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Anatomy of Physician Distribution in Taiwan: A Spatial Quantile Regression Analysis

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Recent expansion in medical education has substantially increased the supply of physicians. The literature has documented that a greater supply of physicians may not reduce the inequality of physician distribution measured by the Gini Coefficient or other single measures of inequality. However, more careful evaluation is required to determine the keys to addressing the allocation problems. We use a quantile regression with a spatial lag setup to investigate the distributional patterns of physician density among townships in Taiwan between 2010 and 2018. We find that the increased total number of physicians improved the physician density more in the townships on the lower quantiles than elsewhere in the distribution. This implies that physicians have been allocated more to the needier areas and this therefore improves the access to health care in these areas even though the inequality measured by the Gini coefficient gets worse. In general, the share of the aged population, median income, and whether a place has a medical center have greater and positive impacts on physician density in the higher quantiles. On the contrary, having a regional hospital generates a larger positive impact in the lower quantiles. The results suggest that regional hospitals have greater policy implications than medical centers in improving the allocation of physician services.

Keywords: physician distribution, instrumental variable quantile regression, spatial dependence, spatial lag model
JEL classification: I14, I18, J01

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1 Introduction

The Institute of Medicine of the United States defines access to health care as "the timely use of personal health services to achieve the best possible health outcomes" (Millman, 1993). Barriers to access can be financial, structural, personal or cultural. Financial barriers are low in Taiwan since the country's health care system has attended universal coverage for more than two decades, and residents are paying low out-of-pocket costs for most medical procedures and medications (Lu and Hsiao, 2003). Structural barriers are more challenging for Taiwan. While hospital beds per person in Taiwan were 7.1 beds per 1,000 population in 2019 compared to an average of 4.4 per 1,000 population across the OECD countries in the same year (Ministry of Health and Welfare, 2022; OECD, 2021), physician density in Taiwan is worse than that in most of the OECD countries (2.1 versus the OECD-average 3.6 per 1,000 population). Even worse, a proper distribution of doctors is lacking in Taiwan to guarantee timely access to health services, which is more of a concern than the deficiency of physician density. There are some contributory benefits of having three new post-graduate medical programs planned in 2022 to enroll 90 state-financed students in total who are required to serve in areas with limited medical resources for six years after graduation.

Recent expansion in medical education, in terms of medical schools and the number of medical school graduates (from 1,473 in 2010 to 1,680 in 2019), would substantially increase the supply of physicians (Taiwan Medical Association, 2011, 2020). Literature has documented that an increase in the supply of physicians may not reduce the inequality of physician distribution measured by the Gini Coefficient or other single measure of inequality. However, more careful evaluations are required to find out the keys to addressing the allocation problems. Simply put, policy makers wish to encourage physicians to move from the areas with a higher physician density to the areas with a lower one but also to the neediest areas. A single measure of inequality, such as the Gini coefficient can only help to learn the outcome of the overall distribution, but not the reasons contributing to the inequality in physician allocation.

To better assess the inequality in physician allocation and understand the factors related to it, we propose to use quantile regression to understand how the distribution evolves and how the effects of factors vary by quantile of the distribution. Due to the fact that patients are free to go to neighboring

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townships for physician services, we further incorporate a spatial lag setup of quantile regression models, namely the smoothed instrumental variable quantile regression (SIVQR) and the censored instrumental variable quantile (CQIV) regression with the spatially lagged dependent variable, to account for both spatial dependency and heterogeneity, in comparison with the estimates from the models based on conditional-means. Furthermore, we also explore the spatial dependency and the drivers of specialist's spatial allocation for each of the top seven ranked specialties individually to assess policy implications.

2 Literature review

Researchers have been interested in how physicians make their practicing location choice for decades. Most spatial competition models assume that physicians choose to practice in locations that provide the largest potential demand for medical services to maximize their income. Thus, the demand should be proportional to the number of people in the surrounding area. However, the literature concerns more on the inequality issues of rural and urban physician distributions. For example, Brown (1993) estimates that one urban patient needs to have a demand weight that equals 2.32 rural patients if physicians choose a practicing location according to the standard theory. The inequality between urban and rural physician density can be partly explained by socio-economic factors such as income (Dionne, Langlois, and Lemire, 1987; Doorslaer, Koolman, and Jones, 2004; Hurley, 1991; Rimlinger and Steele, 1963; Russo et al., 2012) and age structure of the area (Baumgardner, 1988; Hann and Gravelle, 2004; Hara et al., 2017).

Standard spatial competition models predict that as the number of physicians increases, the population required to support the first physician would fall (Newhouse, 1990). The prediction implies that physicians would disperse to low physician density areas as the number of physicians increases. The competition models are challenged by the hypothesis that physicians could induce their desired demand by taking advantage of the asymmetric information between physicians and patients. Specifically, if generating demand is a utility-decreasing behavior for physicians (McGuire and Pauly, 1991), the induced demand may fully compensate for the loss of demand led by the increased number of physicians. Therefore, the resulting lower utility provides physicians incentives to move away from physician concentrated areas so that the induced demand hypothesis could still work with the com-

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petition model (Newhouse et al., 1982). Empirical evidence about the role of induced demand in the physician distribution is inconclusive (Feldman and Sloan, 1988; Rice and Labelle, 1989).

Regarding the inequality issue, the Gini coefficient and other single measures of inequality, such as the Atkinson Index, coefficient of variation, and decile ratio, have been commonly used in studies to investigate the distribution of physicians empirically. Gini coefficients are usually calculated against population or against the population adjusted by socio-economic factors to represent market demand better. These inequality measures are also used in literature for evaluating the efficiency of redistribution policies or programs (Kralj, 2001; Ünal, 2015). This group of literature finds no evidence supporting that an increase in the supply of physicians leads to a more equally distributed physician allocation (Gravelle and Sutton, 2001; Hann and Gravelle, 2004; Hara et al., 2017; Horev, Pesis-Katz, and Mukamel, 2004).

