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The financial health of “swing hospitals” during the first COVID-19 outbreak☆

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Abstract

The hospitals in Japan have hitherto had complete autonomy in deciding whether to admit COVID-19 patients. In fact, they were “swinging” between admitting or not COVID-19 patients, especially during the initial COVID-19 outbreak. To address endogenous decision making, we estimated the effects of admitting COVID-19 patients on hospital profits using instrumental variable (IV) regression. We derived the IVs from the guidelines of the national government on which hospital types should admit COVID-19 patients. Our empirical results revealed that the monthly profits per bed decreased by approximately JPY 600,000 (≈ USD 4615), which is 15 times the average monthly profit in 2019. This overwhelming financial damage indicates that it is costly for some hospitals to treat COVID-19 patients because of their low suitability in admitting such patients. Based on the implications of our main results, we propose an alternative strategy to handling patient surges in case of new infectious disease outbreaks.

1. Introduction

During the first COVID-19 outbreak, the potential financial meltdown of hospitals due to the admission of COVID-19 patients has become a worldwide policy issue. This problem was especially relevant in countries such as the US and Japan, where the private hospitals predominantly provide care for COVID-19 patients (American Hospital Association, 2020; Japan Hospital Association, 2020). In the US, the AHA estimated a total financial loss of $202.6 billion for hospitals and the health system in the first four months of the pandemic (American Hospital Association, 2020).

Today, hospital financial health in Japan has a positive outlook because of the subsidies implemented by the government, but the situation during the first COVID-19 outbreak was very different. In fact, over 40% of Japanese medical institutions lowered their bonuses for nurses and other staff members in 2020 (Japan Times, 2020) to overcome the related financial difficulties, which could have potentially reduced staff motivation. To support the hospitals admitting COVID-19 patients, the government implemented large subsidy programs from June 2020 and expanded them afterward. As a result, hospitals recorded an unprecedented surplus in fiscal year 2020 (MOF, 2021). During the peak of the delta variant in August 2021, it was criticized that many public hospitals such as national hospitals and the hospitals in the Japan Community Health Care Organization (JCHO) did not admit enough COVID-19 patients despite having received large subsidies.

The experience of the two years following the initial outbreak clearly demonstrates the importance of implementing a prompt but well-designed hospital subsidy system commensurate with the incentives hospitals have. In doing so, it is especially important to ascertain information accuracy regarding the amount of financial damage caused by the admission of COVID-19 patients and the mechanisms by which it occurs.

Despite the importance of this topic, to the best of our knowledge, there is no empirical analysis on this topic using hospital-level data. We...
were provided access to extremely valuable data the Tokyo Metropolitan Government collected to review hospitals’ financial standing during the COVID-19 outbreak. Therefore, by utilizing unique monthly panel data on the hospitals in Tokyo, we explore how a pandemic outbreak affects hospital finances.

However, it is challenging to estimate the financial consequences of admitting COVID-19 patients because the hospitals in Japan have complete autonomy in deciding whether to admit these patients. Japanese hospitals always have the option of admitting or rejecting patients. Although a limited hospital capacity was the main reason for implementing measures that restrict people’s daily lives, hospitals are free to reject COVID-19 patients for legitimate reasons, such as insufficient staff to treat them. In this paper, we refer to Japanese hospitals as “swing hospitals” for simplicity, similar to the term “swing states” used for US elections, in that both options (i.e., admitting patients or not) are feasible.

In such an environment, hospital self-selection behavior must be considered when estimating the impact of admitting COVID-19 patients on profits. A simple comparison of the profits of the hospitals that admit COVID-19 patients with those that do not without considering self-selection behavior could result in a significant understimation of the financial impact of admitting COVID-19 patients, since the hospitals that might incur huge financial losses are less likely to admit COVID-19 patients. Therefore, to solve the self-selection behavior of admitting or not COVID-19 patients, we used instrumental variables (IVs). These IVs are derived from the national government guidelines on which types of hospitals should admit COVID-19 patients.

In addition, Tokyo is a unique locale and an ideal laboratory for estimating the effects of COVID-19 patient admissions on profits. This is because a large number of hospitals are geographically close and environmentally homogeneous in Tokyo. In fact, the number of hospitals per capita and the hospital bed density in Tokyo are higher than those in New York City, London, or Paris, being probably the highest in the world (Rodwin and Gusmano, 2006). This enabled us to identify the financial consequences of COVID-19 with great precision, because we were able to compare many hospitals with similar environmental characteristics.

Utilizing these advantages in our estimations, the empirical results revealed that the monthly profit per bed decreased by approximately JPY 600,000 (= USD 4615), that is, 15 times the average monthly profit in 2019. Further, we also conducted a detailed analysis of hospital characteristics by hospital type, which revealed the mechanism of the large losses among swing hospitals. Indeed, this huge reduction in profits was driven by the cancellation of standard medical care. The main reason for the high number of cancellations for general patients was the difficulty to separate patients due to reasons such as old architecture (American Hospital Association, 2020; Japan Hospital Association, 2020; Moynihan et al., 2020; GHC, 2020), thus making it impossible to balance the care of COVID-19 patients with the care of other patients. The difficulty of effective zoning has been repeatedly pointed out for Japan’s urban areas, where many hospital buildings are relatively old.

