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Abstract

How does hospital capacity influence physicians' treatment pattern? We address this question by examining the impact of empty hospital beds on healthcare delivery for the oldest-old population in Japan. Using universal administrative medical claims data from the Ministry of Health, Labour and Welfare, we exploit a unique natural experiment arising from COVID-19 patients across secondary medical service area (SMAs). This policy provides exogenous variation in hospital capacity, enabling us to implement an instrumental variable approach to identify the causal effects. We find that increased bed availability leads to a significant shift from outpatient to inpatient care, with physicians more likely to hospitalize patients and extend hospital stays. These effects are particularly pronounced in less populated regions and areas with higher medical resources availability. This impact is strongest among the most vulnerable groups: the oldest-old and those of lower socioeconomic status. Our findings reveal how healthcare infrastructure shapes treatment decisions and have significant policy implications for hospital resource allocation, particularly in aging societies with universal healthcare system.

1. Introduction

Hospital capacity is a critical factor in healthcare supply, directly influencing the practices and subsequent care provided to patients. The relationship between hospital bed availability and healthcare delivery presents a nuanced trade-off, reflecting the classic economic tension between resource allocation efficiency and service provision incentives. While expanded hospital capacity can improve healthcare accessibility, it may also create agency problems between physicians and patients, potentially leading to supplier-induced demand. Indeed, previous research has revealed that increased bed availability can create financial incentives for unnecessary service provision, leading to over-utilization of healthcare services without corresponding health improvements (Fisher et al., 2000; Freedman, 2016). Moreover, healthcare expenditure is directly correlated with hospital bed availability (Gaynor & Anderson, 1995), suggesting that excess capacity can result in inefficient resource allocation and over-investment in medical infrastructure. The intricate dynamic underscores the importance of understanding how physicians' treatment patterns respond to the changes in hospital capacity to maintain the efficiency and sustainability of the healthcare system.

Empirically measuring the causal relationship between hospital capacity and physicians' treatment pattern poses significant methodological challenges due to endogeneity concerns. Healthcare delivery and bed availability exhibit reverse causality, as treatment patterns can influence bed capacity. This bidirectional relationship complicates causal inference, necessitating careful identification strategies. Previous studies have documented nuanced findings across different medical contexts. Sharma et al. (2008) found that constrained hospital capacity led to earlier discharges while admission decisions are less affected, providing evidence that physicians alter treatment decisions with constrained hospital capacity. In addition, previous studies by

Watts et al. (2011) and Walsh et al. (2022) reported positive correlations between bed capacity and length of stay in psychiatric and emergency settings, respectively. In childbirth settings, Freedman (2016) provided pioneering causal evidence demonstrating that neonatal intensive care unit (NICU) bed availability minimally impacted the sickest infants, but increased utilization for the infants with more discretionary admission criteria. Building on this, Goodman et al. (2024) observed that NICU utilization increased for late preterm and non-preterm newborns as bed supply expanded, without reducing adverse events. While these studies consistently indicate a positive relationship between hospital capacity and utilization, causal evidence remains limited, particularly beyond childbirth contexts.

This study investigates how hospital capacity affects the composition and quantity of treatments provided by physicians, offering critical policy implications for healthcare system optimization. Utilizing unique administrative data from Japan's Ministry of Health, Labor and Welfare (MHLW), we make three primary contributions. First, we focus on the oldest-old population aged 75 and above (75+), a demographic of increasing global significance given rapid population aging (WHO, 2024). This population is particularly vulnerable to both physical and mental health challenges, often requiring intensive healthcare services and experiencing information asymmetries that can make them susceptible to induced demand (Hay and Leahy, 1982; Johnson, 2014; Johnson and Rehavi, 2016; Mohammadshahi et al., 2019). Second, we extend the scope of existing research beyond childbirth, establishing a causal relationship between hospital capacity and healthcare delivery across general healthcare services. This approach allows us to provide a more comprehensive understanding of supply-side responses across diverse medical conditions, especially for older patients requiring complex, long-term care. Third, to address endogeneity concerns, we employ a novel instrumental variable approach using the Japanese government's "Hospital Beds Securing Plan" implemented during the COVID-19 pandemic (MHLW, 2024c).[2] This policy designated specific hospital beds exclusively for COVID-19 patients across secondary medical service area (*Niji-Iryoken* in Japanese, explained in detail in the next section), providing exogenous variation in hospital capacity for non-COVID patients. Further, the timing and magnitude of bed designations were largely independent of pre-existing healthcare utilization patterns.

Our findings reveal several important insights. We observe a significant substitution from outpatient to inpatient services, where a 1% increase in bed availability leads to a 0.014 percentage point reduction in doctor visits with a reduction of 0.7 times in the frequency, and a 0.017 percentage point increase in hospital admissions with an extension of 0.2 days of hospitalization. Second, our analysis uncovers multiple mechanisms through which hospital capacity influences treatment patterns: (a) physicians in less populated areas demonstrate stronger responses due to income effects; (b) regions with higher bed availability show larger change in physicians' treatment patterns, potentially to justify capacity investments; and (c) regions with fewer physicians exhibit limited increase in inpatient services while regions with more physicians show a significant shift from outpatient to inpatient services, suggesting leisure-motivated behaviors. The effects are particularly pronounced among oldest-older patients and those with lower socioeconomic status, indicating that these groups are more susceptible to physicians' decisions. Our findings suggest that careful government oversight of hospital bed

[2] The MHLW outlined a detailed plan for securing hospital beds, which includes provisions for temporary medical facilities and inpatient waiting areas designated as secured beds, for the period from April 2021 to March 2024. This information (in Japanese) is available on the MHLW website: https://www.mhlw.go.jp/stf/seisakunitsuite/newpage_00062.html (accessed November 8, 2024).

allocation is crucial for preventing healthcare service over-utilization and managing medical expenses effectively, particularly in a healthcare system with constrained physician resources like Japan's.

The remainder of this paper is structured as follows: Section 2 provides institutional background. Section 3 presents the conceptual framework and Section 4 describes data and measurements with basic statistics. Section 5 elucidates the identification strategy. Section 6 presents the main results, robustness and heterogeneity analyses. Lastly, Section 7 offers concluding remarks.

2. Institutional background

2.1 Population aging and healthcare utilization in Japan

Japan and other East Asian countries have been experiencing unprecedented demographic aging. As of 2023, Japan leads the 38 OECD countries with 16.6% of its population aged 75+, a proportion projected to increase to 23.7% by mid-century (United Nations, 2023).[3] This rapid aging has placed extraordinary pressure on the healthcare system, as evidenced by hospitalization patterns. The age-related healthcare burden is stark: hospitalization rates for individuals aged 75+ reach 3,568 per 100,000 inhabitants, compared to just 302 per 100,000 for younger populations (MHLW, 2020). Japan’s healthcare system presents a unique research

[3] In 2023, individuals aged 75 and above comprised 11.3% of the total population in Germany, 10.4% in France, 9.3% in the UK, 7.7% in South Korea, and 7.3% in the US. By 2050, these proportions are projected to reach 18.4% in Germany, 16.9% in France, 14% in the UK, 24.1% in South Korea, and 12.8% in the US, with an average rate of 15.6% among 38 OECD countries. These statistics indicate that South Korea's population is aging at a pace surpassing that of Japan (United Nations, 2023).

context, characterized by the world's highest hospital capacity at 27.3 beds per 1,000 inhabitants—more than three times the OECD average of 8.1.

Despite gradual reductions in recent decades, Japan maintains exceptionally long hospital stays. The national average of 12.6 days significantly exceeds the OECD average of 4.3 days, second only to South Korea's 12.8 days (Hashimoto et al., 2011; OECD, 2024).[4] For the 75+ age group, average hospitalization duration extends to 45 days (MHLW, 2020), reflecting the complex healthcare needs of an aging population. Financially, these extended stays represent a substantial healthcare expenditure. In 2022, inpatient care for the 75+ population reached 8.5 billion USD (calculated at 1USD=100JPY), accounting for approximately 51% of Japan's total inpatient care costs (MHLW, 2024b).