In another line of research, some studies apply regression analysis to examine the association between the number of physicians and the number of residents in geographic divisions. Foster and Gorr (1992) find that the states with lower densities of primary care physicians experienced higher growth rates than the states with higher densities, led by an increased supply of physicians in the U.S. Isabel and Paula (2010) find that the growing number of physicians had little impact on the geographical distribution of physicians in Portugal. Asaria et al. (2016) show that programs such as establishing new health centers can reduce inequality in the primary care physician supply. There are also works modeling whether a town has a physician as a function of its market demand (Dionne, Langlois, and Lemire, 1987; Lábaj et al., 2018; Newhouse et al., 1982).

Physicians may also respond to other factors besides income in their location choice. Studies on medical graduates find that physicians tend to be affected by the location of their medical training (Kristiansen and Førde, 1992; Watson, 1980), geographic origin of their spouse or themselves (Kristiansen and Førde, 1992; Watson, 1980), age of spouse or their own (Russo et al., 2012), and religious ties (Watson, 1980) in choosing their practice locations.

Policy makers who aim to reduce the inequality of physician distribution usually focus on the areas with limited medical resources. Such policy concerns cannot be addressed by employing a single measure of inequality, such as Gini coefficient, and require a more sophisticated approach than

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a least square type of regressions to provide useful insights on the keys to the driving mechanism and investigate how they affect the distribution of physicians. In this study, we propose to use a quantile regression approach to account for heterogeneity corresponding to the distribution characteristics of the dependent variable. In addition, Rosenthal and colleagues show that physician-to-population ratios exhibit the largest degree of geographic disparity while distance-traveled and caseload models that allow patients to cross county lines show less disparity (Rosenthal, Zaslavsky, and Newhouse, 2005). Therefore, spatial dependency should also be taken into consideration for modeling the distribution of physicians. To our knowledge, only two articles account for spatial autocorrelation but not quantile regression in relevant subjects. Bolduc, Fortin, and Fournier (1996) model the choice of physician practicing locations, and Lábaj et al. (2018) estimate the number of inhabitants required for the first physician to enter a market. Our attempt to incorporate quantile and spatial analysis approaches in a unified framework will enable us to provide valuable insights for addressing the distributional issues of physician allocation.

3 Data and descriptive analysis

The township-level data used in this study are obtained from various open data sources from 2010 to 2018 in Taiwan. Specifically, the statistics of the number of physicians, number of specialists, number of medical institutions, and the land size of townships are obtained from the site of medical statistics managed by Taiwan Medical Association.[1] The demographic statistics, including total population and population in different age groups of townships, are obtained from the Dept. of Household Registration, Ministry of the Interior (M.O.I.), and the townships' median incomes are from the Fiscal Information Agency, Ministry of Finance (M.O.F.).[2] Our analysis sample includes all but Lianjiang County's, a total of 361 townships (township, town, city, or district).

Table 1 describes the definitions and descriptive statistics of the variables included in our analysis. The dependent variable, physician density, is defi-

[1] The data were accessed from https://www.tma.tw/stats/index_AllPDF.asp.

[2] Please refer to https://www.ris.gov.tw/app/portal/346 for the demographic statistics. Median incomes based on the personal income tax filing were accessed from https://www.fia.gov.tw/multiplehtml/43.

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Table 1: Variable definition and descriptive statistics

Variable	Definition	% to total	mean	sd.	min	max
physician density	physicians per 1,000 population	100.00%	1.18	1.80	0.00	20.51
top 7 specialists	Top 7 specialists per 1,000 population	70.42%	0.83	1.08	0.00	12.66
internal medicine	specialists in internal medicine per 1,000 population	19.68%	0.23	0.44	0.00	4.61
general medicine	specialists in general medicine per 1,000 population	17.30%	0.20	0.19	0.00	2.23
family medicine	specialists in family medicine per 1,000 population	11.03%	0.13	0.12	0.00	1.04
surgery	specialists in surgery per 1,000 population	7.65%	0.09	0.20	0.00	2.49
pediatrics	specialists in pediatrics per 1,000 population	6.27%	0.07	0.13	0.00	1.55
gynecology	specialists in gynecology per 1,000 population	4.38%	0.05	0.10	0.00	0.90
ENT	specialists in ENT per 1,000 population	4.12%	0.05	0.08	0.00	0.59
other specialists	specialists in other specialty per 1,000 population	29.58%	0.35	0.74	0.00	7.85
% aged 0–14	share of population aged 0–14 to total		12.86	2.92	5.27	24.59
% aged $\geq$ 65	share of population aged 65 or above to total		14.48	4.42	5.47	28.91
income	median income of township (NT$10,000)		56.18	7.29	34.80	110.00
ln (income)	log of median income of township		4.02	0.12	3.55	4.70
medical center	1 if having medical center (s); 0 if none		0.06	0.24	0.00	1.00
regional hospital	1 if having regional hospital (s); 0 if none		0.17	0.38	0.00	1.00
area	land size of township (km^2)		100.17	181.28	0.88	1641.86
ln (area)	log of land size of township		3.97	1.09	−0.13	7.40

ned as the number of physicians per 1,000 population. Among the 361 townships from 2010 to 2018, the physician density is averaged at 1.18 per 1,000 people, with 23 (out of 3,249 observations) being zeros and a maximum of 20.51 per 1,000 people. In terms of medical specialty, the top 7 specialties, including internal medicine, general medicine,[3] family medicine, surgery, pediatrics, gynecology and ENT/Otolaryngology, account for 70.42% of total physicians on average, with the remaining 29.58% being the other specialists.

