

Time Dependency in Physician Decision-Making

BY LAWRENCE JIN, RUI TANG, HAN YE, JUNJIAN YI, AND SONGFA ZHONG*

*Jin: Centre for Behavioural Economics, National University of Singapore (email: ljin@nus.edu.sg); Tang: Department of Economics, Princeton University (email: ruit@princeton.edu); Ye: Department of Economics, National University of Singapore (email: yehan0413@gmail.com); Yi: Department of Economics, National University of Singapore (email: junjian.yi@gmail.com); Zhong: Department of Economics, National University of Singapore (email: zhongsongfa@gmail.com).

Patients require medical services 24 hours a day, and thus understanding how hospital productivity varies over the course of the day is essential to improve efficiency in healthcare operations. Substantial research has demonstrated time-of-day effects on productivity; for example, workers' productivity and safety tend to decline at night (Folkard and Tucker, 2003). Students learn better in the morning than in the afternoon (Pope, 2016), and benefit from later school starting times (Carrell, Maghakian, and West, 2011). Several studies have examined differences in patient outcomes between day and night shifts, but the results are inconclusive (Weinger and Ancoli-Israel, 2002; Bailit, 2006). The key challenge in estimating time-of-day effects is that the time of patient treatment is not random, since certain cases might be selectively scheduled at a specific time of day.

In this paper, we investigate time-of-day effects on physician decision-making and patient outcomes using administrative data from over 250,000 visits to an emergency department (ED) in Singapore. The ED provides a quasi-experimental setting in which the time of patient treatment is almost random. We find that, after controlling for case characteristics, physician fixed effects, and the number of hours on duty, cases treated at night have a lower probability of inpatient admission, a reduced number of medical tests, and a higher frequency of revisits to the ED.

I. Institutional Setting and Data

We study a large ED that operates 24 hours a day. Physicians work in shifts, and shift timing varies significantly. This enables us to identify time-of-day effects while controlling for other effects that depend on shift starting time, such as fatigue.

Upon arrival at the ED, patients are assessed by a triage nurse and categorized into one of three severity levels: level 1 is assigned to the most severe cases, level 2 to major emergencies, and level 3 to minor emergencies. Severity levels 1 and 2 (severe

cases henceforth) are usually seen in the acute care area, and level 3 cases (non-severe cases henceforth) in the urgent care area. The order of treatment is determined by patients' severity level and arrival time.¹

The institutional setting ensures that patients and physicians are almost randomly matched in the ED (Chan, 2016, 2018). The rationale is twofold. First, ED visits are unplanned; patients are not likely to select their physicians, due to the unexpected nature of emergency care. Second, the internal shift scheduling of physicians is predetermined, and physicians cannot control the volume of ED arrivals or the types of patients assigned. As a result, the match between patients and physicians is largely random.

We obtain administrative data for all patient visits to the ED from January 1, 2011, through December 31, 2012. The hospital information system compiles comprehensive records for each visit, including patient characteristics, physician identifier, clinical decisions, patient outcomes, and, importantly, timestamps for the patient's path through the ED. These records allow us to track real-time patient flow and the universe of physicians' activities in the ED.

Over the 2 years, we observe 264,115 raw patient visits to the ED. We construct real-

time patient flow volume and physician shift schedules using all visits. We limit our attention to physicians who treated a minimum of 100 patients during the sample period. We also exclude visits in which the patient died upon arrival or at the ED, left before being seen, or discharged against medical advice. Our final sample contains 258,219 patient visits treated by 129 physicians.

II. Empirical Strategy and Results

A. Empirical Strategy

To study the association between time of day and physicians' admission decisions, we estimate the following regression:

$$(1) \quad Y_{ijt} = \alpha + \sum_m \beta_m TD_{itm} + X_i\gamma + \mu_t + v_j + \underline{h}(j, t)\delta + \epsilon_{ijt},$$

where the dependent variable Y_{ijt} is indexed for patient visit i treated by physician j starting consultation at time t . For admission decisions, Y_{ijt} is a dummy variable that equals one if patient i is admitted to inpatient care and zero otherwise.