The combination of Japan's aging population and high hospital capacity creates a unique setting for studying how bed availability affects treatment decisions. The substantial variation in healthcare utilization between age groups, coupled with Japan's exceptionally high bed-to-population ratio, provides an ideal context for examining physician responses to capacity constraints.

2.2 Regulation of hospital beds in secondary medical service areas (SMAs)

Under the Medical Care Act, the Japanese healthcare provision system is organized into a three-tier hierarchical framework of medical service areas (primary, secondary, and tertiary)

[4] In 2023, or the latest year available in OECD health statistics, the number of hospital beds per 1,000 inhabitants was 8.9 in Germany, 9.1 in France, 7.7 in the UK, 19.6 in South Korea, and 6.6 in the US. The average length of hospital stay was 7.7 days in Germany, 5.5 days in France, 2.5 days in the UK, 12.8 days in South Korea, and 2.8 days in the US.

designed to ensure efficient service delivery.[5] This structure was introduced in 1985, when prefectural governments began implementing medical care plans. Among these tiers, the secondary medical service area (SMA: *Niji-Iryoken* in Japanese) serves as the most critical administrative division in healthcare policymaking (Tanihara et al., 1997; Hosokawa et al. 2020; MHLW, 2022a). As of April 2024, Japan comprises 335 SMAs, defined based on geographic conditions, transportation infrastructure, population density, and other relevant factors (MHLW, 2022b; MHLW, 2024d; Ministry of Internal Affairs and Communication, 2024). National and prefectural governments use these SMAs as the primary unit for medical resource allocation, including the distribution of hospital beds and doctors within their medical care plans.

The number of hospital beds in each SMA is legally regulated by prefectural governments according to a uniform nationwide formula.[6] Any modification to bed numbers of facility applications requires submission and approval from the prefectural governor, as stipulated by

[5] The primary medical service area in Japan provides daily outpatient medical care and generally aligns with municipalities, the smallest administrative units, which includes cities, wards, towns, and villages. The secondary medical service area encompasses multiple municipalities, to offer a broader range of healthcare services. The tertiary medical service area covers an even larger region, providing specialized and advanced medical care, typically across an entire prefecture, with the exception of Hokkaido, where multiple zones are designated due to its size and geographical layout (MHLW, 2022b). As of October 2024, Japan has 1,741 municipalities designated as primary medical service areas (Ministry of Internal Affairs and Communication, 2024). Additionally, as of April 2024, there are 52 designated tertiary medical service areas (MHLW, 2024d).

[6] The formula is as follows: $\text{Number of beds} = \big((\text{population by sex and age group}) \times (\text{discharge ratio by sex and age group}) \times (\text{average length of hospital stay}) + (\text{number of inpatients admitted from outside the SMA}) - (\text{number of inpatients admitted to hospitals outside the SMA})\big) \div \text{bed occupancy rate}$.

Article 7 of the Medical Care Act. In regions with bed surpluses, prefectural governors may, after consulting the Prefectural Medical Council, deny approval for bed changes or new medical institution establishments.[7] The SMA-based bed standards are revised every six years, coinciding with medical care plan revisions (MHLW, 2022b). As a country with one of the highest numbers of hospital beds globally, Japan allocates substantial hospital beds for its healthcare services (OECD, 2023b).

In summary, the SMA-level regulation of hospital beds, combined with the geographical and demographic variation across these areas, provides a natural laboratory for studying how capacity constraints influence physician behavior. The standardized nationwide formula for bed allocation, coupled with strict regulatory oversight, creates clear boundaries for hospital capacity that are largely independent of local physician preferences.

2.3 Hospital bed planning during the COVID-19 pandemic

The global COVID-19 pandemic posed unprecedented challenges to healthcare systems worldwide, straining medical resources and disrupting routine services (Sen-Crowe et al., 2021). In response, the Japanese government introduced multiple policy measures. First, it declared a State of Emergency to restrict human mobility (Nakamoto et al., 2022; Okamoto, 2022) and a State of Precautionary Emergency to reduce restaurant operating hour, and crucial to our analysis, the government implemented a "Hospital Beds Securing Plan" to ensure COVID-19 treatment capacity.

[7] However, even in SMAs with an excess of hospital beds, new beds may be established under special exceptions if certain conditions are met. Examples include the creation of specialized hospital beds, such as those for cancer or cardiovascular disease, or the reorganization and integration of multiple medical institutions, including public facilities.

Under this plan, each SMA was required to designate a specific number of hospital beds exclusively for COVID-19 patients. The bed assignment primarily depended on the COVID-19 situation and the total bed capacity in the SMA. Given that the total number of beds in each SMA is regulated by medical care plans, this requirement effectively reduced the availability of beds for other medical services. Critically, the decrease in hospital bed availability for non-COVID-19 conditions was determined by prefectural government directives, providing an exogenous source of variation in hospital capacity that can be leveraged for analytical purposes.

3. Conceptual framework

We propose a conceptual model to examine how hospital capacity influences physicians' treatment decisions. Building on McGuire and Pauly (1991), we model physicians as primary decision-makers whose choices are shaped by earnings, leisure, and ethical considerations. In our framework, physicians choose between two treatment types: inpatient or outpatient services. We focus on the utility derived from providing inpatient services, where negative utility indicates that physicians obtain higher utility from outpatient versus inpatient care. Physicians and hospitals receive both financial and non-financial benefits including professional reputation and career opportunities from service provision. Following McGuire and Pauly (1991), let m be the marginal benefit obtained from providing services, t be the time spent on each patient, and X be the quantity of services provided which, for this study, only depends on the empty beds available b. Physician utility depends positively on their earnings (Y) and leisure (L), and negatively on the level of inducement (I).

$$U(Y, L, I)$$

where

$$Y = mX(b)$$

$$L = 24 - tX(b)$$

$$I = I(b)$$

$$U_Y > 0, U_L > 0, U_I < 0$$

Taking first order derivative with respect to b,

$$U_Y mX'(b) + U_L(-tX'(b)) + U_I I'(b) = 0$$

Solving for the effect of a change in empty beds on the quantity of inpatient services,

$$X'(b) = \frac{-U_I I'(b)}{U_Y m - U_L t} \qquad (1)$$

The sign of the numerator in equation (1) is positive but the sign of the denominator is undetermined. We identify three primary mechanisms through which hospital capacity can affect treatment patterns. First, physicians and hospitals have incentives to induce demand when facing negative income shocks (McGuire and Pauly, 1991; Gruber and Owing, 1996; Gruber et al., 1999; McGuire, 2000; Clemens and Gottlieb, 2014). When facing higher empty bed rates, hospitals and physicians regard this as potential income loss, and hospitals may encourage physicians to adjust treatment patterns to maximize bed utilization. Furthermore, investment decisions are usually made based on the hospitals and physicians' demand for medical facilities (Kamath and Elmer, 1989). High empty bed rates can be a signal of excess capacity, potentially deterring future investments and creating additional economic pressures.

Secondly, patient volume directly impacts physicians' workload and leisure time. Increased patient numbers (fewer empty beds) reduce physicians' discretionary time. The additional effort required may deter providing extra services, introducing a critical work-life balance consideration into treatment decisions. This leisure constraint represents a second significant mechanism through which hospital capacity influences medical practice.

Thirdly, physicians' decisions are fundamentally guided by patient welfare considerations, extending beyond purely economic interests. Following Ellis and McGuire (1986) and McGuire (2000), we incorporate physicians' ethical constraints through the inducement term $I(b)$ in our utility function. This captures the psychological cost or "internal conscience" that physicians experience when contemplating potentially unnecessary interventions. Physicians recognize that excessive or unwarranted services may harm patients both physically and financially, creating a moral constraint on their decision-making. This ethical dimension is represented in our model through $U_I < 0$, indicating that higher levels of inducement reduce physician utility. When hospital capacity is high (more empty beds), the pressure to fill beds may conflict with these ethical considerations, creating a tension between institutional pressures and professional medical judgment.