We employ demographic compositions, including the youth and the elderly share in the township's population, the median income, the land size, and whether there is medical center(s) or regional hospital(s) in the township. Among the 361 townships, the share of the young population (aged 0–14) to total is averaged at 12.86%, ranging from the lowest being 5.27% to the highest being 24.59%. There is also a wide range in shares of the elderly population (aged 65 and above), ranging from 5.47% to 28.91% among the townships. It is observed a trend of population aging in Taiwan as the mean share of the elderly to population was 13.2% in 2010 and steadily increased to 16.5% with an averaged 0.4% rate of growth, with most aging growth concentrated in the townships of Taipei City (+0.56% yearly), New Taipei City (+0.55% yearly) and Kaohsiung City (+0.54% yearly). For 2010–2018, the average of median income of townships in Taiwan is NT$561,800. The ones with the lowest median incomes are in aboriginal townships, while Zhubei City in Hsinchu County (NT$1,100,000), Daan District, and Songshan District in Taipei City are among the townships with the highest median incomes.

As to controlling for hospital allocation, we define a "medical center" dummy with the value of 1 if the township has one or more medical center(s) and 0 if otherwise, and a "regional hospital" dummy variable taking the value of 1 if there is any regional hospital in the township and 0 if otherwise. Generally speaking, medical centers and regional hospitals are not different in terms of ownership but differ in capacity and functions. Either of these two types of institutions can be public or private. Public hospitals are funded by public sources such as the Ministry of Health and Welfare, municipalities, public medical schools, veterans, and military. Hospitals affiliated with medical care foundations, religious organizations, private medical colleges,

[3]Although general medicine is not a specialty per se, we treat it as one specialty for the convenience of writing.

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or charitable corporations are considered non-profit and non-public. Alternatively, private hospitals and hospitals affiliated with medical care corporations are non-public for-profit hospitals. Medical centers have greater capacity (more beds) and more advanced medical equipment and technology than regional hospitals and emphasize the functions of teaching, research, emergency care, and intensive care. The differences in their functions and services are also reflected in differences in the workload of physicians. A survey shows that the total work hours per week for physicians in medical centers on average is 64.98 compared to 56.87 in regional hospitals, while clinical work hour in medical centers is averaged 46.56 per week compared to 43.43 in regional hospitals (Hsiung, 2019). Although we cannot identify what had driven the locational decisions in building medical centers and regional hospitals, the differences in functions, services, and the workload of physicians between the two types of hospitals are likely attractive to physicians differently, especially for different specialties or geographic locations. On average only 6% of the 361 townships have medical centers, and about 17% townships have regional hospitals. Those medical centers and hospitals are believed to have clustering impacts on the allocation of physicians, especially some specialists. Since our dependent variable is physician density, we employ the land size of the township instead of population density as one of our explanatory variables, as the latter may exhibit endogeneity issues in regression analysis. According to the statistics in Table 1, we observe a wide range of land sizes of townships, as the smallest is 0.88 km^2 while the biggest one is 1641.86 km^2, which is 1,865 times the smallest one.

3.1 Inequality measures and Gini decomposition by specialty

To analyze descriptively the inequality in physician density, referred to total physicians per 1,000 population, among townships, we employ two measures of inequality: the modified concentration index (C.I.) and the Gini index, of which the former capturing the covariance between township i's physician density and its relative income rank, via the formula:

$$\text{C.I.} = \frac{1}{n}\sum_{i=1}^{n}\left\{\frac{d_i}{\mu_d - \min_d}(2R_i - 1)\right\}, \tag{1}$$

where d_i is the township i's physician density, R_i denotes the relative income rank of the township among a population of N townships, and μ_d and

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$\min_d$ denote the mean and minimum of d in all of the townships.[4] After modification, the index ranges from -1 to $+1$, reflecting negative or positive associations between individual townships' physician density and income rank.

The Gini coefficient measures the statistical dispersion of the variable of interest, commonly used in studying income inequality but also applied to studying the issues of inequality in household consumption (e.g., Fisher, Johnson, and Smeeding (2013); Mookodi (2021); Norris and Pendakur (2015)), in energy emissions (e.g., Chen, Zhang, and Wang (2022); Chen, Cheng, and Song (2017); Duan and Chen (2018)), in health (e.g., Olsen, Norheim, and Memirie (2021); Steinbeis et al. (2019)), and so on. Herein the Gini index is applied to measure income inequality and inequality in physician density. In addition, we adopt the approach described in Lerman and Yitzhaki (1985) and in Stark, Taylor, and Yitzhaki (1986) to decompose the Gini coefficient by physician specialty in terms of the share of each medical specialty in total inequality and the impact that a 1% change in the respective medical specialty will have on inequality in physician density.[5]

Table 2 describes the various inequality measures in physician density in Taiwan from 2010 to 2018. First, the estimated modified concentration indices range between 0.3017 and 0.3199, indicating a positive association between physician density and income distribution among 361 townships. The degree of inequality in town-level median income among townships is in a downward trend with a relatively small scale of Gini coefficient — around 0.06, considerably less than the one for household income, about 0.34 for the same period of time in Taiwan (Textor, 2021). Unlike median income, the Gini coefficients of physician density are in an increasing trend over time, from 2010's 0.5533 to 2018's 0.5811, implying a worsening of inequality in physician density among townships in Taiwan even though the mean physician density had increased from 1.096 physicians per 1,000 population in 2010 to 1.275 (a 16% increase) in 2018. These results are consistent with the findings in the literature, in which there has no evidence supporting that an improvement in the overall number of physicians leads

[4]The concentration indices and Gini coefficients are calculated using the user-written Stata command "conindex". Refer to O'Donnell et al. (2016) for the description of the command and its user guide.

[5]The Gini decomposition is conducted using the Stata command "descogini", written by Lopez-Feldman (2006).