By considering hospitals’ heterogeneity regarding their suitability of admitting COVID-19 patients, we have identified important implications concerning hospital capacity policy for COVID-19 patients as follows. In fact, many hospitals in Japan had only 5 to 10 beds for COVID-19 patients, but once a COVID-19 patient is admitted, the financial loss was usually enormous due to other patient cancellations. After the initial outbreak ended, the government implemented large subsidies to maintain the number of beds for COVID-19 patients in such hospitals, although only few COVID-19 patients could be admitted. However, given our result that the marginal profit reduction from admitting COVID-19 patients was very large, we believe that this policy led to excessive subsidies for most hospitals. In fact, the subsidies based on the lessons learned from the first outbreak led to unprecedented financial surpluses for hospitals during FY2020 and perhaps even during FY2021 (MOF, 2021). This study thus suggests that the government needs to implement a subsidy policy to compensate hospitals for their financial losses that is commensurate with the nature of the outbreak of an infectious disease.

2. Background

2.1. COVID-19 outbreak in Tokyo

Throughout the fight against COVID-19, Japan has had the lowest numbers of confirmed COVID-19 infections and of related deaths among the G7 countries. Even in the early April 2020, the number of newly confirmed cases in Tokyo did not exceed 200 per day. The number of inpatients with COVID-19 was approximately 3000 in Tokyo at the peak of the pandemic. Given that the population in Tokyo is around 14 million and that the Japanese government did not implement strict measures, these statistics are inordinately positive (Aldrich and Yoshida, 2020).

Most COVID-19 patients are treated by nongovernmental hospitals in Tokyo, without any explicit support from the government. Therefore, regardless of the relatively mild spread of COVID-19 compared to the rest of the world, the increase in the number of COVID-19 inpatients put pressure on each private hospital and posed a serious threat to the continued functioning of hospitals. More details on hospital ownership and the COVID-19 outbreak in Tokyo are provided in Online Appendix A.

2.2. Expanding hospital capacity

To deal with the surge in COVID-19 patients and strike a balance between medical care for patients with and without COVID-19, many countries have constructed so-called “temporary hospitals” for COVID-19 patients with mild to moderate symptoms. In these countries, the care for COVID-19 patients was mainly provided in large hospitals. For example, in the UK, Barts Health NHS Trust, which has 1800 beds, offered 800 beds to patients with COVID-19 at the end of January 2021 (NHS England and NHS Improvement Website, 2021).

This approach has not yet been adopted in Japan. Instead, on February 9, 2020, the Ministry of Health, Labour and Welfare (MHLW) ordered local governments to expand hospital capacity for COVID-19 patients and provided brief guidelines regarding which types of hospitals should treat patients with COVID-19. Through these guidelines, the MHLW stated the following three requirements for general hospitals that admitted COVID-19 patients.

First, hospitals were to prioritize private rooms for new COVID-positive admissions, while patients with a confirmed diagnosis can continue to be treated in the same room. Second, the toilets used by COVID-positive patients were not to be used by other patients. Finally, hospitals were to strongly adhere to the requirements for infectious diseases for a designated medical institution (i.e., institutions designated to treat patients with new infectious diseases) when admitting COVID-

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1 In the US, it is possible for a state governor to implement a “surge and flex” protocol and mandate hospitals to expand their bed capacity, as Andrew M. Cuomo did in New York State.
2 The exchange rate is JPY 130 for USD 1.
19 patients. As suggested by the third requirement, the most important requirement is that “one or more physicians with medical experience of treating infectious diseases should always be on duty.” When it comes to the cases of COVID-19 in which patients exhibit symptoms similar to pneumonia, this requirement is naturally interpreted as “one or more physicians with medical experience in treating infectious ‘respiratory’ diseases should always be on duty.”

Note that these requirements do not consider the non-negligible costs related to admitting COVID-19 patients, namely the cancellation costs of usual medical care, which consequently led to the large financial losses of swing hospitals.

Although each hospital can freely choose whether to admit COVID-19 patients, these guidelines have affected some hospitals’ decisions. Further, the local governments’ requests to some hospitals to admit COVID-19 patients influences hospitals’ decision-making to some degree. In response to such requests, each hospital decides whether to accept COVID-19 patients based on its resources and the content of the guidelines provided by the MHLW.

The details of actual negotiation between hospitals and local governments (i.e., prefectures) over how many beds each hospital allocates for COVID-19 patients are not published by reliable sources. However, the national guidelines are an important criterion for prefectures to request beds to be allocated to COVID-19 patients because COVID-19 was a completely unknown diseases during the initial outbreak and there were no other authoritative guidelines on which hospitals should treat COVID-19 patients. Additionally, prefectural governments are tasked with approving the number of beds for each hospital during regular times. Therefore, it was difficult for each hospital to completely ignore requests from the prefectural government, fearing that if they did not expand the number of beds allocated to COVID-19 patients, they would not be allowed to expand the number of beds after the infection was under control. Given this institutional setting, we construct IVs based on the national guidelines.

Eventually, 95 out of the 638 hospitals in Tokyo offered a total of 2980 beds by August 2020. Although many hospitals have a large number of beds, the number of beds for COVID-19 patients per hospital was very small. For example, the University of Tokyo Hospital only offered 30 beds for COVID-19 patients out of around 1200 beds. The strongest feature of Japan’s handling of the surge in COVID-19 patients was that the care was shared by many hospitals without concentrating those patients in large hospitals.

In addition to securing beds, the government doubled the treatment fee for COVID-19 patients in April 2020 to provide an incentive to admit these patients. However, this financial incentive was not sufficient to compensate the large cancellation costs that were inevitable when admitting COVID-19 patients. In fact, during the first COVID-19 outbreak, hospitals had to admit COVID-19 patients without receiving subsidies to compensate the cancellation costs of regular medical care. Afterward, in June 2020, the government began to implement large and even excessive subsidization policies.

3. Research design

Here, we first present the proposed ordinary least squares (OLS) model without considering the self-selection of each hospital, as a baseline model. Next, we present our identification strategy, which overcomes the endogeneity of the OLS model by employing IV estimation.