Our conceptual framework demonstrates how these three mechanisms - financial incentives, leisure constraints, and ethical considerations - interact to influence physician decision-making. The sign of $X'(b)$ in equation (1) captures these competing effects: while financial pressures from empty beds may encourage increased inpatient services (through the U_Y term), both leisure constraints (U_L) and ethical considerations (U_I) may counteract this tendency. This theoretical tension aligns with empirical realities of medical practice, where physicians must balance institutional pressures, professional obligations, and patient welfare. By modeling these distinct yet interconnected mechanisms, our framework provides a more nuanced understanding of how hospital capacity shapes physician behavior. The model suggests that the ultimate impact of hospital capacity on treatment decisions depends on the relative strength of these competing forces, highlighting the complexity of healthcare delivery systems and the multiple factors that influence clinical decision-making.

4. Data and measurements

4.1 Data

This study integrates three primary datasets to provide a comprehensive analysis of the treatment patterns provided to Japan's oldest old population. The first dataset, the "Medical Claims Data with Income Tax Information for the Oldest-Old in Japan (MCD-Tx)," is provided by the MHLW. This individual-level panel dataset represents a pioneering effort in Japan, combining monthly medical claims with income data for individuals aged 75+. As of September 2022, the dataset covers 18.52 million individuals, representing 98.6% of Japan's 75+ population and encompassing those enrolled in the Latter-Stage Elderly Healthcare System (LSEH).[8] The second dataset, the "Hospital Report," offers detailed information on hospital characteristics, including total bed numbers and patient occupancy. This source enables the computation of empty beds for each SMA on a monthly basis. The third dataset, also provided by the MHLW, records COVID-19 patient bed allocations, documenting the total beds designated for COVID-19 patients and current hospitalizations. Data collection for this dataset began in December 2021.

[8] The LSEH system, launched in 2008, provides targeted healthcare coverage for Japanese seniors aged 75+. By focusing on reduced copayments and equitable access to care, the program addresses the specific healthcare needs of an aging population while managing costs through municipal-level administration and a cost-sharing model. Funding is derived from contributions by the national and local governments (50%), occupation-based and community-based healthcare insurance schemes for individuals under 75 (40%), and premiums paid by those aged 75+ (10%). Emphasizing preventive care and chronic disease management, the LSEH seeks to reduce long-term healthcare expenses by encouraging healthier lifestyles among elderly participants (Ikegami et al., 2011; MHLW, https://www.mhlw.go.jp/stf/newpage_40287.html, access November 11, 2024).

The research period spans from December 2021 to November 2022, strategically chosen to align with the 6th and the 7th waves of the COVID-19 pandemic in Japan. This timeframe corresponds to the Omicron wave, characterized by heightened pandemic awareness with no mobility restrictions. Such conditions ensure consistent healthcare-seeking behaviors across the study period. Through merging these datasets by SMA and month, we developed a comprehensive analytical sample. We excluded individuals who were ever diagnosed with COVID-19 to maintain the precision of our identification strategy. The final sample comprises 175,040,107 observations, with 68,826,402 male and 106,213,705 female participants.

4.2 Measurements

Hospital capacity is operationalized through the share of empty beds, calculated as the ratio of unoccupied empty beds to total beds in each SMA. We evaluate treatment patterns across multiple dimensions. For inpatient treatment, we develop two measures: a binary variable indicating the likelihood of hospital admission, with "1" representing at least one inpatient service provided in a month and "0" otherwise; and a continuous variable capturing the hospital length of stay in days. Similarly, for outpatient treatment, we construct two measures: a binary variable indicating the likelihood of doctor visits, with "1" representing at least one outpatient service provided by a physician in a month, and "0" otherwise; and a continuous variable measuring the frequency of doctor visits.

The claims data encompasses patients with various chronic conditions, including infectious diseases, cancer, blood and immune system disorders, endocrine diseases, psychiatric conditions, neurological disorders, eye and ear diseases, circulatory and respiratory conditions, digestive and kidney diseases, musculoskeletal disorders, accident-related conditions, and other diseases.

3.3 Basic statistics

Table 1 provides summary statistics for individual characteristics, SMA characteristics, and healthcare utilization. As our study focuses on Japan's oldest-old population, the minimum age in the sample is 75 years, with a mean age of 83. The average annual income is 2,030,973 JPY (approximately 20,301 USD). Regarding SMA characteristics, the total number of beds and empty beds varies across areas. The average occupancy rate is 2.3%, with an empty bed rate of approximately 27%. Healthcare utilization patterns reveal that the probability of physicians providing inpatient services is 4%, while the probability of outpatient services is 79%. This high level of outpatient care utilization is likely attributable to the advanced age of the population.

[Table 1]

5. Identification

The primary methodological challenge in identifying the causal effect of hospital capacity on treatment patterns lies in the endogeneity problem of reverse causality. Hospital capacity can influence treatment patterns, while simultaneously, physicians' treatment decisions reversely affect bed availability. To address this endogeneity, we constructed an instrumental variable (IV) to isolate the causal effect of hospital capacity on physicians' treatment patterns. The Japanese government's "Hospital Beds Securing Plan" provides an exogenous source of variation by reserving a specific number of hospital beds exclusively for COVID-19 patients in each SMA. The total number of beds is legally regulated and predetermined by prefectural medical care plans, which remained unchanged during our observation period from December 2021 to November 2022. We calculate the occupancy rate as the ratio of beds assigned or occupied by COVID-19 patients to the total number of beds in SMA j at month t, which serves as an instrument for the share of empty beds available. The IV is defined as below.

$$COVID\ occupancy\ rate_{jt} = \frac{number\ of\ beds\ assigned\ to\ COVID\ patients_{jt}}{total\ number\ of\ beds_{jt}} \quad (2)$$

[Figure 1]

Figure 1 illustrates the variations in average occupancy and empty bed rates across SMAs during the observation period. We address two critical requirements for IV validity. First, the IV must strongly correlate with the causal variable of interest (Angrist and Pischke, 2009). Our analysis demonstrates a strong negative correlation between occupancy rate and empty bed share: as the occupancy rate rises, the available beds for non-COVID patients decreases. The first-stage result in column 2 of Table 2 confirms this relationship, showing that a 1 percentage point increase in occupancy rate reduces the empty bed rate by 0.66 percentage points. The F-statistics validate that the instrument passes the weak instrument test. The second crucial requirement is the exclusion restriction, which stipulates that the IV must be uncorrelated with outcome variables through any channel other than the primary mechanism (Angrist and Pischke, 2009). The occupancy rate, determined by government-assigned COVID-19 bed allocations and predetermined total bed numbers, is unlikely to correlate with healthcare utilization for non-COVID-19 conditions except through bed supply.

[Table 2]

We carefully address a potential identification threat: the possibility that individuals might avoid medical facilities due to the pandemic fears (Haritha & Praseeda, 2024; Zhang, 2021). Our study focuses on Japan’s 6th and 7th Omicron waves, characterized by lower severity and reduced mortality compared to the previous waves (Esper et al, 2022; Uemura et al., 2023). During this period, individual mobility remained unrestricted, and individuals had already developed protective strategies such as masking and vaccination, reducing virus-related anxiety.

As a result, individuals requiring healthcare services would continue visiting medical facilities. Moreover, previous research suggests that hospital avoidance primarily affects younger adults and less-educated populations (Haritha & Praseeda, 2024). We concentrate on Japan's oldest-old population, whose demand for medical services is relatively inelastic. Figure 2 substantiates this, demonstrating a consistent 80% medical care utilization rate regardless of the COVID-19 case numbers.