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Table 2: Inequality in physician density and Gini decomposition by specialty

year	2010	2011	2012	2013	2014	2015	2016	2017	2018
Modified C.I.	0.3017	0.3041	0.3149	0.3094	0.3193	0.3199	0.3111	0.3039	0.3038
Gini of median income	0.0659	0.0685	0.0646	0.0655	0.0615	0.0602	0.0571	0.0564	0.0560
Gini of physician density	0.5533	0.5575	0.5599	0.5622	0.5684	0.5728	0.5759	0.5797	0.5811
Gini Decomposition of Physician Density by Specialty: Share (% Change)									
internal medicine	0.2468	0.2440	0.2338	0.2331	0.2302	0.2305	0.2318	0.2242	0.2263
	(0.047)	(0.044)	(0.037)	(0.037)	(0.035)	(0.036)	(0.035)	(0.030)	(0.029)
general medicine	0.0250	0.0383	0.0654	0.0664	0.0695	0.0660	0.0647	0.0737	0.0692
	(−0.145)	(−0.134)	(−0.117)	(−0.112)	(−0.110)	(−0.109)	(−0.103)	(−0.095)	(−0.096)
family medicine	0.0557	0.0546	0.0513	0.0495	0.0512	0.0521	0.0507	0.0524	0.0515
	(−0.056)	(−0.057)	(−0.059)	(−0.061)	(−0.057)	(−0.059)	(−0.062)	(−0.059)	(−0.056)
surgery	0.1033	0.1030	0.0972	0.0949	0.0942	0.0931	0.0934	0.0911	0.0926
	(0.022)	(0.021)	(0.020)	(0.019)	(0.018)	(0.018)	(0.019)	(0.018)	(0.018)
pediatrics	0.0732	0.0715	0.0683	0.0689	0.0696	0.0699	0.0705	0.0699	0.0684
	(0.010)	(0.010)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.006)	(0.004)
gynecology	0.0567	0.0548	0.0545	0.0530	0.0522	0.0516	0.0519	0.0518	0.0517
	(0.010)	(0.010)	(0.010)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
ENT	0.0495	0.0481	0.0469	0.0465	0.0444	0.0437	0.0439	0.0435	0.0429
	(0.007)	(0.006)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
others	0.3897	0.3857	0.3827	0.3877	0.3887	0.3931	0.3930	0.3934	0.3974
	(0.103)	(0.099)	(0.096)	(0.096)	(0.094)	(0.095)	(0.092)	(0.089)	(0.089)

Note: The Gini decomposition of physician density by specialty is indicated by two measures: 1) the share of each medical specialty in total inequality in physician density, and 2) the results in parentheses: (% Change) refers to the impact that a 1% change in the respective specialty will have on inequality in physician density.

to a more equally distributed physician allocation.[6]

In terms of the share of physician density, the top 7 specialists are 19.68% in internal medicine, 17.30% in general medicine, 11.03% in family medicine, 7.65% in surgery, 6.27% in pediatrics, 4.38% in gynecology, 4.12% in ENT/Otolaryngology, and the remaining 30% being other specialists on average as seen in Table 1. Table 2's Gini decomposition results indicate that the share of each medical specialty in total inequality among the top 7 specialists is topped by internal medicine's (22.42% – 24.68%) and bottomed by ENT's (4.29% – 4.95%). The results in parentheses of the table represent the impacts that a 1% change in the respective specialty will have on inequality in physician density. Among the specialties, the increases in general and family medicine specialists have negative marginal impacts on inequality in physician density. In particular, a 1% increase in general specialists leads to -9.5% to -14.5% of changes in total inequality, and marginal effects of changes in family medicine specialists range between -6.2% and -5.6%. On the other hand, changes in other specialties, including internal medicine, surgery, pediatrics, gynecology, ENT, and others, positively contribute to total inequality in physician density among townships. Especially, on the other (unlisted) specialties, including, for example medical genetics, neurology, nuclear medicine, and so on, a 1% increase in those specialists contributes to a 9–10% increase in inequality of physician density. This is a plausible result since many of those specialists are physicians in larger hospitals or clinics, like medical centers or regional hospitals, and such concentration increases disparity.

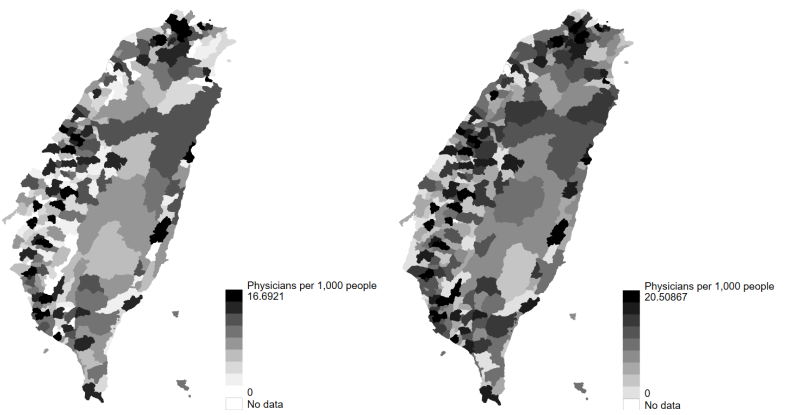
3.2 Spatial patterns of locational distribution

Figure 1 shows the locational distribution of physician density of the 361 townships in Taiwan for the first (2010) and the last year (2018) in our 9-year analysis sample. There are some but not visually significant changes between the two maps, both exhibiting weakly negative autocorrelation in physician density, as we find that dissimilar values (darker and lighter ones) are more often neighboring than in a random distribution. It implies a possible existence of spatial dependency.

We plot the locational distribution maps of the top 7 specialists, including internal medicine, general medicine, family medicine, surgery, pe-

[6]See, for example, Gravelle and Sutton (2001); Hann and Gravelle (2004); Hara et al. (2017); or Horev, Pesis-Katz, and Mukamel (2004).