### 3.1. Baseline model

In the regression analysis, we begin by estimating the following OLS as a baseline model:

\[
\Delta Y_i = \alpha_0 + \alpha_1 \text{COVID} + \beta X_i + \epsilon_i \tag{1}
\]

where \(Y_i\) is the outcome variable in hospital \(i\), such as the profit per bed.

Since we are interested in the change in the outcome variable during the first COVID-19 wave, we use the outcome that captures the changes from February 2020 to April and May 2020. We first calculate the average \(Y\) in April and May 2020, \(Y_{\text{April and May 2020}}\), because the effect on hospitals was severe during these two months. Second, to capture the change from before to after the COVID-19 outbreak, we subtract \(Y_{\text{Feb. 2020}}\) from \(Y_{\text{April and May 2020}}\). In addition, even without the effect of COVID-19, there should be usually some seasonal trend from February to April and May, which can be obtained from the previous year data. Therefore, we subtract the seasonal trend captured by \(Y_{\text{April and May 2019}} - Y_{\text{Feb. 2019}}\) from \(Y_{\text{April and May 2020}} - Y_{\text{Feb. 2020}}\). Then, outcome variable \(Y\) can be written as \((Y_{\text{April and May 2020}} - Y_{\text{Feb. 2020}}) - (Y_{\text{April and May 2019}} - Y_{\text{Feb. 2019}})\).

Note that this expression can also be interpreted as the change in the outcome variables during the COVID-19 outbreak and controls for hospital fixed effects because the first difference is taken for the outcomes in each month. This interpretation is possible because we use panel data.

Independent variable COVID is a dummy that takes one if hospital \(i\) admitted COVID-19 patients, and zero otherwise. \(X_i\) is a vector of predetermined covariates, such as the local prevalence of COVID-19. We call this variable “Case.” To evaluate the local prevalence of COVID-19, we construct the average number of newly confirmed COVID-19 cases around each hospital in April and May. Specifically, using the exact addresses of all hospitals in Tokyo, we measure the distance from the city center to each hospital and use it as a weight to construct Case.

Note that this OLS model does not consider the fact that each hospital can decide whether to admit COVID-19 patients, which makes the status of admitting COVID-19 patients endogenous. Therefore, it is expected that the OLS estimate of the coefficient on COVID suffers from bias by ignoring endogeneity. For example, hospitals expecting improved finances from admitting COVID-19 patients might be likely to do so, if their decision is made based on comparing costs and benefits. In this case, the endogenous decision will upwardly bias the estimated effects on profits in the OLS analysis.

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5 More details and an English translation of this guideline are provided in Online Appendix A.
6 These are tentative data provided by the Tokyo Metropolitan Government.
7 Even the Tokyo Medical and Dental University Medical Hospital, which admitted the largest number of COVID-19 patients, offered only 56 beds for COVID-19 patients out of its 753 beds.
8 Due to the subsidies provided to hospitals with COVID-19 patients, the hospital’s industry financial results for FY2020 were unprecedentedly positive (MOF, 2021).
9 Since we use the double differences of \(Y\) as an outcome, the estimation of Eq. (1) is essentially the same for the triple-differences analysis that uses the level of \(Y\) as an outcome. Online Appendix B shows that the trend of the outcome variables seems parallel. However, \(\alpha_1\) in Eq. (1) measures the effect of admitting COVID-19 patients among hospitals; thus, it is different from the effect we were interested in, as will be explained later.
10 Case is calculated with inverse distance weighting as per the following equation:

\[
\text{Case} = \frac{\sum_{j=1}^{N} 1/d_{ij} \times N_j}{\sum_{j=1}^{N} 1/d_{ij}}
\]

where \(d_{ij}\) is the distance from hospital \(i\) to city \(j\) and \(N_j\) is the number of COVID-19 patients per 100,000 people in city \(j\) in April and May.
3.2. Identification

To consider the endogenous decision-making of admitting COVID-19 patients, we implement IV regressions. Note that ideal IVs strictly satisfy the conditions of relevancy and exclusion restriction. To satisfy both conditions, we use two of the characteristics in the national government guidelines as our IVs. In Section 2.2, we already confirmed that the relevancy condition was likely to be satisfied, that is, the guideline requirements affect hospitals’ decision-making.

By contrast, to satisfy the condition of exclusion restriction, IVs must affect hospital finances only through COVID-19 patient admission. The guidelines did not consider the potential detrimental effects of admitting COVID-19 patients on hospital finances because they were issued in early February when the number of COVID-19 cases was low. Therefore, the guidelines can be regarded as an exogenous shock to hospitals and their financial situations.

Fortunately, the characteristics of hospitals in the guidelines are an ideal set of IVs (MHLW, 2020b); thus, we exploit the characteristics of hospitals as IVs. Our first IV is the number of respiratory specialists per bed. This corresponds to the third requirement presented in Section 2.2. Because COVID-19 is a respiratory disease, it is difficult for hospitals without respiratory specialists to admit patients even if they want to. More importantly, since respiratory care only accounts for a small part of the medical revenue of average hospitals, it is reasonable to assume that respiratory specialists affect hospital finances only through the admission of COVID-19 patients.

Our second IV is the number of private rooms per bed, corresponding to the first requirement in Section 2.2. Since COVID-19 is a highly infectious disease, even since early February 2020, the MHLW recommended that patients stay in private rooms (MHLW, 2020b). This recommendation was strictly enforced during the first outbreak in Tokyo. The number of private rooms per bed may not have normally a large influence on hospital finances, but it is strongly associated with the admission of COVID-19 patients; therefore, it is expected to work well as an IV.