TD_{itm} is a dummy variable indicating whether the patient starts consultation in time period m . In our baseline analysis, we divide each day into four periods: afternoon (12:00 to 17:59), evening (18:00 to 20:59), night (21:00

¹ See Online Appendix for more details.

to 05:59), and morning (06:00 to 11:59). Afternoon is the omitted base period. Therefore, each estimate of β_m provides the change in admission probabilities between patients starting consultation at period m and those starting consultation in the afternoon.

We control for case characteristics X_i (patient's gender, age, race, triage severity level, and diagnostic categories), time fixed effects μ_t for day of week and month-year interactions, and physician fixed effects v_j . We also account for physician's duty hours, where $\underline{h}(j, t)$ measures the number of hours elapsed since the beginning of the physician's shift (rounded down to the nearest integer). Finally, the error term, ϵ_{it} , captures measurement errors. We cluster standard errors throughout at the physician level.

A key assumption in estimating Equation (1) is that, conditional on observable case characteristics, physician fixed effects, day of week, and month-year interactions, the excluded patient characteristics are orthogonal to the consultation time of day. We find little variation in observable patient characteristics and predicted admission rates across different times of the day, which provides suggestive evidence that ED visits are less prone to selection (Figure A1, Online Appendix).

B. Results

Panel (a) of Table 1 presents the estimation results from Equation (1). Column (1) shows that the unconditional admission rate is 3.3 percentage points lower at night and 1.8 percentage points lower in the morning than in the afternoon, though both differences are statistically insignificant at the 10% level. The magnitude of the coefficients remains largely unchanged in column (2), which controls for various case characteristics. Again, this is consistent with our assumption that patients arrive at the ED without any systematic selection regarding time of day.

Through columns (3) to (5), results remain qualitatively similar after we control for time fixed effects, physician fixed effects, and the physician's working hours. In the full model (column (5)), night and morning are associated with 2.8 and 2.0 percentage points lower admission rates, respectively, than afternoon, and both are statistically significant at the 1% level. The two estimates translate into a reduction of 12.5% at night and 9.1% in the morning, given the sample mean admission rate of 22%. The admission rate is only marginally higher in the evening than in the afternoon.

Columns (1) to (3) in Panel (b) check the robustness of the estimated time-of-day effect using different subsamples. Column (1) shows

that the estimates remain essentially unchanged for patients brought in by ambulance, who are least likely to be able to select the time of their ED arrival. Columns (2) and (3) find that the estimated time-of-day effect persists for both severe and non-severe cases.

Panel (a) of Figure 1 provides a more detailed look at the time-of-day effect on admission decisions. We divide each day into eight 3-hour intervals, where “noon to 3 pm” is the omitted period. Figure 1 plots coefficient estimates of Equation (1) based on the eight-period divisions (and their respective 95% confidence intervals), controlling for case characteristics, time fixed effects, physician fixed effects, and hours on duty. Panel (a) shows that the probability of inpatient admission is significantly influenced by the 3-hour time period in which patient consultation starts. The admission rate increases slightly after midday, reaches the peak level around 3 pm-6 pm, and remains high until 9 pm. A dramatic decline occurs after 9 pm, when the admission rate falls to its lowest level between midnight and 3 am. Cases that start consultation in the morning have significantly higher admission rates than those that start at night, but lower than those that start in the afternoon.

Next, we examine the time-of-day effect on the number of medical tests ordered for each patient. Consistent with our earlier results, we find that the number of tests declines by 5.9% and 2.3% at night and in the morning, respectively, compared with the afternoon (column (4) in Panel (b) of Table 1). Both are statistically significant at the 1% level. Panel (b) of Figure 1 plots the coefficient estimates for the 3-hour periods with their respective 95% confidence intervals. The number of tests is highest during the afternoon and evening and lowest at night, especially between midnight and 3 am.