[Figure 2]

To estimate the first-stage, we used the following equation:

$$Empty\ Rate_{jt} = \pi_0 + \pi_1 Occupancy\ Rate_{jt} + D_{jt}\theta + \gamma_j + \lambda_t + e_{jt} \quad (3)$$

where $Empty\ Rate_{jt}$ represents the share of empty beds available and $Occupancy\ Rate_{jt}$ is the proportion of beds assigned to COVID-19 patients, in SMA j in month t. We controlled for regional characteristics (D_{jt}), including the number of confirmed cases and hospitalized COVID-19 patients to account for potential physician allocation to COVID sectors. Additionally, we controlled for the proportion of days that the SMA was under the "State of Precautionary Emergency" in a given month. We include SMA fixed effect (γ_j) and time fixed effect (λ_t), with standard errors clustered at SMA level. The parameters to be estimated are π_0, π_1, and θ with e_{jt} representing an error term.

In the second-stage regression, we estimated:

$$y_{ijt} = \beta_0 + \beta_1 Empty\ Rate_{jt} + X_{ijt}\delta + D_{jt}\zeta + \mu_i + \eta_j + \phi_t + \varepsilon_{ijt} \quad (4)$$

where y_{ijt} represents the treatment provided to individual i in SMA j in month t, encompassing hospital admission, length of hospital stays, doctor visits, and frequency of doctor visits. The variable X_{ijt} denotes individual characteristics, including a male dummy, age, income (JPY), and a dummy variable indicating whether the individual used medical services in that month, controlling for potential hospital avoidance. We also incorporate fixed effects for individual, regional, and time periods (μ_i, η_j, and ϕ_t) with standard errors clustered at the individual level. The parameters to be estimated are β_0, β_1, δ, and ζ, with ε_{ijt} as a residual.

Finally, we conducted robustness checks by excluding individuals diagnosed with any diseases related to respiratory system since physicians treating respiratory diseases may be assigned to treat COVID patients and the level of physician supply is more likely to be affected in this sector.

6. Results

6.1 Main results

Table 3 presents the baseline results using IV estimates and Ordinary Least Square (OLS) estimates for four treatment pattern measures: hospital admission, length of hospital stays, doctor visits, and frequency of doctor visits. All regressions are adjusted for individual, regional, and time fixed effects.

The IV results, adjusted for all covariates, reveal significant effects on inpatient care. Specifically, a one percentage point increase in the share of empty beds raises the probability of hospital admission by 0.017 percentage points, which represents 42.5% of the mean. The increase is accompanied by an approximate 0.2-day extension in hospital stay, indicating a statistically significant change in inpatient service provision. For outpatient care, the same IV specification demonstrates a contrasting pattern. A one percentage point increase in the share of empty beds decreases the probability of doctor visits by 0.014 percentage points and reduces the frequency of doctor visits by approximately 0.7 times. The findings indicate a substitution in treatment patterns from outpatient to inpatient services as hospital capacity increases. The OLS estimates differ markedly from the IV estimates, with some signs reversed. This discrepancy suggests potential significant bias in OLS results, likely stemming from reverse causality where increased hospital admission and length of stay might decrease the share of empty beds. The results demonstrate varying sensitivity to additional covariates, with inpatient care effects remaining relatively stable across model specifications, while outpatient care effects show greater variability.

[Table 3]

6.2 Robustness check

We conducted robustness by excluding individuals diagnosed with any respiratory system related diseases since physicians specialized in treating respiratory diseases might be assigned to treat COVID-19 patients and the level of physician supply is mostly likely to be influenced in this sector.

[Table 4]

From Table 4, a one percentage point increase in the share of empty beds increases the probability of inpatient service provision by 0.024 percentage point. On average, the length of hospital stay increases by one-third of a day. Simultaneously, a one percentage point increase reduces the probability of doctor visits by 0.022 percentage point with a decreased frequency of 0.733 times. The results are robust and indicate a consistent shift from outpatient services to inpatient services when there is a larger share of empty beds available. The magnitude of the change is larger than the baseline results, implying that level of physician supply may potentially affect the treatment pattern.

6.3 Heterogeneity

6.3.1 Heterogeneity by SMA's characteristics

[Table 5]

To deepen our understanding of the supply-side effect and its underlying mechanisms, we conducted several heterogeneity analyses by segmenting the sample based on population density, physician density, and bed capacity per capita within each SMA. We define these characteristics as follows: population density is calculated as the total population divided by the SMA's area; physician density represents the total number of physicians per capita; and bed capacity per capita is determined by the total number of hospital beds relative to the total population.[9] For each density measure, we divide the samples into two groups: those at or above mean and those below the mean. Regressions were then run separately for each group. The results of these analyses are presented in Table 5.

The 1st panel of Table 5 exhibits that, in SMAs with lower population density, we observe a pronounced effect where a one percentage point increase in the empty bed share raises the probability of hospital admission by 0.016 percentage point, with an average increase in the length of hospital stay by approximately one-third of a day. At the same time, it lowers the probability of doctor visits by 0.012 percentage point and reduces the probability of doctor visits by 0.6 times on average. While SMAs with higher population density also demonstrate a shift to

[9] SMA population is obtained by aggregating municipality population obtained from Ministry of Internal Affairs and Communications (https://www.soumu.go.jp/menu_news/s-news/01gyosei02_02000259.html). Area of SMA is calculated by aggregating the area of municipalities obtained from Geospatial Information Authority of Japan (https://www.gsi.go.jp/KOKUJYOHO/MENCHO-title.htm).

inpatient services, the magnitude of the change is smaller especially on the intensive margin. This differential response can be attributed to variations in physicians' and hospitals' utility, which correlates with both financial and non-financial earnings (Y). In less populated SMAs, the limited patient base potentially constrains overall earnings. Consequently, physicians may be incentivized to offer more services to compensate for lower level of demand. This finding aligns with established economic literature suggesting that physicians may induce demand in response to negative income shocks (McGuire and Pauly, 1991; Gruber and Owings, 1996, McGuire, 2000).

Second, we examined heterogeneity based on physician density within each SMA, as presented in the 2nd panel of Table 5. SMAs with higher physician-to-population ratios demonstrate a 0.039 percentage point increase in hospital admission and a 0.6-day extension of hospital stay, with a 0.021 percentage point reduction in doctor visits and 0.7 times decrease in frequency. In contrast, SMAs with fewer physicians show insignificant impact on inpatient care and minimal change on outpatient care. This variation likely stems from physician supply constraints and individual professional considerations. Physician utility is intricately linked to leisure time (L). In SMAs with limited physician numbers, the marginal cost of additional patient admissions is substantially higher. Each physician faces a more significant reduction in personal time, thereby diminishing incentives for admitting new patients. Conversely, in physician-dense areas, the individual burden of additional admissions is mitigated, facilitating more flexible treatment patterns. Notably, SMAs with greater physician density exhibit a significant increase in inpatient care at both extensive and intensive margins (Table 5), supporting our hypothesis about supply-side mechanisms.

Finally, we analyzed heterogeneity by bed capacity per capita in each SMA. The findings closely mirror the physician density results. SMAs with higher bed allocations demonstrate a more pronounced substitution from outpatient to inpatient care where a one percentage point increase in empty bed share leads to a 0.079 percentage point increase in the probability of hospital admission with an average increase of more than 1.5 days in the length of stay, and a reduction of 0.025 percentage point in doctor visits with a reduction of 0.6 times in the frequency. In contrast, SMAs with fewer beds per capita show only marginal reductions in outpatient care and negligible inpatient care effects. This pattern suggests that hospitals in resource-rich SMAs have stronger incentives to optimize bed utilization. The significant infrastructure investment creates a compelling rationale for maximizing resource development, potentially driving physicians to adjust treatment patterns to justify existing healthcare investments

These heterogeneous effects underscore the complex interplay between healthcare supply-side characteristics and treatment decisions. The findings highlight how local healthcare infrastructure, physician availability, and population dynamics intersect to shape medical service delivery. The analysis reveals that supply-side constraints and opportunities are not uniform across different SMAs. Instead, local context plays a crucial role in mediating how empty bed availability influences treatment patterns. This nuanced understanding contributes to our broader comprehension of healthcare resource allocation and physician behavior.

6.3.2 Heterogeneity by individual characteristics

[Table 6]

We conducted a detailed analysis of treatment pattern variations by segmenting the sample according to age (mean: 83 years) and income (mean: 2,027,419 JPY), with results shown in Table 6.