3.3. Covariates

The local prevalence of COVID-19 cases can directly affect the financial outcomes of hospitals. Further, especially in areas where the local prevalence of COVID-19 is high, it might be possible that the presence of respiratory specialists in a hospital can prevent people from going to the hospital because they may expect that the hospital can handle patients suspected of being infected with COVID-19, meaning the risk of infection inside the hospital would be high. As such, whether there are respiratory specialists in a hospital could affect hospital finances by the decrease in the number of potential non-COVID-19 outpatients, regardless whether they admit COVID-19 patients, and this could occur especially in hospitals near epidemic areas. To consider this possibility, although we already use an ideal set of IVs, we also control for the local prevalence of COVID-19 using Case for the results to be more robust against the violation of the exclusion restriction.

Additionally, we control for two covariates on hospital characteristics (i.e., the number of beds and the number of physicians per bed) because these characteristics may be related to both the magnitude of the profit decline and COVID-19 admissions. Therefore, the results may change if these variables are included in the analysis. However, given that we use differentiated outcomes (\(Y_{\text{April and May 2020}} - Y_{\text{Feb 2019}}\)) rather than the level of \(Y\), it is not natural to assume that the “trend” of outcomes variables varies greatly according to these hospital characteristics in the absence of admitted COVID-19 patients. In other words, two additional covariates are related to the differentiated outcomes, mostly through the admission of COVID-19 patients, being similar to IVs. Therefore, while we present the results that control for these covariates as a robustness check, we introduce the results without controlling for them as a preferred specification.

3.4. IV regression

To determine the effects of admitting COVID-19 patients on financial variables after considering the self-selection behavior of each hospital, we conduct IV regressions using the IVs presented in the previous section.

First, we check that the IVs are sufficiently correlated with the admission status (COVID) in the first stage, as follows:

\[
\text{COVID}_i = \beta_0 + Z_i \beta_1 + X_i \beta_2 + \epsilon_i,
\]

where \(Z_i\) is a vector of the IVs and \(X_i\) is an exogenous variable common to the second-stage regression, that is, the local prevalence of COVID-19, “Case.” \(\epsilon_i\) denotes the error term. In this specification, \(\beta_1\) captures the effect of each IV on the admission of COVID-19 patients.

Next, the second-stage regression is estimated using the predicted value of COVID, obtained from the first-stage regression, as follows:

\[
\Delta Y_i = \gamma_0 + \gamma_1 \text{COVID}_i + X_i \phi + \varphi_i,
\]

where COVID, is COVID, instrumented by the IVs and exogenous variable \(X_i\). As explained in Section 3.2, for the results to be more robust against violation of the exclusion restriction, we control for the local prevalence of COVID-19 as \(X_i\), which is represented by “Case.” In this equation, \(\phi_i\) is interpreted as LATE, which measures the effect of COVID-19 patient admission among compliers (i.e., swing hospitals, namely the hospitals in which the admission status can be changed by the instruments). Finally, standard errors clustered at the 12 medical areas were reported.

4. Data and descriptive statistics

4.1. Data

The data used in this study were collected by the Tokyo Metropolitan Government in July 2020 to uncover the financial effects of the COVID-19 outbreak on hospitals. The survey was sent to all hospitals in Tokyo (\(N = 642\)) and we received 332 responses (response rate = 51.7%). To confirm the representativeness of our sample, we checked the response rate by hospital size: 50.5% of hospitals had less than 200 beds and 54.1% of hospitals had more than 200 beds, suggesting that our data did not include hospitals of a specific size.

The data cover the period from February to May 2020. We also surveyed all variables in the same months of 2019 to compare the pre- and post-COVID-19 financial situations of the analyzed hospitals. The data include a variety of financial variables, such as profit and total medical revenue,\(^{12}\) as well as the number of patients, but do not include information on the number of physicians by specialty.

Therefore, to compensate for the lack of information on the number

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\(^{11}\) Note that the local prevalence of COVID-19 through “Case” can affect the potential number of patients when the hospital admits COVID-19 patients and, hence, the decision to admit such patients.

\(^{12}\) Note that the profit and total medical revenue during the study period do not include the subsidies, which were implemented afterward. As noted in Section 2, only in June 2020 the government began to support hospitals with large subsidies.
of physicians by specialty, we used the physician data compiled by Nihon Ultmarc as of October 2017 (Takaku, 2020). Using this database, we can know the number of respiratory and other specialists for the period before the COVID-19 outbreak, which is necessary because the number of respiratory specialists per bed is one of our IVs.

Further, we excluded data on 50 hospitals for the following two reasons. First, some specialty hospitals will never be able to accept COVID-19 patients, in which case, there is no self-selection behavior among hospitals. For example, 36 hospitals are psychiatric hospitals and six are rehabilitation ones; some other hospitals provide only dental care or care for children with special needs and were thus excluded from our analysis. Second, 40 public hospitals were also excluded because their financial structure is completely different from that of private hospitals. After eliminating some missing values, the sample included 222 general private hospitals.

### 4.2. Descriptive statistics

The descriptive statistics of our main analysis are shown in columns (1)–(3) of Table 1. The sample size in each column of Table 1 indicates that 68 hospitals admitted COVID-19 patients during the first outbreak, while 154 hospitals did not. It is striking that the treatment group (i.e., the hospitals that admitted COVID-19 patients) experienced an average reduction in profit per bed by JPY 358,600 (≈ USD 2758) during April–May, while the reduction in profit per bed among the control group is only JPY 161,500 (≈ USD 1242). We also observe a large difference in the reduction in total revenue per bed between the treatment and control groups. According to Table 1, the average number of beds before the COVID-19 outbreak for the treatment group is 363, but only 137 for the control group. This suggests that large hospitals are more likely to admit COVID-19 patients. The number of newly confirmed cases around hospitals is also larger in the treatment group.

