-profit non-rural teaching hospitals. In addition, not all of them constantly provided 24-hour emergency care during my study period. Given that they might have different objective functions, including only a handful of non-profit hospitals might introduce broad variation(Newhouse 1970, Pauly & Redisch 1973, Lakdawalla & Philipson 1998).

B Effects of the Taiwan Triage and Acuity Scale (TTAS) Reform

The TTAS went from four to five levels in 2010. Level one categorizes the most urgent patients, and level five (or level four before 2010) indicates the least urgent patients. This policy should not affect the demand for emergency care. Indeed, Figure 1 displays no discontinuity around 2010 when I plot the average volume at the month level between 2008 and 2011. However, the reform had an effect on the denominator when I use the share of night admissions among the least urgent patients as an outcome variable.

To rule out this concern, I plot the average daily ED volume among the least urgent patients (level four before 2010 and level five after 2010). Figure A1a shows that the volume increased significantly around January 2010, and started to return to the pre-2010 level. I further plot the raw data on the outcome variable—the share of night admissions at the month level—between 2008 and 2011. Figure A1b presents a significant and clear jump in January 2010. The share fluctuated within a certain range both before and after the policy change and does not reflect the pattern of the denominator from Figure A1a. The flat trends before and after 2010 support my assumption that the time a patient enters an ED is random.

One might argue that the jump might be driven by the TTAS reform that more patients are classified into the bottom triage level when they are admitted at night. However, hospitals have little incentive to do this because they are paid more diagnostic fees when diagnosing a higher triage-level patient. In addition, the subsidy program incentivizes hospitals to treat more higher triage-level patients at night. When the number of total admissions remained stable (Figure 1), it is unlikely that hospitals downgrade patients' triage levels on purpose.



(a) Daily Volume

(b) Share of Night Admission

Figure A1: Raw Data Among Bottom Triage Level, 2008–11

C Do Hospitals of Different Ownership Types Respond to Financial Incentives Differently?

My sample contains public and nonprofit hospitals. Previous literature finds conflicting results about whether nonprofit hospitals are mostly altruistic.[1] Some studies find that

[1]The objective function of nonprofit hospitals has been unclear, and thus researchers have proposed different models (Newhouse 1970, Pauly & Redisch 1973, Lakdawalla & Philipson 1998).

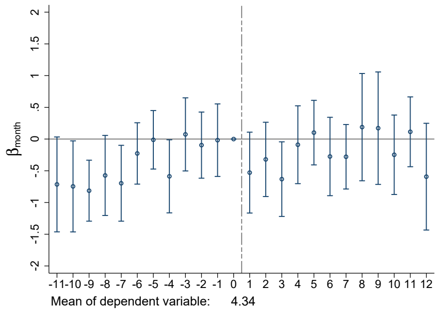
nonprofit hospitals are profit maximizers (e.g., Duggan (2000)), while some find nonprofit hospitals more altruistic (e.g., Dafny (2005)). Sometimes, nonprofit hospitals change behaviors based on how competitive the local market is (Silverman & Skinner 2004). Meanwhile, most studies show that public hospitals are not profit maximizers because of soft budget constraints.

I test whether hospitals of different ownership types respond to the subsidy program differently by estimating

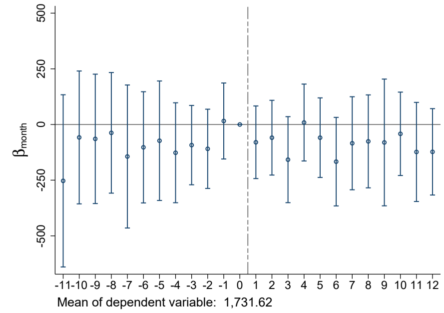
$$Y_{htw} = \alpha_0 + \sum_{p=-11}^{12} \beta_p \times \mathbf{1}_{t=p} \times NP_h + \alpha_1 NP_h + \tau_h + \tau_m + \epsilon_{htw} \tag{3}$$

Here, notations follow Equation 1. h denotes hospital, t time, w week, and m month. NP is an indicator for nonprofit hospitals. τ_h represents hospital fixed effects and τ_m month fixed effects. ϵ_{htw} represents hospital-specific idiosyncratic shocks that are not observed, and assumed to be independent of all observable and unobservable factors. Estimates are clustered at the hospital level. The coefficient of December 2009 (β_0), the last month in the pre-policy period, is normalized to zero.