We also study the time-of-day effect on patient outcome, which may reflect physician decision quality. Specifically, we determine whether the patient revisited the same ED within 24 hours.² As shown in column (5) of Panel (b) in Table 1 and Panel (b) of Figure 1, revisit rates are highest for patients treated at night. Another interesting finding is that patients treated in the evening also have a high probability of ED revisits, even given the high levels of inpatient admissions and medical tests.

² Since our data are confined to what happens within the specific ED, we are only able to measure revisits to the same ED.

III. Discussion and Conclusion

We find robust evidence of time dependency in physician decision-making in an ED. Controlling for case characteristics, physician fixed effects, and hours on duty, ED visits at night have significantly lower probability of inpatient admission, fewer medical tests ordered, and a higher revisit rate.

The less intensive treatment and worse outcomes at night may reflect a decline in physician performance: Given that the time-of-day effect persists after accounting for the number of hours on duty, physician fatigue cannot explain our results.

Our findings seem to be most consistent with the disruption of circadian rhythms—the physical, mental, and behavioral changes that follow a daily cycle. Much of the circadian rhythm literature suggests that human performance increases during the daytime and decreases during the nighttime (Valdez, 2019). Overnight operations induce a misalignment between internal circadian rhythms and requisite behavioral cycles, which results in reduced alertness, compromised productivity, and elevated risk during nighttime (Smith, Folkard, and Poole, 1994; Folkard and Tucker, 2003; Chellappa, Morris, and Scheer, 2018). In particular, our results coincide with the circadian variations in cognitive processes: Attention and executive functions improve in

the afternoon and early evening hours, and reach the lowest levels during nighttime and early morning (Valdez, 2019).

Hospital logistics, such as staffing levels and medical device availability, may also cause the observed time variations. It is possible that the ED reduces hospital staffing levels and specialized diagnostic and treatment options at night, which affects both physicians' medical choices and patients' health outcomes.

These explanations are neither exhaustive nor mutually exclusive. Due to data constraints, we are unable to disentangle the disruption of circadian rhythms and different hospital arrangements. Despite these shortcomings, our results show that patients treated at night receive less intensive care and have worse outcomes. These results shed light on management practices that could improve efficiency in healthcare delivery. We leave to future research the identification of the underlying mechanisms of the observed time dependency in physician decision-making.