Further, we have also checked the external validity of our findings. As both in the US and Japan private hospitals predominantly provide care for COVID-19 patients, we have already external validity toward the US because of the similar systems. In addition, we compare the average number of beds per hospital among OECD countries because it is the most representative and widely cited characteristic of hospitals and can be compared across countries with high accuracy. According to Figure A1, the average number of beds per hospital in our dataset is very close to the average in the OECD countries. Therefore, while healthcare systems greatly differ across countries, the size of hospitals in our dataset is rather common for OECD countries.

### 4.3. Complier characteristics

The IV estimate represents LATE, which is the average treatment effect among compliers. Therefore, it is important to understand the characteristics of compliers. To this end, we estimate the average characteristics of compliers in comparison with those of always-takers and never-takers, employing the method used in previous studies (Kowalski, 2016; Abrigo et al., 2019; Marbach and Hangartner, 2020). During this process, we transform our two continuous IVs in our preferred specification into one binary indicator using principal component analysis (for details, see Online Appendix C). Our results are shown in columns (4)–(6) of Table 1.

If we compare the predetermined variables among the three groups, the most notable difference between compliers and other types of hospitals is size. The average number of beds for always-takers is 157 and 134 for never-takers. By contrast, the average number of beds for compliers is 328, suggesting that the size of the hospitals among compliers is more than twice that of always- and never-takers in terms of the number of beds.

Despite a much smaller hospital size than that of compliers, the revenue per bed in 2019 was larger for always-takers than for compliers—JPY 1,955,830 (≈ USD 15,044) for always-takers. This is approximately 25% more than the revenue of compliers. Note that there is no such large difference in the total costs in 2019 between the two types, which implies the low profitability among compliers; this is consistent with the average amount of profit per bed in 2019. In sum, compliers are originally relatively large hospitals with low profitability.

By contrast, it always-takers admitted COVID-19 patients despite their smaller size and fewer respiratory specialists and private rooms per bed, compared to the compliers.

Therefore, it would have been very difficult, especially for compliers (mostly large hospitals), to implement effective zoning because they usually treat a many patients with various severities. Additionally, the low profitability of these hospitals, even in the period before the COVID-19 outbreak, suggests they were originally accepting large numbers of mild/moderate patients rather than severely ill ones. As a result, there should have been more general practice cancellations among compliers than always-takers.

Next, we confirm the changes in outcome variables from before to after the COVID-19 outbreak. The average changes in the numbers of surgeries per bed and inpatients, whose values are presented under the category “Dependent Variable” in Table 1, provide strong evidence for the large-scale cancellation of standard medical care among compliers. Specifically, the decrease in the number of inpatients per bed among compliers is much larger than that among always-takers.

Finally, despite the higher number of cancellations of standard medical care, the number of COVID-19 patients for compliers is lower (14.262) than that for always-takers (18.064). This is again consistent with the fact that compliers had been “swinging” between admitting COVID-19 patients or not, while always-takers had originally decided to admit such patients. This difference in their behaviors should reflect the fact that compliers are mostly “unsuitable” hospitals for admitting COVID-19 patients.

### 5. Regression results

#### 5.1. First-stage regression results

Columns (1) and (2) of Table 2 report the results of the first-stage regression of the IV estimations when COVID is regressed on our IV(s) and Cases, while column (3) reports the results when the numbers of beds and physicians are also controlled for.

According to Table 2, both IVs, that is, the number of respiratory specialists per bed and number of private rooms per bed, correlate positively with the probability of hospitals admitting COVID-19 patients even at the 1% significance level. Note that the positive correlation between the IVs and COVID is exactly what we expected in Section 3.2.

When we control for the numbers of beds and physicians in column (3), the coefficients of IVs become much lower than these in column (2).

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13 Nihon Ultmarc gathers detailed information on clinically active physicians for medical representatives (MRs), whose job is to meet with physicians and provide them with information on pharmaceutical products. When the MRs meet physicians, they report those physicians’ basic information to Nihon Ultmarc, who then immediately shares the information with all MRs registered in their system. In this way, Nihon Ultmarc successfully gathers information for almost all clinically active physicians in Japan.

14 A direct method to estimate the average characteristics of compliers for multiple continuous IVs has not been proposed yet, but it is still useful to discuss the average characteristics of compliers by transforming multiple IVs into one binary IV.
This is because hospitals with many beds and physicians are more likely to admit COVID-19 patients, but even after controlling for these covariates, our IVs are still strongly correlated with the admission of COVID-19 patients.

Finally, we explore the association between our IVs and the number of hospital admissions of COVID-19 patients in column (4). As found in the case of binary dependent variable in columns (1)–(3), the coefficients on the IVs are statistically significant.

### 5.2. Main results on profits

Table 3 reports the main results on profits. The results of OLS appear in columns (1)–(4), without and with covariates, respectively. Columns (5)–(9) show the results of the IV regressions. Columns (5)–(6) and columns (8)–(9) report the results without and with covariates on hospital size controlled for, respectively. With regard to the diagnostic tests, the F-statistics from the F-test are also large enough to pass the F-test, which indicates that the IVs strongly satisfy the IV relevancy condition. Additionally, Hansen’s J test in columns (6), (7), and (9) suggests that the over-identification restrictions are valid.

In columns (4) and (7), we use the number of admitted COVID-19 patients as a treatment variable. In column (4), we add the square term of the number of admitted COVID-19 patients to confirm whether the average profit reduction differs by the number of admitted COVID-19 patients.

#### 5.2.1. OLS results

Concerning the OLS results, note that the dependent variable defined in the table above is conceptually equivalent to the graphical representation in Figure B(a) in Online Appendix B because we use adjusted and de-trended outcomes in the regression model in Table 3.