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(a) 2010 (b) 2018

Figure 1: Locational distribution map of physicians per 1,000 population in Taiwan, 2010 and 2018

diatrics, gynecology and ENT, and other specialists in Figure 2. As shown in the graphs, very different locational distribution patterns are observed among the specialties. The physician densities in general and family medicine specialists are higher in the mountain areas. In contrast, internal medicine, surgery, pediatrics, gynecology, and ENT specialists concentrate on flat areas of Taiwan. This observation is consistent with what we have observed in the Gini decomposition, where both general and family medicine specialties exhibit negative marginal effects on total inequality in physician density in the opposite of the rest of the other specialties. For the specialties, like surgery, pediatrics, gynecology, and ENT, it is observed that there is a seemly clustering phenomenon. The one for the top 7 specialists combined, as in chart (8), presents a similar distributional pattern to the ones for physician density displayed in Figure 1, while the pattern of the other specialists, as in chart (9), appears to be similar to the ones for relatively minor specialties described above. Those less-representative specialists are more likely residents in medical centers or regional hospitals rather than in small clinics. Figure 3 depicts the locational distribution of medical centers and regional hospitals in Taiwan. They are likely located in cities or densely populated areas.

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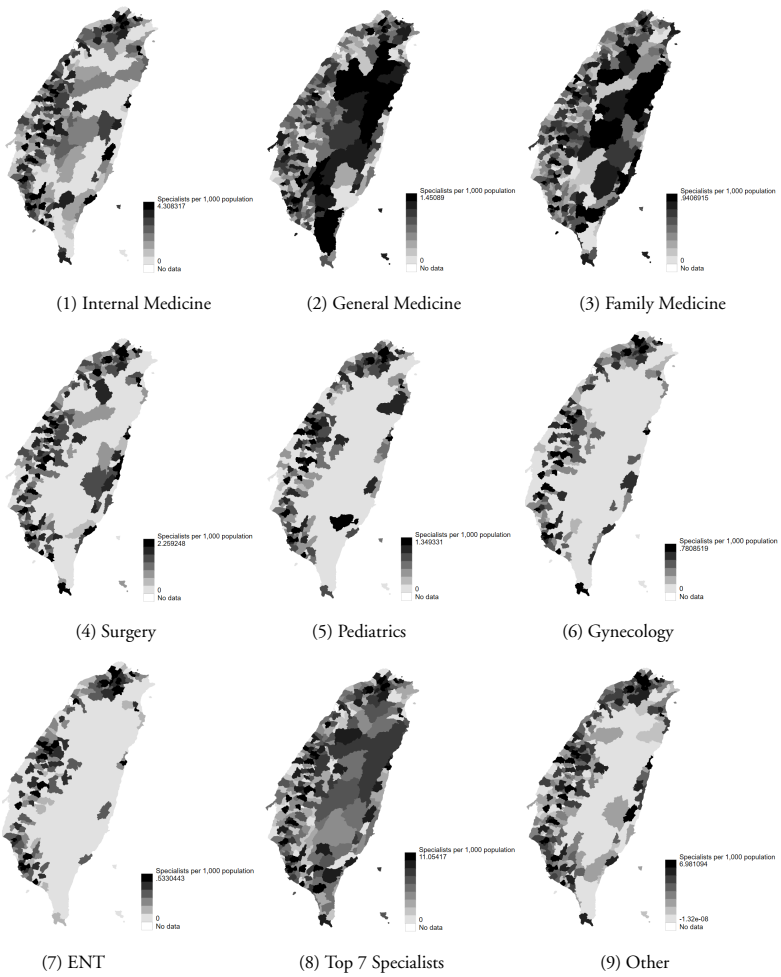
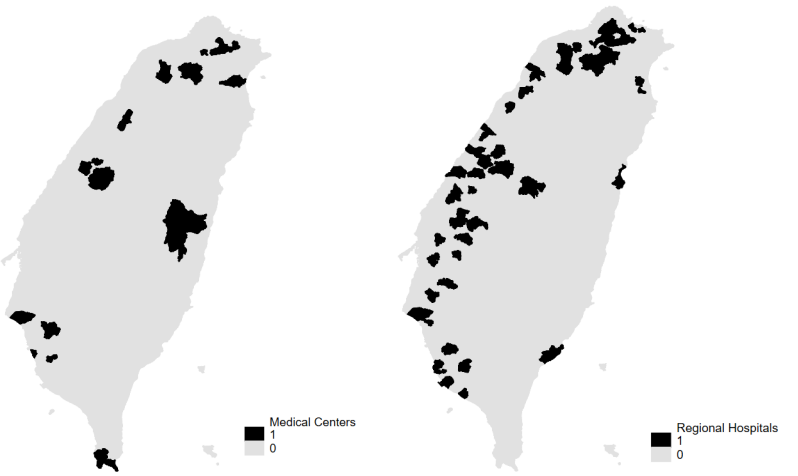


Figure 2: Locational distribution map of specialists per 1,000 population in Taiwan, the yearly average

4 Empirical models

In this study, we incorporate both spatial autoregressive and quantile regression models to reveal the driving mechanism of physician allocation. Considering spatial autoregressive features alone, the traditional spatial models emphasize spatial dependence effect and marginal effects on the means. In this study, we use smoothed instrumental variable quantile regression

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(a) Medical Centers (b) Regional Hospitals

Figure 3: Locational Distribution of Medical Centers and Regional Hospitals

(SIVQR) model, including the spatially lagged dependent variable, to account for both spatial dependence and heterogeneity under different quantiles. In particular, we adopt the spatial autoregressive (SAR) model, or so-called spatial lag model, estimated in a two-stage least squares IV approach for the base model of spatial analysis to be comparable with a quantile regression model setup, which is not applicable to the estimation of other types of the spatial regression model, like spatial error model, as documented in the literature (Liao and Wang, 2012).[7]

First, a general form of the SAR model can be expressed in Eq. (2):

$$y = \rho \mathbf{W} y + \mathbf{X}\beta + \varepsilon, \tag{2}$$

where y represents an $n \times 1$ vector of our dependent variable, the physician density, $\mathbf{X}$ represents an $n \times k$ matrix of k explanatory variables including the demographic compositions (the youth and the elderly share in township's population), median income, land size, and whether having medical

[7]For comparison purposes, we adopt the two-stage least squares (2SLS) instrumental variable approach to estimate the conditional-mean SAR regression model. Alternatively, it can also be estimated in a nonlinear parametric approach, which has only been applied to assess conditional means but not conditional quantiles in the existing literature.