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FIGURES & TABLES

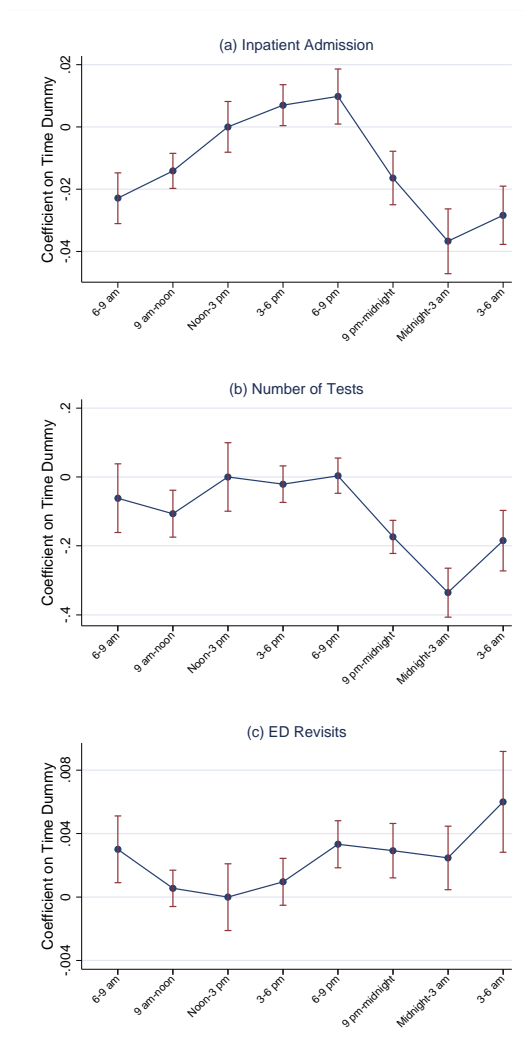


FIGURE 1. PHYSICIAN DECISIONS AND PATIENT OUTCOMES
BY TIME OF DAY

Note: This figure shows β_m from an OLS regression of Equation (1) with 95% confidence intervals. Dependent variables are a dummy variable for inpatient admission (Panel (a)), number of diagnostic tests (Panel (b)), and a dummy variable for revisiting the ED in the next 24 hours (Panel (c)). Each day is divided into eight 3-hour periods, where “Noon-3 pm” is the omitted period and therefore its coefficients are normalized to 0. Control variables include case characteristics, physician fixed effects, hours on duty, and time indicators for day of week and month-year interactions. All regressions are based on the full analytic sample and clustered at the physician level.

TABLE 1—TIME OF DAY EFFECTS ON PHYSICIAN DECISIONS

	(1)	(2)	(3)	(4)	(5)
Panel (a)					
	<i>inpatient admission</i>				
Evening	0.0058 (0.0126)	0.0028 (0.0032)	0.0025 (0.0031)	0.0030 (0.0028)	0.0066* (0.0034)
Night	-0.0333 (0.0243)	-0.0347*** (0.0038)	-0.0352*** (0.0036)	-0.0298*** (0.0030)	-0.0276*** (0.0033)
Morning	-0.0178 (0.0179)	-0.0193*** (0.0024)	-0.0201*** (0.0023)	-0.0164*** (0.0022)	-0.0202*** (0.0023)
Case characteristics	N	Y	Y	Y	Y
Time FE	N	N	Y	Y	Y
Physician FE	N	N	N	Y	Y
Hours on duty	N	N	N	N	Y
Observations	258,219	258,219	258,219	258,219	258,219
Sample mean outcome	0.220	0.220	0.220	0.220	0.220
Panel (b)					
		<i>inpatient admission</i>		<i>test count</i>	<i>ED revisits</i>
Evening	0.0027 (0.0081)	0.0127* (0.0065)	0.0026 (0.0023)	0.0138 (0.0218)	0.0026*** (0.0007)
Night	-0.0340*** (0.0077)	-0.0409*** (0.0077)	-0.0201*** (0.0026)	-0.2146*** (0.0189)	0.0027*** (0.0008)
Morning	-0.0280*** (0.0068)	-0.0271*** (0.0053)	-0.0180*** (0.0020)	-0.0826*** (0.0306)	0.0010* (0.0006)
Sample	Ambulance arrivals	Severe cases	Non-severe cases	All	All
Observations	37,877	74,350	183,869	217,498	258,219
Sample mean outcome	0.593	0.560	0.083	3.617	0.015

Notes: This table reports coefficients from OLS regressions using Equation (1). Each day is divided into four periods: morning (6 am to 12 pm), afternoon (12 pm to 6 pm), evening (6 pm to 9 pm), and night (9 pm to 6 am). Evening, night, and morning are dummy variables indicating whether the patient is seen by the physician in the respective time period, and afternoon is the omitted base period. Panel (a) shows results for inpatient admission with varying sets of controls, where the dependent variable equals one if the patient is admitted for inpatient care and zero otherwise. Case characteristics include patient demographic characteristics (indicators for gender, race, and age group), triage severity level, and diagnostic categories. Time fixed effects include day of week and month-year interactions. Hours on duty measure how many hours the physician has worked in the current shift.

Columns (1) to (3) in Panel (b) report inpatient admission results using different subsamples. Column (1) restricts the sample to cases brought in by ambulance. Columns (2) and (3) use severe and non-severe cases, respectively. Column (4) shows results for the number of medical tests using the full analytic sample with non-missing test information. The dependent variable in column (5) is a dummy variable that indicates whether the patient revisits the ED within 1 day. All columns in Panel (b) control for case characteristics, time fixed effects, physician fixed effects, and hours on duty.

Standard errors in parentheses are clustered at the physician level. *** Significant at the 1% level. * Significant at the 10% level.