According to columns (1) and (2), regardless of controlling for Case, the OLS estimates on the coefficient of COVID are significantly negative even at the 1% significance level, the coefficients suggesting that the monthly profits decreased by approximately JPY 170,000 to 190,000 (≈USD 1307 to 1462) per bed. Based on the results in column (1), the coefficient on the constant term is –16.154, suggesting that the profit of hospitals decreased by JPY 160,000 even if they did not admit COVID-19 patients. Therefore, the average monthly reduction of profit per bed in COVID-19 hospitals was around JPY 350,000 (190,000 + 160,000). This decrease in profit is equivalent to JPY 100 million (≈USD 770,000) for a 300-bed hospital, which is the typical size among the hospitals admitting COVID-19 patients.

For the other OLS results, in column (3), we control for two covariates on hospital size. Since large hospitals admit COVID-19 patients in Japan, the coefficient on COVID decreases when controlling for them. In column (4), we report the results from the specification with the number of admitted COVID-19 patients and its squared term. Here, the coefficient on the squared term is positive (0.006), suggesting that the negative impacts of admitting COVID-19 patients is ameliorated as hospitals admit larger numbers of COVID-19 patients. This is because the cancellation of general medical care to prevent in-hospital infection of COVID-19 works as a type of large fixed cost. Initially, hospitals had to bear this fixed cost even if the number of COVID-19 admissions was low because of unknown nature of the new infectious disease. However, once all fixed costs are paid, the hospital profits will recover by admitting more COVID-19 patients.

#### 5.2.2. IV results

While the OLS results provide some insights on how the financial
COVID-19 patients. According to Shin et al., 2020, the average LOS for symptoms was cancelled or postponed based on the worst-case scenario. In-hospital COVID-19 infection. Because COVID-19 was an unknown general medical care, as pointed out in some reports (Japan Hospital Association, 2020; American Hospital Association, 2020). There are cases which are the monthly number of COVID-19 patients around each hospital. **p < 0.01; ***p < 0.05; *p < 0.1.

health of hospitals was affected by COVID-19, we should not forget that these estimates do not consider the self-selection behavior of hospitals. In the IV regressions, the estimated coefficients on COVID are much smaller (i.e., larger negative) than in the OLS regression. We can understand the difference between the OLS and IV estimates as being consistent with the upward bias suggested in Section 3.1. In addition to this potential bias in the OLS caused by ignoring the self-selection behavior of hospitals, the difference between the OLS and the IV estimates can also stem from the fact that the IV estimates are LATE (i.e., effects among compliers only). Thus, the difference between the OLS and IV estimates in Table 3 is also consistent with the fact that the IV estimates reflect only the extremely large damage to the profits of compliers, while the OLS estimates also include the relatively small damage incurred by always-takers.

In column (6), we use two instrumental variables and control for the local prevalence of COVID-19, which is the most preferred specification in this analysis. In this specification, the coefficient on COVID is −59,950 and significantly negative, even at the 1% significance level. The monthly profits decreased by approximately JPY 600,000 (≈ USD 4612) per bed, and this result is stable across specifications, as well as the choice of IVs. Surprisingly, JPY 600,000 is 15 times the average monthly profits in 2019 (JPY 39,980) according to Table 1.

This drastic reduction in profits is mainly due to the cancellation of general medical care, as pointed out in some reports (Japan Hospital Association, 2020; American Hospital Association, 2020). There are mainly two reasons for these cancellations. First, as is widely known, hospitals had to cancel elective medical procedures to prevent in-hospital COVID-19 infection. Because COVID-19 was an unknown infection during the first outbreak, the treatment of non-emergent symptoms was cancelled or postponed based on the worst-case scenario. The second reason is due to relatively long length of stay (LOS) of COVID-19 patients. According to Shin et al., 2020, the average LOS for COVID-19 patients was approximately 10–15 days at the time of the first outbreak. This length is similar to or slightly longer than the LOS of other patients in acute care hospitals, such as DPC hospitals (approximately 12 days in 2019). Thus, the long LOS of COVID-19 patients might have limited hospitals’ ability to treat other patients.

The coefficients estimated by the IV estimation are robust and stable across specifications and IV choices. In column (7), we use the number of admitted COVID-19 patients as an endogenous variable. In this specification, the coefficient is −1.680 and is statistically significant. Given the average number of admitted COVID-19 patients in COVID-19 hospitals in Table 1, the average monthly reduction in profits per bed derived from this result would be about JPY 400,000.

In addition, in columns (8) and (9), we also control for two covariates on hospital size (i.e., the number of beds and physicians). As explained previously, we use the differentiated outcome rather the level; thus, it is natural to assume that there is no direct path from hospital size to Y. However, even when these covariates are controlled for, the coefficients on COVID are still high and statistically significant.

5.3. Results on other outcomes

Next, to explore the mechanisms behind the large deterioration in profits, we also report the results for other outcome variables in Fig. 1, while the detailed regression table is presented in Online Appendix D.

From the IV estimates in Fig. 1, the reduction in profits was driven by the sharp reduction in the number of inpatients, as well as the number of surgeries. The IV results on the revenue per bed reveal a reduction of JPY 937,000, suggesting that the cancellation of general medical care is a non-negligible cost of admitting COVID-19 patients (American Hospital Association, 2020; GHC, 2020). In addition, the total cost decreased by JPY 334,000 due to the cancellation of general medical care. Note that the decrease in revenue by around JPY 900,000 and cost by JPY 300,000 accounts for the reduction in total profits by around JPY 600,000 in Table 3.