The impact of empty bed availability demonstrates marked differences across age groups. For individuals under 83, increased empty bed share has a minimal effect, marginally decreasing doctor visit frequency by approximately 0.8 times, with no significant impact on inpatient care. In stark contrast, patients aged 83 and above exhibit more substantial treatment pattern modifications. A one percentage point increase in empty bed share for this age group yields notable changes: it raises hospital admission likelihood by 0.026 percentage points (53% of the mean) and increases the length of hospital stay by more than one-third of a day. Simultaneously, it reduces doctor visit probability by 0.018 percentage points, while decreasing the frequency by approximately 0.62 times. These pronounced differences suggest that physicians' treatment strategies vary more significantly for older patients. This variation likely stems from the older population's more complex health status and reduced bargaining power in treatment decisions. The heightened responsiveness may reflect physicians' greater discretion in treatment approaches for patients with more vulnerable health conditions.

Income-level analysis reveals nuanced treatment pattern variations. For individuals with incomes below the mean, a one percentage point increase in empty beds leads to a notable increase in hospital admission and reduction in doctor visit with decreased frequency by approximately 0.7 times. Conversely, those with above-mean incomes only experience a reduction on doctor visits frequency.

These findings suggest that individuals with lower socioeconomic status are more susceptible to shift in physicians' treatment behaviors. This vulnerability may stem from reduced healthcare negotiation capabilities, limited alternative medical options, or greater dependence on existing healthcare infrastructure. The heterogeneity analyses illuminate the complex interactions between healthcare supply-side characteristics and individual patient attributes. The results highlight how age and income modulate the relationship between empty bed availability and treatment patterns, demonstrating that medical decision-making is not uniform but deeply contextual. The findings underscore the importance of considering individual-level characteristics when analyzing healthcare resource allocation and physician behavior. They reveal how structural healthcare constraints interact with patient vulnerabilities to shape medical service delivery.

7. Discussion and Conclusion

Our study addresses the longstanding challenge of identifying the causal relationship between hospital capacity and healthcare provision. Using an innovative instrumental variable approach based on the share of beds assigned to COVID-19 patients, we uncovered significant insights into how physicians modify treatment patterns in response to bed availability. Our primary findings reveal a distinct shift in healthcare delivery: as the share of empty beds increases, we observe a notable reduction in outpatient doctor visits coupled with an increase in both hospital admission probability and length of hospital stay. This pattern suggests that physicians strategically adjust their treatment decisions based on available hospital capacity, potentially inducing demand when capacity increases.

Our analysis demonstrates heterogeneous effects across different SMAs. Physicians in less-populated regions exhibit stronger inclinations toward inpatient care, likely as a compensation strategy for lower earnings. Similarly, SMAs with higher bed capacity demonstrate greater propensity to maximize inpatient care, possibly to justify facility investments and cover fixed costs. In contrast, SMAs with physician shortages show less responsiveness to bed availability, suggesting constraints from physicians' workload and leisure time limitations.

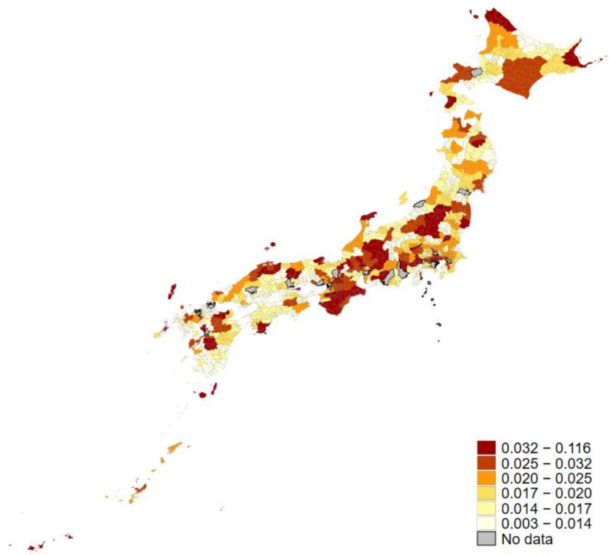
These findings extend the existing literature on physicians' financial incentives beyond childbirth contexts (McGuire and Pauly, 1991; Gruber and Owings, 1996), providing new evidence of how treatment patterns respond to changes in healthcare infrastructure. Notably, our results have particular significance for vulnerable populations, with stronger effects observed among older individuals and those with lower socioeconomic status. This suggests these groups may be more susceptible to supply-side variations in healthcare delivery.

Several limitations warrant acknowledgment. Our primary data constraint is the inability to observe precise physician allocation within hospitals or SMAs. If physicians are reassigned to treat COVID-19 patients, this could reduce physician availability in other medical sectors, potentially affecting treatment patterns. This consideration is particularly relevant in Japan, which has a lower fewer physicians-to-population ratio than most OECD countries (OECD, 2023a and 2024). [10] To address this limitation, we controlled for confirmed COVID-19 cases and hospitalized COVID-19 patients, factors likely correlated with physician allocation to COVID-19 care. Our robustness checks, which excluded patients diagnosed with respiratory system-related diagnoses, maintained consistent results. However, future research with more detailed physician allocation data could enhance our understanding of these dynamics.

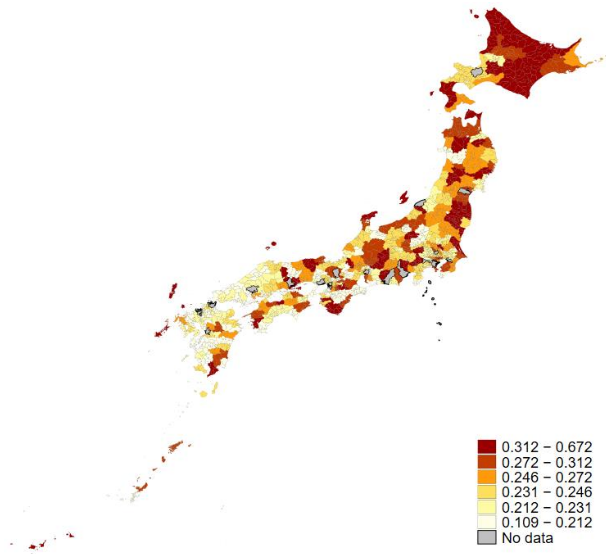
[10] In 2023, or the latest year available in OECD health statistics, Japan had 2.7 physicians per 1,000 inhabitants, which is below the OECD average of 3.7. For comparison, Germany reported it 4.6 physicians per 1,000 inhabitants, France 3.2, the UK 3.3, South Korea 2.6, and the US 2.7.

Out findings have important policy implications for the Japanese healthcare system. They suggest the need for careful government oversight of resource allocation and bed supply across hospital sectors to prevent healthcare service over-utilization and manage medical expenses effectively. Furthermore, the relationship between treatment variations and patient health outcomes requires careful examination. Given that treatment methods may vary with bed availability, it is critical to evaluate whether such variations impact patient health outcomes, particularly under resource constraints. Future research should focus on analyzing mortality rates and other key health indicators to provide a comprehensive understanding of how hospital capacity affects patient care quality.

Figures and Tables



(a) Occupancy rate



(b) Empty bed rate

Figure 1. Variation of Occupancy Rate and Empty Bed Rate across Prefectures

Source: “Hospital report” and COVID-19 data from obtained from the MHLW.