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center(s) and/or regional hospital(s) in the township, ε is an $n \times 1$ vector of disturbances, β denotes the vector of parameters, ρ denotes the spatial dependence (lag correlation) parameter, $\mathbf{W}$ denotes the $n \times n$ spatial weight matrix, defined with inverse distance elements as in Eq. (3), and $n = 361$ is the number of observations. Specifically, the spatial weight matrix in our analysis is defined as the following:

$$\mathbf{W} = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & \cdots & w_{nn} \end{bmatrix}, \tag{3}$$

where $n \times n$ spatial weight matrix, w_{ij} is the element in the ith row and jth column, and $w_{ij} = 1/d_{ij}$ where d_{ij} is the geographic distance calculated by the Euclidian distance of longitude and latitude between any two locations. The choice of an inverse distance as the spatial weight is in line with the costs associated with cross-township search for physicians or medical services, likely increasing with the distance of travel, which gives a larger weight in spatial dependence to observations that are closer geographically. $\mathbf{W}$ is normalized or column standardized (i.e., the sum of the weights in all columns for the same row equals 1).

The quantile regression model addresses the heterogeneity in the impacts of influential factors on the entire distribution of the dependent variable, thereby providing a better view of the distributional relationship of y and $\mathbf{X}$. Specifically, the spatial lag quantile regression model in this study is built by embedding the quantile regression into the spatial lag model which is depicted as:

$$y = \rho^{(\tau)}\mathbf{W}y + \mathbf{X}\beta^{(\tau)} + \varepsilon^{(\tau)}, 0 < \tau < 1, \tag{4}$$

where the coefficients to be estimated, including the spatial lag parameter $\rho^{(\tau)}$ and the vector of the coefficients $\beta^{(\tau)}$, are both dependent of the quantile, τ. Following Gu and You (2022), Kim and Muller (2004), and others, a two-stage approach of instrumental variable quantile regression is adopted in our study, of which the detailed procedures are as follows:

$$\text{The first stage:} \quad \mathbf{W}y = \mathbf{X}\theta^{(\tau)} + \mathbf{Z}\gamma^{(\tau)} + \mathbf{u}^{(\tau)}, \tag{5}$$

$$\text{The second stage:} \quad y = \rho^{(\tau)}\widehat{\mathbf{W}y} + \mathbf{X}\beta^{(\tau)} + \varepsilon^{(\tau)}. \tag{6}$$

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In relevant spatial studies, the low-order spatial lags of the exogenous variables (namely $\mathbf{WX}$, $\mathbf{W^2X}$, and $\mathbf{W^3X}$) are commonly taken as potential candidates of instruments ($\mathbf{Z}$) for the spatially lagged endogenous variable ($\mathbf{W}y$) in the first stage of estimation. Despite the potential bias and inconsistent issues that may arise from the choice of instrumental variables, the existing spatial analysis studies that adopt the IV approach typically use all of the lower-order (either the first-order or the first- and the higher-order) spatial lags of the explanatory variables. To evaluate the appropriateness of the instruments, we conduct the following three more rigorous criteria: (1) the Wu-Hausman specification test for endogeneity, (2) the Sargan-Hansen test for over-identifying restrictions, and (3) the partial R^2 from excluded instruments to be significant enough for ruling out the case of weak instrumental variables (Bound, Jaeger, and Baker, 1995), for choosing among possible combinations of variables steamed from the set of potential instruments: $\mathbf{WX}$, $\mathbf{W}^2\mathbf{X}$, and $\mathbf{W}^3\mathbf{X}$.[8] Basically, these criteria examine whether (1) the suspect variable ($\mathbf{W}y$) is endogenous and so an IV estimation is needed; (2) the number of instruments is not too many; and (3) the excluded instruments overall provide sufficient explanatory power (partial R^2) to the endogenous explanatory variable of interest.

With such a validation strategy, we finally adopt the second- and third-order spatially lagged "medical center" dummy variables as our choice of instruments for $\mathbf{W}y$, since (1) the Wu-Hausman test statistics being 10.4552 ($p-$value $= 0.0012$) is significant, i.e. the null hypothesis (H_0: the variables are exogenous with the least-squares estimates) being rejected, (2) the Sargan-Hansen's test statistics being 0.1754 ($p-$value $= 0.6753$) implies that the null hypothesis (H_0: the instruments do not violate over-identification restrictions) cannot be rejected, and (3) the partial R^2 from excluded instruments being 0.4530 is statistically significant ($p-$value $<$

[8] For further theoretical backgrounds, refer to Wu (1974), Hausman (1978) on the specification test for endogeneity. In addition to the endogeneity test, researchers often use tests of the overidentifying restrictions proposed by Sargan (1958) and Hansen (1982) to assess the validity of the moment conditions when the model is overidentified with multiple instruments. We rely on both test results for our choice of appropriate instruments, despite debate on the appropriateness of applying tests of overidentifying restrictions in literature, such as a cautionary note by Parente and Silva (2012). Interested readers can also refer to Bound, Jaeger, and Baker (1995) for cautionary remarks on the problem of the estimation with weak instrumental variables.