The large number of cancellations for inpatients and surgeries is consistent with ii and Watanabe (2021), who explore how medical utilization decreased during the COVID-19 outbreak by using insurance claims data. As pointed out in ii and Watanabe (2021), a wide range of elective medical treatments was postponed or cancelled in the first wave of the COVID-19 outbreak, irrespective of whether they required surgery or not. For example, admissions of patients with cataract and other lens disorders (most of them needing surgeries) decreased by 35.2% and admissions of the patients with type 2 diabetes (most of them not needing surgeries) decreased by 30.4%. These reductions account for the decrease in surgeries and number of inpatients in the hospitals with COVID-19 patients (ii and Watanabe, 2021). Our results on the number of inpatients per bed and surgeries per bed are consistent with these findings based on insurance claims data.

Note that our additional results in Online Appendix D and E also support the view that the main costs of admitting COVID-19 patients arise from the cancellation of general medical care, rather than from the direct medical costs of treating COVID-19 patients. In addition, the magnitude of the IV estimates is far larger than that of the OLS ones for these outcomes.

5.4. Identifying assumptions

While our IVs (i.e., the number of respiratory physicians and private rooms per bed) do not typically affect hospital finances, there are several threats to the exclusion restrictions. A potentially serious threat is that these IVs are proxies for large hospitals. This is important for evaluating the validity of our IVs because, as is explained in Online Appendix A, the MHLW requested hospitals to postpone non-urgent elective procedures on March 26, 2020 (MHLW, 2020a). Given that large hospitals generally conduct more surgeries than others, our IVs may capture the direct effects of MHLW’s request to postpone surgeries, which are assumed to be more intensive as hospital size increases.

To address this threat, we implement a placebo test by using the
number of physicians with other specialties per bed as a fake IV for the
total number of respiratory physicians per bed. The idea is that the number of
physicians with other specialties is regarded as a proxy for large hos-
pitals, while only the number of respiratory physicians affects the de-
cision to admit COVID-19 patients. In other words, if the number of
respiratory physicians is associated with the trend in profits owing to not
only admitting COVID-19 patients and also the intensive postponement
of surgeries and new admissions induced by MHLW’s request (MHLW,
2020a), it is likely that the number of physicians with other specialties
would also be associated with the profit trend (i.e., outcome) and the
decision whether to admit COVID-19 patients (i.e., endogenous
variable).

The results of the placebo tests are shown in Fig. 2, namely, the co-
efficient and 95% confidence intervals on the number of physicians with
various specialties, including respiratory diseases (i.e., the real IV).
Here, for the first-stage and reduced-form regressions, the largest coef-
ficient is for the real IV, namely, the number of respiratory physicians
per bed. Some fake IVs are also statistically significant in the first-stage
and reduced-form regressions, which can occur as long as they are
correlated with hospital size. However, the point estimates of those fake
IVs are small even if they are statistically significant. Therefore, we can
reasonably conclude that our real IV (i.e., the number of respiratory
physicians) is associated with the outcome variables mostly
because of admitting COVID-19 patients.

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because of admitting COVID-19 patients.

Similarly, it is well-known that the impact of COVID-19 on the
healthcare demand differs by specialty (GHC, 2020). Specifically, the
ratios of specific types of physicians might directly affect hospital rev-
enue through healthcare demand changes. This is a potentially relevant
threat for the exclusion restriction. In fact, Fig. 2 shows that the number
of physicians specializing in rehabilitation and dermatology, which are
typical examples of non-urgent care specialties, is associated with
changes in profit. This suggests that the demand changes for these
specialties directly explain the deterioration of hospital finances. How-
ever, we again identify the highest point estimate for the true IV (i.e., the
number of respiratory physicians), suggesting that the differential
changes in healthcare demand across specialties are not a serious threat
for the exclusion restriction of our IVs.

Next, we check how our IVs were associated with the trend in profits
before the COVID-19 outbreak (see Online Appendix F). The results
suggest that both our IVs are not associated with the year-to-year
changes in profits in February 2020 when COVID-19 had not yet
spread throughout Japan. Again, this suggests that our IVs have no
explanatory power for the trend in profits in the absence of COVID-19,
but have a strong influence on the admission of COVID-19 patients.
These results reinforce the validity and reliability of our IVs.

Finally, some technical reasons also support the validity of our IVs.
Most importantly, a COVID-19 patient generally requires two to three
more nursing staff than a typical patient (Japan Hospital Associ-
ation, 2020). This restricts the capacity for other inpatient care because
hospitals had to forgo caring for two to three inpatients per COVID-19
patient. Therefore, even if our IVs have some minor direct effects on
profits, the effect of admitting COVID-19 patients itself overwhelms
those from other side channels.

5.5. Robustness check

As shown in many epidemiological studies, the care burden for
COVID-19 patients with severe symptoms is totally different from that
for patients with mild symptoms.15 For patients with severe symptoms,
hospital treatment regimens switch to costly high-tech treatments, such
as extracorporeal membrane oxygenation. The reimbursement for pa-
tients with severe symptoms is also very high. Therefore, we also check
the robustness of our results by excluding 32 hospitals that admitted
COVID-19 patients in their ICUs (see Online Appendix E). The results for

15 According to Khan et al. (2020), on average, the cost per COVID-19 patient
in an intensive care unit (ICU) is about twice that in a general medical ward.