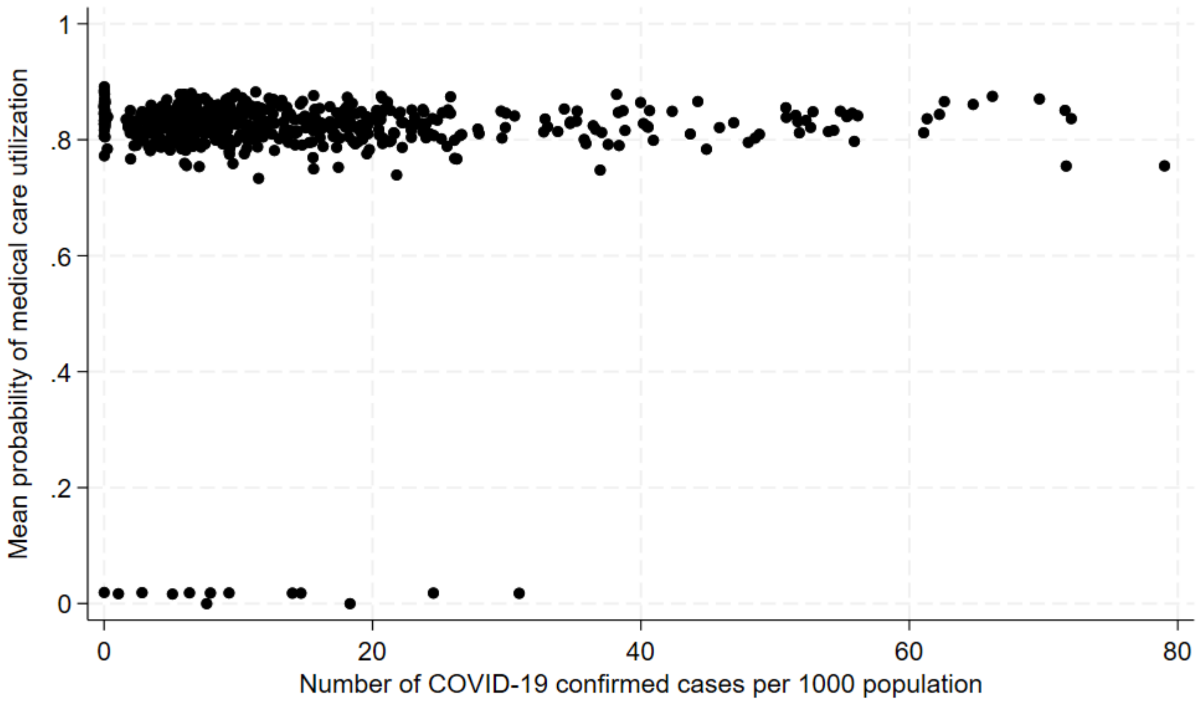


Figure 2. Correlation between Number of COVID-19 Confirmed per 1,000 Population and Probability of Medical Care Utilization

Source: "Medical Claims Data with Income Tax Information for the Oldest-Old in Japan (MCD-Tx)" obtained from the MHLW.

Table 1 Summary statistics

	Mean	SD	N	Min	Max
Covariates					
Individual characteristics					
Male	0.39	0.49	175,040,107	0	1
Age	82.50	5.71	175,040,107	75	115
Income (JPY)	2,027,419	3,935,030	174,834,868	0	5,790,000,000
Meical service usage	0.81	0.39	175,040,107	0	1
SMA's characteristics					
Total number of beds	4,508.41	4,981.46	4,020	55	41,527
Total number of empty beds	1,176.20	1,334.40	4,020	18	12,977
Empty bed rate	0.27	0.08	4,020	0	1
COVID-19 beds	123.71	153.96	3,888	2	1,539
Occupancy rate	0.02	0.01	3,888	0	0
COVID-19 patients in hospital	37.40	65.42	3,888	0	1,132
Share of days under the "State of Precautionary Emergency"	0.14	0.30	3,240	0	1
Number of confirmed cases	40831.77	72177.11	564	0	757,621
Total number of physicians	980.27	1,456.22	334	27	11,029
Outcomes					
Healthcare utilization					
Hospital admission	0.04	0.19	175,040,107	0	1
Length of hospital stay	0.79	4.50	175,040,107	0	64
Doctor visits	0.79	0.41	175,040,107	0	1
Frequency of docutor visits	2.01	2.61	175,040,107	0	131

Source: For individual characteristics and healthcare utilization, we use the “Medical Claims Data with Income Tax Information for the Oldest-Old in Japan (MCD-Tx),” provided by the MHLW. For SMA’s characteristics, we use the “Hospital Report” and the data on the number of beds designated for COVID-19 patients at each medical facility in Japan, both also provided by the MHLW.

Note: Our study period spans from December 2021 to November 2022, encompassing the 6th and 7th waves of the COVID-19 pandemic in Japan. All statistics represent averages for the entire observation period.

Table 2 First stage of IV estimation

	Empty bed rate	
	(1)	(2)
Occupancy rate	-0.500***	-0.665***
	(0.071)	(0.079)
Region FE	X	X
Regional Characteristics		X
F-statistics	49	30
Observations	175,040,107	145,196,993

Source: We used the "Hospital Report" and the data on the number of beds designated for COVID-19 patients at each medical facility in Japan, both provided by the MHLW.

Note: Column (1) shows the coefficient of $Occupancy\ Rate_{jt}$ without regional characteristics and column (2) shows the coefficient with regional characteristics. Both regressions are adjusted for regional, and time fixed effects. Regional characteristics include the number of confirmed COVID-19 cases and hospitalized COVID-19 patients in each SMA, as well as the proportion of days the SMA was under a "State of Precautionary Emergency" in that month. Standard errors are clustered at the individual level. "***" "**" and "*" indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3 Effects of share of empty beds on healthcare utilization (IV and OLS)

	(1) Hospital admission		(2) Length of hospital stay		(3) Doctor visits		(4) Frequency of doctor visits	
Regression methos								
IV	0.034***	0.017***	0.266**	0.218**	0.318***	-0.014***	0.492***	-0.703***
	(0.005)	(0.005)	(0.108)	(0.095)	(0.010)	(0.003)	(0.053)	(0.044)
OLS	-0.019***	-0.013***	-0.248***	-0.141***	-0.091***	-0.001	-0.373***	-0.121***
	(0.001)	(0.001)	(0.017)	(0.017)	(0.002)	(0.001)	(0.008)	(0.008)
Covariates								
Individual Characteristics		X		X		X		X
Regional Characteristics		X		X		X		X
F-statistics	49	30	49	30	49	30	49	30
Y-mean	0.04	0.04	0.79	0.81	0.79	0.8	2.01	2.01
Observations	174,727,188	144,719,124	174,727,188	144,719,124	174,727,188	144,719,124	174,727,188	144,719,124

Source: For individual characteristics and healthcare utilization, we use the "Medical Claims Data with Income Tax Information for the Oldest-Old in Japan (MCD-Tx)," provided by the MHLW. For SMA's characteristics, we use the "Hospital Report" and the data on the number of beds designated for COVID-19 patients at each medical facility in Japan, both also provided by the MHLW.

Note: The parameters for both IV and OLS show coefficients of $Empty\ Rate jt$. All regressions are adjusted for individual, regional, and time fixed effects. Individual characteristics include a male dummy, age, income (JPY), and a dummy variable indicating whether the individual used medical services that month, controlling for potential hospital avoidance. Regional characteristics include the number of confirmed COVID-19 cases and hospitalized COVID-19 patients in each SMA, as well as the proportion of days the SMA was under a "State of Precautionary Emergency" in that month. Standard errors are clustered at the individual level. "***" "**" and "*" indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4 Robustness excluding any diseases related to respiratory system

	(1) Hospital admission		(2) Length of hospital stay		(3) Doctor visits		(4) Frequency of doctor visits	
Regression methos								
IV	0.046***	0.024***	0.617***	0.318**	0.384***	-0.022***	0.379***	-0.733***
	(0.006)	(0.005)	(0.114)	(0.102)	(0.012)	(0.003)	(0.059)	(0.049)
OLS	-0.014***	-0.009***	-0.178***	-0.090***	-0.089***	0.0001	-0.327***	-0.089***
	(0.001)	(0.001)	(0.018)	(0.019)	(0.002)	(0.001)	(0.009)	(0.009)
Covariates								
Individual Characteristics		X		X		X		X
Regional Characteristics		X		X		X		X
F-statistics	49	30	49	30	49	30	49	30
Y-mean	0.03	0.03	0.69	0.71	0.75	0.76	1.75	1.76
Observations	107,880,861	89,146,002	107,880,861	89,146,002	107,880,861	89,146,002	107,880,861	89,146,002

Source: For individual characteristics and healthcare utilization, we use the "Medical Claims Data with Income Tax Information for the Oldest-Old in Japan (MCD-Tx)," provided by the MHLW. For SMA's characteristics, we use the "Hospital Report" and the data on the number of beds designated for COVID-19 patients at each medical facility in Japan, both also provided by the MHLW.