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0.0001) to rule out the weak instrument problem.[9] It is conceptually argued that the lower-order spatial lags of "medical center" dummy, indicating the weighted likelihood of having medical centers in the neighboring areas, likely have impacts on the physician density in the neighboring areas but not directly on the physician density in the township of interest.[10] The neighboring impacts would pass through the spatial dependence between physician allocations indirectly. In the second stage, the predicted value of $\mathbf{W}y$, i.e., $\widehat{\mathbf{W}y}$, from the first stage regression is included for quantile regression.

In this study, we have the total physician density and the top-7 combined physician density (PD equation), and the individual specialist density (SD equation) in the top seven ranked specialties to be explained by the demographic compositions, median income, land size, and whether having medical center(s) and/or regional hospital(s) in the township. In the PD and top-7 specialist density equations, we apply both the spatial lag model and the instrumental variable quantile regression with spatial dependence term to evaluate the impacts of driving factors. In the SD equations, we use the spatial lag Tobit model and the censored quantile IV regression (CQIV) model with the spatially lagged dependent variable for our analysis focusing on spatial dependence. Notably, there are significant number of observations of specialist density with a value of 0 in the SD equations. In particular, there are 995 left-censored observations in the specialist density of internal medicine specialty, 180 in general medicine, 1,532 in family medicine, 520 in surgery, 1,549 in pediatrics, 1,722 in gynecology, and 1,767 in ENT specialty. Hence, a Tobit model or a quantile regression approach dealing with a censored continuous dependent variable, proposed by Chernozhukov, Fernández-Val, and Kowalski (2015), is adopted to estimate the SD equations. However, the censoring issue is relatively insignificant in physician density or top-7 combined, of which only 0.70% or 0.77% observations of the dependent variable are censored, respectively. Hence, the spatial quan-

[9]Another model setup with a set of instruments, including the first- and third-order spatially lagged "regional hospital" dummy variables, also satisfies the criteria. The model yields similar regression results compared to the chosen one, indicating that the estimation with the instrumental variables of our choice is robust.

[10]As seen in most studies involving IV estimation approach, it should be taken as a conceptual argument or assumption that the instruments are correlated with the endogenous explanatory variable but have no direct association with the outcome under study so that the IV estimates of the effect of the endogenous variable are consistent, even though our research makes rigorous attempts to ensure an appropriate choice of instrumental variables.

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tile regression for the PD equation is done with a (non-censoring adjusted) smoothed IV quantile regression (SIVQR) approach proposed by Kaplan and Sun (2017), in which the mean squared error minimization estimation leads to a simpler and more reliable computation, especially with endogenous regressors. The choice of instruments in the PD and the SD equations follows the one adopted in the equation of total physician density, as stated in above.

Functional form-wise, we adopt log form for our dependent variables, physician density and specialist density, and for the two explanatory variables, median income and area (land size) of a township. It is worth noting that the coefficients for median income and for area are in elasticity values in our setup of functional forms.

Followin LeSage (2015), LeSage and Pace (2009), and others, we can decompose the marginal effects of the explanatory variables into direct and indirect effects. In the general spatial lag model setting as in Eq. (2), the solution for the dependent variable y can be written as:

$$y = (I_N - \rho \mathbf{W})^{-1} [\mathbf{X}\beta + \varepsilon], \tag{7}$$

and so

$$E(y) = (I_N - \rho \mathbf{W})^{-1} \mathbf{X}\beta. \tag{8}$$

Let $\mathbf{G} \equiv (I_N - \rho \mathbf{W})^{-1}$ and let G_{ij} be the (i, j)th element of $\mathbf{G}$. Then, the marginal effect of a change in x_i on all of the other elements of $E(y_j) \forall j \neq i$ can be expressed as:

$$\frac{\partial E\left(y_j\right)}{\partial x_i} = G_{ij}\beta \quad \text{(total effect)}. \tag{9}$$

That is, a change in explanatory variable x_i would be expected to affect its neighboring units and impact the dependent variable of the jth unit. The effects described in Eq. (9) are the total marginal effects. In the presence of spatial dependence, the impacts beyond the direct effects of x on y (represented by the coefficient estimates, β) could be referred to as the indirect effects, or so-called "spillover effects", being given by:

$$\left(G_{ij} - 1\right)\beta \quad \text{(indirect effect)}. \tag{10}$$

The total and indirect marginal effects can be estimated by the nonlinear approximation after the coefficients of spatial dependence ($\hat{\rho}$) and of explanatory variables ($\hat{\beta}$) are estimated from the two-stage least squares (2SLS) and quantile regressions.

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5 Results and discussion

There are two sets of equations to run, one for physician density and the top-7 specialists combined, and the other for the specialist density for the top 7 specialties individually. For the former, both the two-stage least squares regression and the smoothed IV quantile (SIVQR) regression models with the spatially lagged dependent variable are employed to investigate the driving mechanism of physician density allocation. For the latter, the spatial lag Tobit and the CQIV regression model with the spatially lagged dependent variable are applied to analyze and compare the spatial dependence and the determinants of specialist density among specialties.

5.1 Spatial lag quantile regression results: physician density (PD) equations

The spatial instrumental variable quantile regression results of the total physician density equation are reported in Table 3, including the spatial mean's (2SLS) and SIVQR's estimates for the quantiles of 0.05, 0.25, 0.50, 0.75, and 0.95. The spatial lag coefficient estimate measuring the average relationship based on the conditional mean function shows a weakly negative spatial autoregressive relationship between townships' self and neighbors' physician densities. That is, averagely dissimilar values of physician density are located in neighboring townships than in a random distribution. The spatial IV quantile regression results also indicate negative spatial lag correlations overall, especially for the higher conditional quantiles (85th — 95th), statistically significant at the 5% level of significance (see Table 5 for the detailed estimates of spatial coefficients). As illustrated in Figure 4 (a), the spatial dependence coefficient estimates peaked in the middle range of the percentiles between the 25th and 35th and tailed lower on the higher end of the quantiles.