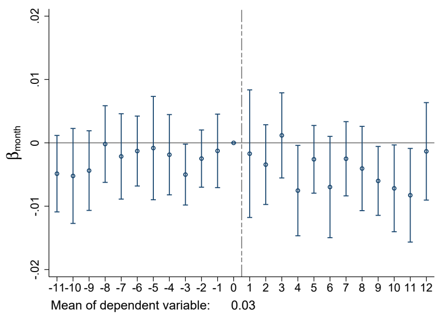
Coefficients of interest, β_p, estimate how nonprofit hospitals respond differently from public hospitals. I focus on the same set of outcomes—numbers of doctors at night, treatment expenditure at night, shares of nonurgent visits, shares of night admission, and 7-day and 30-day mortality at night. I plot estimates, β_p, for all outcomes in Figure A2. My estimation concludes that nonprofit hospitals behave similarly to public hospitals in response to this specific policy.



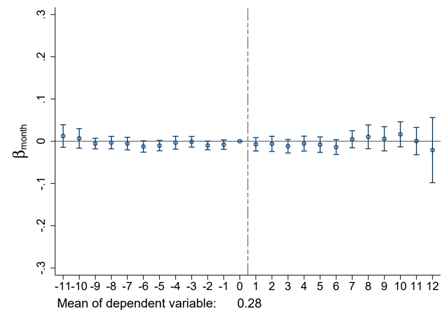
(a) Numbers of ED Doctors



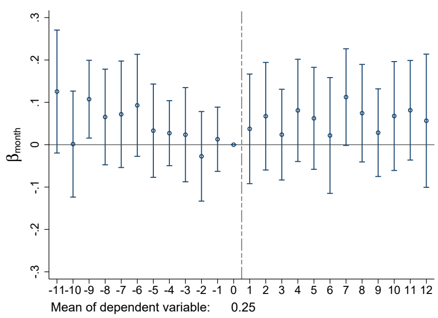
(b) Treatment Expenditure



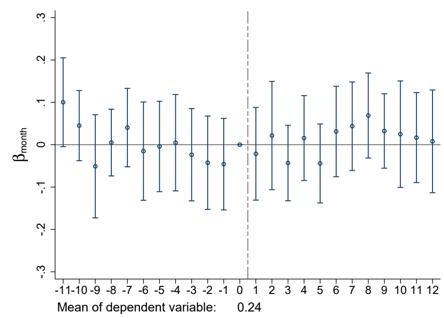
(c) Substitution between EDs and Primary Care



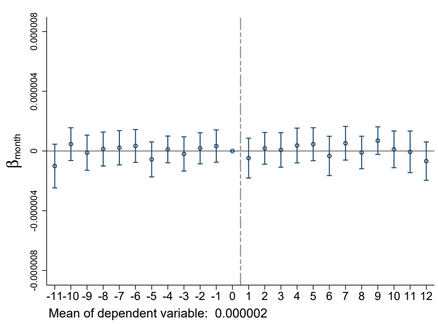
(d) Shares of Admissions



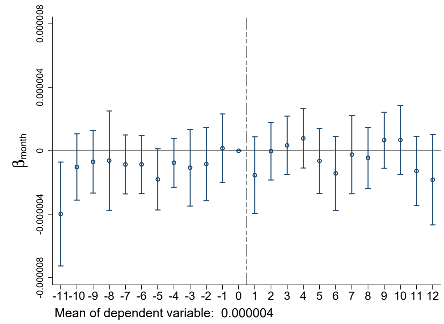
(e) Shares Among the Least Urgent



(f) Shares Among AMI Patients



(g) 7-Day Mortality



(h) 30-Day Mortality

Figure A2: Impacts on Admission at Night by Ownership Types