Note: The parameters for both IV and OLS show coefficients of $Empty\ Rate_{jt}$. All regressions are adjusted for individual, regional, and time fixed effects. Individual characteristics include a male dummy, age, income (JPY), and a dummy variable indicating whether the individual used medical services that month, controlling for potential hospital avoidance. Regional characteristics include the number of confirmed COVID-19 cases and hospitalized COVID-19 patients in each SMA, as well as the proportion of days the SMA was under a "State of Precautionary Emergency" in that month. Standard errors are clustered at the individual level. "***" "**" and "*" indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5 Heterogeneity by SMA's characteristics

	Hosptial admission	Length of hospital stay	Doctor visits	Frequency of doctor visits
SMA's characteristics				
Heterogeneity by population density				
Below mean	0.016**	0.319**	-0.012**	-0.610***
	(0.007)	(0.139)	(0.004)	(0.060)
Y-mean	0.04	0.91	0.78	1.92
Observations	84,707,663	84,707,663	84,707,663	84,707,663
Above mean	0.015**	0.292**	-0.018***	-0.470***
	(0.006)	(0.115)	(0.004)	(0.066)
Y-mean	0.03	0.66	0.81	2.15
Observations	60,011,461	60,011,461	60,011,461	60,011,461
Heterogeneity by physician density				
Below mean	0.004	0.024	-0.007*	-0.626***
	(0.007)	(0.129)	(0.004)	(0.059)
Y-mean	0.04	0.8	0.79	1.93
Observations	80,913,913	80,913,913	80,913,913	80,913,913
Above mean	0.039***	0.603***	-0.021***	-0.701***
	(0.007)	(0.134)	(0.004)	(0.065)
Y-mean	0.04	0.87	0.81	2.12
Observations	63,805,210	63,805,210	63,805,210	63,805,210
Heterogeneity by beds per capita				
Below mean	0.009*	0.140	-0.012***	-0.642***
	(0.005)	(0.101)	(0.003)	(0.049)
Y-mean	0.03	0.67	0.8	2.01
Observations	103,901,948	103,901,948	103,901,948	103,901,948
Above mean	0.073***	1.544***	-0.025**	-0.617***
	(0.014)	(0.278)	(0.009)	(0.112)
Y-mean	0.05	1.16	0.79	2.01
Observations	40,816,954	40,816,954	40,816,954	40,816,954

Source: For individual characteristics and healthcare utilization, we use the "Medical Claims Data with Income Tax Information for the Oldest-Old in Japan (MCD-Tx)," provided by the MHLW. For SMA's characteristics, we use the "Hospital Report" and the data on the number of beds designated for COVID-19 patients at each medical facility in Japan, both also provided by the MHLW.

Note: The parameters for the IV regressions represent the coefficients of $Empty\ Ratejt$. All regressions are adjusted for individual, regional, and time fixed effects. Individual characteristics include a male dummy, age, income (in JPY), and a dummy variable indicating whether the individual used medical services during the month, controlling for potential hospital avoidance. Regional characteristics include the number of confirmed COVID-19 cases and hospitalized COVID-19 patients in each SMA, as well as the proportion of days the SMA was under a "State of Precautionary Emergency" during the month. Standard errors are clustered at the individual level. "***" "**" and "*" indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6 Heterogeneity by individual characteristics

	Hosptial admission	Length of hospital stay	Doctor visits	Frequency of doctor visits
Individual characteristics				
Heterogeneity by age				
Below median (age<83)	0.002	-0.070	-0.005*	-0.786***
	(0.006)	(0.101)	(0.003)	(0.061)
Y-mean	0.03	0.52	0.79	1.98
Observations	81,464,332	81,464,332	81,464,332	81,464,332
Above median (age>=83)	0.026**	0.348**	-0.018**	-0.617***
	(0.008)	(0.170)	(0.005)	(0.064)
Y-mean	0.05	1.19	0.8	2.06
Observations	63,092,775	63,092,775	63,092,775	63,092,775
Heterogeneity by income				
Below mean(income<2,027,419)	0.014**	0.129	-0.016***	-0.778***
	(0.006)	(0.119)	(0.004)	(0.052)
Y-mean	0.04	0.89	0.79	1.98
Observations	95,056,953	95,056,953	95,056,953	95,056,953
Above mean (income>=2,027,419)	0.010	0.107	-0.003	-0.560***
	(0.009)	(0.156)	(0.005)	(0.083)
Y-mean	0.04	0.66	0.81	2.08
Observations	49,654,071	49,654,071	49,654,071	49,654,071

Source: For individual characteristics and healthcare utilization, we use the "Medical Claims Data with Income Tax Information for the Oldest-Old in Japan (MCD-Tx)," provided by the MHLW. For SMA's characteristics, we use the "Hospital Report" and the data on the number of beds designated for COVID-19 patients at each medical facility in Japan, both also provided by the MHLW.

Note: The parameters for the IV regressions represent the coefficients of $Empty\ Rate_{jt}$. All regressions are adjusted for individual, regional, and time fixed effects. Individual characteristics include a male dummy, age, income (in JPY), and a dummy variable indicating whether the individual used medical services during the month, controlling for potential hospital avoidance. Regional characteristics include the number of confirmed COVID-19 cases and hospitalized COVID-19 patients in each SMA, as well as the proportion of days the SMA was under a "State of Precautionary Emergency" during the month. Standard errors are clustered at the individual level. "***" "**" and "*" indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

References

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

Clemens, J., & Gottlieb. J. D. (2014). Do Physicians' Financial Incentives Affect Medical Treatment and Patient Health? *American Economic Review*, 104 (4): 1320–49. doi: 10.1257/aer.104.4.1320.

Ellis, R. P., & McGuire, T. G. (1986). Provide behavior under protective reimbursement. Journal of Health Economics, 5: 129-151.

Esper, F. P., Adhikari, T. M., Tu, Z. J., Cheng, Y. W., El-Haddad, K., Farkas, D. H., Bosler, D., Rhoads, D., Procop, G. W., Ko, J. S., Jehi, L., Li, J., & Rubin, B. P. (2023). Alpha to Omicron: Disease Severity and Clinical Outcomes of Major SARS-CoV-2 Variants. *The Journal of Infectious Diseases*, 227(3) 344–352. https://doi.org/10.1093/infdis/jiac411.

Fisher, E S., Wennberg, J E., Tukel, T A., Skinner, J S., Sharp, S M., Freeman, J L., & Gittelsohn, A M. (2000). Associations Among Hospital Capacity, Utilization, and Mortality of US Medicare Beneficiaries, Controlling for Sociodemographic Factors." Health Services Research, 34(6): 1351–1362.

Freedman S. (2016). Capacity and Utilization in Health Care: The Effect of Empty Beds on Neonatal Intensive Care Admission. American Economic Journal: Economic Policy, 8(2):154-185. https://doi.org/10.1257/pol.20120393.

Gaynor, M., & Anderson, G F. (1995). Uncertain demand, the structure of hospital costs, and the cost of empty hospital beds. Journal of Health Economics, 14(3): 291-317. https://doi.org/10.1016/0167-6296(95)00004-2.

Goodman, D. C., Stuchlik, P., Ganduglia-Cazaban, C., Tyson, J. E., Leyenaar, J., Avritscher, E. B. C., Rysavy, M., Gautham, K. S., Lynch, D., & Stukel, T. A. (2024). Hospital-Level NICU Capacity, Utilization, and 30-Day Outcomes in Texas. JAMA Netw Open, 7(2): e2355982. doi:10.1001/jamanetworkopen.2023.55982.