Table 3
Main results on profit.

| Dependent Variable: \( Y = (\text{April and May, 2020} - \text{Feb, 2020}) / (\text{April and May, 2019} - \text{Feb, 2019}) \) |
|---|
| (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| COVID | 19.706*** (4.758) | 17.156*** (4.495) | -9.471* (4.623) | 60.191*** (12.061) | 58.950*** (11.597) | 88.270*** (24.764) | 80.701*** (21.322) |
| Cases | -0.339*** (0.105) | -0.305** (0.111) | 0.338** (0.107) | -0.14 (0.141) | -0.146 (0.140) | -0.225 (0.139) | -0.029 (0.170) | -0.058 (0.161) |
| N. of Beds | -0.022* (0.014) | 0.050** (0.024) | 0.043** (0.020) |
| N. of Physicians | -6.707 (8.575) | | |
| N. of COVID Patients | | 1.111*** (1.680*** (0.168) | (0.205) |
| N. of COVID Patients, Squared | 0.006*** (0.001) |
| Constant | -16.154*** (4.133) | 5.609 (2.657) | -1.146 (3.423) | 3.489 (3.175) | 3.406 (2.954) | 2.03 (5.522) | -3.835 (4.627) | -2.927 (4.205) |
| R-squared | 0.084 (0.080) | 0.602 (2.657) | 5.609 (3.423) | 3.406 (3.175) | 3.489 (2.954) | 2.03 (5.522) | -3.835 (4.627) | -2.927 (4.205) |
| Mean of \( Y \) with COVID = 0 | -16.15 | -16.15 | -16.15 | -16.15 | -16.15 | -16.15 | -16.15 | -16.15 |
| Observations | 222 | 222 | 222 | 222 | 222 | 222 | 222 | 222 |

Notes: The dependent variable is represented by the year-on-year differences in each variable, divided by the number of beds. The unit is JPY 10,000. Cases is the monthly number of COVID-19 patients around each hospital. Standard errors clustered at the level of 12 medical areas are reported between parentheses. *** \( p < 0.01; ** p < 0.05; * p < 0.1 \).

(a) First-Stage Regression
(b) Reduced-Form Regression

Fig. 2. Placebo test. Notes: In the first-stage regressions, we estimate Eq. (2) with the number of physicians of various specialties as fake IVs after controlling for the local prevalence of COVID-19 (Cases). In the reduced-form regression, we estimate the same regression using Eq. (2) by replacing the outcome variable with \( \hat{Y} \). The number of physicians was standardized by the number of beds in all estimations. The unit of the outcome variable in the reduced-form regression is JPY 10,000.
this subsample analysis support our main finding, that is, the strong negative effects of admitting COVID-19 patients among compliers is preserved even when we exclude hospitals that provide care for patients with severe symptoms.

Finally, although we have already discussed and confirmed the external validity of our data, we also evaluate the external validity of our findings. Specifically, we implement supplemental analyses based on the marginal treatment effects approach (Heckman and Vytlacil (2005, 2007)) (see Online Appendix G). The results indicate no strong selection based on unobservable resistance to treatment, suggesting our results have relatively high external validity in terms of unobservable characteristics that determine the selection for treatment.

6. Concluding remarks

In this study, we employed unique monthly longitudinal data on hospital finances in Tokyo and explored how a pandemic deteriorates hospital finances—considering the heterogeneity in the suitability of admitting COVID-19 patients among hospitals.

By exploiting the homogeneous environment in the hospital sector in Tokyo and using IV analysis to incorporate the endogenous decision of each hospital to admit COVID-19 patients, we found that admitting COVID-19 patients severely deteriorated hospital finances, especially among compliers. Specifically, our main IV estimate revealed that admitting COVID-19 patients lowered the monthly profits by around JPY 600,000, which is 15 times the average monthly profit in the previous year. This IV estimate is about three times the OLS estimate, which does not consider self-selection behaviors.

To better understand hospitals’ heterogeneity and their self-selection behaviors, we examined the characteristics of always-takers and compliers explicitly (Heckman and Vytlacil, 2001; Kowalski, 2016; Abrero et al., 2019). Our analysis uncovered that compliers are relatively large hospitals with lower profits compared to always-takers. Due to the difference in their characteristics, compliers had to cancel their usual provision of medical care to inpatients more frequently than always-takers because of their ineffective zoning.

Our findings have an important implication for hospital capacity policy in handling the surge of COVID-19 patients. Whether the simultaneous provision of standard healthcare is possible or not for each hospital to admit COVID-19 patients, we found that admitting COVID-19 patients lowered the monthly profits by around JPY 600,000, which is 15 times the average monthly profit in the previous year. This IV estimate is about three times the OLS estimate, which does not consider self-selection behaviors.

Therefore, it is necessary to admit COVID-19 patients predominantly to large hospitals and encourage other hospitals to continue their usual medical care, as was done in the UK and other countries. We recommend avoiding missteps from the earlier phase of the pandemic to prevent large financial losses. In addition, our analysis in column (4) of Table 3 suggests non-linear effects of admitting COVID-19 patients. Namely, hospitals had to incur a huge reduction in profit because of the fixed costs to admit COVID-19 patients, but once they began to admit, the deterioration of profits was ameliorated. This result also justifies the policies intended to gather the patients and physicians in some large hospitals, rather than sharing the burden of patients with many hospitals.

Another implication of our paper is that the government should promptly implement subsidization programs for hospitals when unknown infectious diseases began to spread. As revealed in this paper, the hospitals in Japan were not supported sufficiently during the first 3 months (i.e., March to May) of the COVID-19 outbreak. This led to increased demand for subsidies from hospital groups and the Japanese Medical Association, and the government was subsequently forced to set excessive subsidies. In fact, due to these subsidies, the financial results in FY2020, and probably FY2021 too, were unprecedentedly positive. Given these results, we must use alternative strategies to subsidize hospitals. For example, it would be a worthwhile measure to try to promptly guarantee hospitals the same level of medical revenue as in the previous year and separately provide strong financial incentives to treat COVID-19 patients (Takaku, 2022).

Although the number of COVID-19 cases in Japan was the lowest among G7 countries, the hospitals in Japan were, ironically, on the verge of a financial meltdown during the first outbreak. Overall, these policy implications for Tokyo are extremely important for the future policies related to a pandemic of an unknown infectious disease, especially in countries with a large private healthcare sector.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.jjie.2022.101218

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