Gruber, J., & Owings, M. (1996). Physician financial incentives and cesarean section delivery. RAND Journal of Economics, 27(1): 99-123.

Gruber, J., Kim, J., & Mayzlin, D. (1999). Physician fees and procedure intensity: the case of cesarean delivery. Journal of Health Economics, 18(4): 473-490.

Haritha, B., & Challapalli, P. (2024). Anxiety-Induced Hospital Avoidance Behaviours During The Covid-19 Pandemic. Educational Administration: Theory and Practice, 30(4): 9224–9236. https://doi.org/10.53555/kuey.v30i4.3421.

Hashimoto, H., Ikegami, N., Shibuya, K., Izumida, N., Noguchi, H., Yasunaga, H., Miyata, H., Acuin, J.M., Reich, M.R. (2011). Cost containment and quality of care in Japan: Is there a trade-off? The Lancet, 378 (9797): 1174-1182. doi: 10.1016/S0140-6736(11)60987-2.

Hay, J., & Leahy, M. J. (1982). Physician-Induced Demand: An Empirical Analysis of the Consumer Information Gap. Journal of Health Economics, 1: 231-244. https://doi.org/10.1016/0167-6296(82)90002-9.

Hosokawa, R., Ojima, T., Myojin, T., Aida, J., Kondo, K., & Kondo, N. (2020). Associations between Healthcare Resources and Healthy Life Expectancy: A Descriptive Study across Secondary Medical Areas in Japan. Int. J. Environ. Res. Public Health, 17, 6301. https://doi.org/10.3390/ijerph17176301.

Johnson, E. M. (2014). Physician-induced demand. Encyclopedia of Health Economics, 3: 77-82. doi:10.1016/B978-0-12-375678-7.00805-1.

Johnson, E. M., & Rehavi, M. M. (2016). Physicians Treating Physicians: Information and Incentives in Childbirth. American Economic Journal: Economic Policy, 8(1): 115-141. doi: 10.1257/pol.20140160.

Kamath, R. R., & Elmer, J. (1989). Capital investment decisions in hospitals: Survey results. *Health Care Management Review*, 14(2): 45-56.

McGuire, T. G., & Pauly, M. V. (1991). Physician response to fee changes with multiple payers. Journal of Health Economics, 10(4): 385-410. https://doi.org/10.1016/0167-6296(91)90022-F.

McGuire, T. G. (2000). Physician Agency. Handbook of Health Economics, 1: 461-536. https://doi.org/10.1016/S1574-0064(00)80168-7.

Ministry of Health, Labour and Welfare. (2020). “Summary of 2020 Patient Survey (in Japanese).” https://www.mhlw.go.jp/toukei/saikin/hw/kanja/20/index.html (access November 8, 2024)

Ministry of Health, Labor and Welfare. (2022a). About Medical Areas, Baseline Beds Number, and Target (in Japanese). Retrieved August 13, 2024, from https://www.mhlw.go.jp/content/10800000/000946893.pdf.

Ministry of Health, Labour and Welfare. (2022b). Medical Regions, Number of Standard Beds, and Indicators: The 8th Meeting of the 8th Medical Care Plan, May 25, 2022 Document 1 (in Japanese). https://www.mhlw.go.jp/content/10800000/000946893.pdf (access November 15, 2024)

Ministry of Health, Labor and Welfare. (2024a) Implementation of Priority Measures to Prevent the Spread of COVID-19 (in Japanese). Retrieved August 30, 2024, from https://www.mhlw.go.jp/content/10900000/000766549.pdf. (access November 15, 2024)

Ministry of Health, Labour and Welfare. (2024b). Overview of National Healthcare Expenditures in FY2022 (in Japanese). https://www.mhlw.go.jp/toukei/saikin/hw/k-iryohi/22/dl/data.pdf (access November 8, 2024)

Ministry of Health, Labour and Welfare. (2024c). Plan for Securing Hospital Beds, Including Capacity for Temporary Medical Facilities and Inpatient Waiting Areas Designated as Secured Beds from April 2021-March 2024. (in Japanese). https://www.mhlw.go.jp/stf/seisakunitsuite/newpage_00062.html (access November 15, 2024)

Ministry of Health, Labour and Welfare. (2024d). Medical treatment to be aimed for through the new regional medical care concept: The 7th Study Group on the New Regional Medical

Treatment Plan August 26, 2024 Document 1 (in Japanese). https://www.mhlw.go.jp/content/10800000/001294917.pdf (access November 15, 2024)

Ministry of Internal Affairs and Communication. (2024). Regional Administration and Municipal Mergers (in Japanese). https://www.soumu.go.jp/kouiki/kouiki.html (access November 15, 2024)

Mohammadshahi, M., Yazdani, S., Olyaeemanesh, A., Akbari Sari, A., Yaseri, M., & Emamgholipour Sefiddashti, S. (2019). A Scoping Review of Components of Physician-induced Demand for Designing a Conceptual Framework. Journal of Preventive Medicine and Public Health, 52(2), 72–81. doi: 10.3961/jpmph.18.238.

Nakamoto, D., Nojiri, S., Taguchi, C., Kawakami, Y., Miyazawa, S., Kuroki, M., & Nishizaki, Y. (2022). The impact of declaring the state of emergency on human mobility during COVID-19 pandemic in Japan. Clinical Epidemiology and Global Health, 17, 101149. https://doi.org/10.1016/j.cegh.2022.101149.

OECD. (2023a). “Doctors (overall number)”, in Health at a Glance 2023: OECD Indicators, OECD Publishing. https://doi.org/10.1787/9f24c36f-en.

OECD. (2023b). “Hospital beds and occupancy”, in Health at a Glance 2023: OECD Indicators, OECD Publishing. https://doi.org/10.1787/bdd23022-en.

OECD. (2024). “OECD health statistics 2024”. Retrieved November 18, 2024 from https://data-explorer.oecd.org.

Okamoto, S. (2022). State of emergency and human mobility during the COVID-19 pandemic in Japan. Journal of Transport & Health, 26, 101405. https://doi.org/10.1016/j.jth.2022.101405.

Sharma, R., Stano, M. &Gehring, R. (2008). Short-term fluctuations in hospital demand: implications for admission, discharge, and discriminatory behavior. *RAND Journal of Economics*, 39(2): 329-616. doi: 10.1111/j.0741-6261.2008.00029.x.

Statistics Bureau of Japan. (2023). Current Population Estimates as of October 1, 2023. Retrieved September 18, 2024 from https://www.stat.go.jp/english/data/jinsui/2023np/index.html

Sen-Crowe, B., Sutherland, M., McKenney, M., & Elkbuli, A. (2021). A Closer Look Into Global Hospital Beds Capacity and Resource Shortages During the COVID-19 Pandemic. Journal of Surgical Research, 260, 56-63.

Tanihara, S., Zhang, T., Ojima, T., Nakamura, Y., Yanagawa, H., & Kobayashi, M. (1997). Geographic distribution of medical supplies and the numbers of hospital inpatients in the secondary medical areas in Japan. Nihon Koshu Eisei Zasshi, 44 (9):688-93.

Uemura, K., Kanata, T., Ono, S., Michihata, N., & Yasunaga, H. (2023). The disease severity of COVID-19 caused by Omicron variants: A brief review. *Annals of Clinical Epidemiology*, 5(2): 31-36.

United Nations Department of Economic and Social Affairs, Population Division. (2024) “World Population Prospect 2024”. https://population.un.org/wpp/Download/Standard/Population/ (access November 7, 2024)

Walsh, B., Smith, S., Wren, MA., Eighan, J., & Lyons, S. (2022). The impact of inpatient bed capacity on length of stay. The European Journal of Health Economics, 23: 499-510.

Watts, B.V., Shiner, B., Klauss, G., & Weeks, W B. (2011). Supplier-induced demand for psychiatric admissions in Northern New England. BMC Psychiatry, 11. https://doi.org/10.1186/1471-244X-11-146.

WHO. (2024). “Ageing and Health”. Retrieved November 18, 2024 from https://www.who.int/news-room/fact-sheets/detail/ageing-and-health.