The SIVQR results also provide a more comprehensive and vibrant picture of the effects of the factors on the physician density of townships. In terms of the young population, a one percentage point increase in the share of the young population leads to a 0.74% (insignificant) increase in physician density based on two-stage least squares (2SLS) estimation, while the quantile estimates range from 0.39% (insignificant) at the 5th percentile to 5.21% at the 75th percentile, and then down to 1.74% at the 95th percentile. The pattern shows that physician density responds more to an incr-

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Table 3: Spatial lag and smoothed IV quantile regression, ln (physicians per 1,000 population)

	(1)	(2)	(3)	(4)	(5)	(6)
		Smoothed Instrument Variable Quantile Regression				
VARIABLES	2SLS	0.05	0.25	0.50	0.75	0.95
Spatial dependence (ρ)	−0.1801	−0.2515	−0.1782	−0.3001*	−0.4000	−1.1713***
	(0.1938)	(0.1730)	(0.1561)	(0.1634)	(0.3046)	(0.1320)
% Aged 0–14	0.0074	0.0039	0.0492***	0.0316***	0.0521***	0.0174*
	(0.0201)	(0.0195)	(0.0115)	(0.0109)	(0.0094)	(0.0096)
% Aged ≥ 65	−0.0268***	−0.0327***	−0.0251***	−0.0317***	−0.0112	0.0215**
	(0.0104)	(0.0103)	(0.0059)	(0.0075)	(0.0088)	(0.0105)
ln (income)	−0.2082	−0.6181*	0.3604**	0.3011	0.8269***	0.8109***
	(0.2969)	(0.3261)	(0.1505)	(0.2820)	(0.2596)	(0.1991)
Medical center	1.5817***	1.3658***	1.1601***	1.4354***	1.3236***	2.1490***
	(0.0983)	(0.0992)	(0.0595)	(0.0760)	(0.2623)	(0.0914)
Regional hospital	1.4864***	1.8156***	1.2061***	1.2222***	1.1600***	1.1671***
	(0.0821)	(0.0907)	(0.0642)	(0.0478)	(0.0410)	(0.0819)
ln (area)	0.0187	0.0612**	−0.0476*	−0.0843***	−0.1256***	−0.1566***
	(0.0515)	(0.0309)	(0.0252)	(0.0137)	(0.0287)	(0.0202)
d_2018	0.2121**	0.2882***	0.2832***	0.2582***	0.2006**	0.0841
	(0.0943)	(0.0789)	(0.0533)	(0.0931)	(0.1003)	(0.0886)
Other control variables	constant term and year dummies (d_2011 – d_2017) included but not reported					
Observations	3,249	3,249	3,249	3,249	3,249	3,249
R-squared	0.2601					

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Column (1) reports the estimates from spatial lag (2SLS) regression. Columns (2) — (6) are the estimates from the smoothed IV quantile regression at the specified quantile. Bootstrapped standard errors are in parentheses.

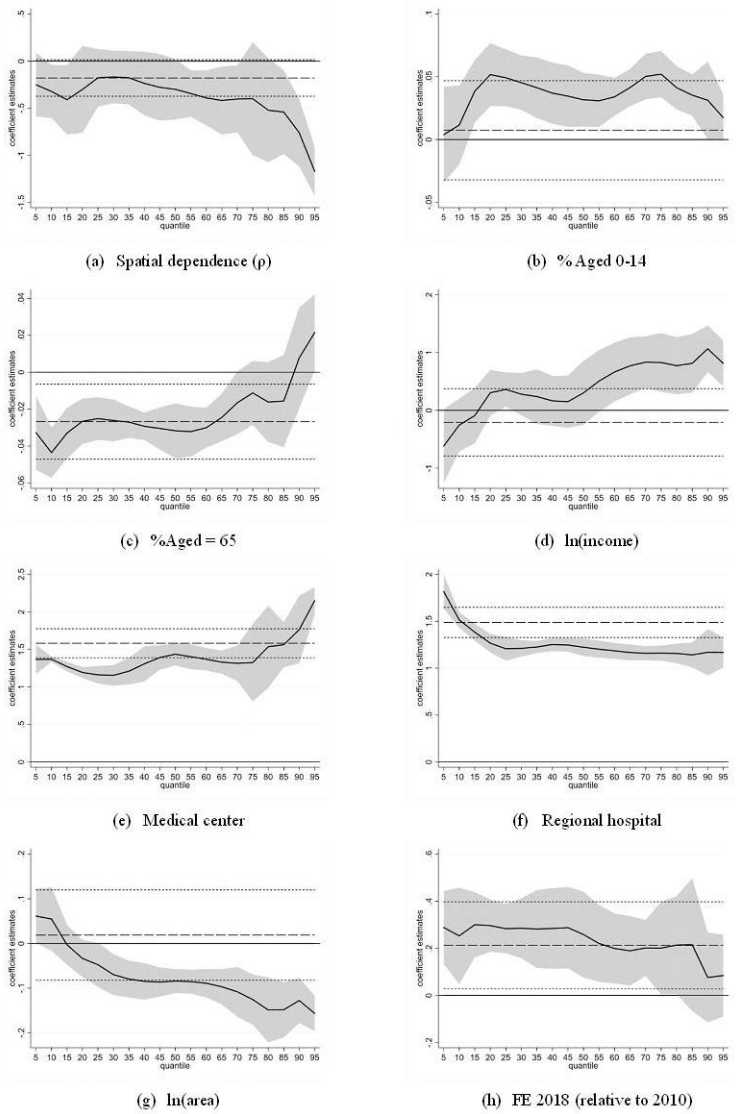


Figure 4: Spatial IV quantile regression, ln (physicians per 1,000 population)

Note: The dash line depicts the spatial lag (2SLS) coefficient estimates, and the dot lines indicate its associated 95% confidence interval. The solid line depicts the coefficient estimates for 5th — 95th percentiles, and the grey shaded area represents the associated 95% confidence interval.

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ease in the share of the young population in the townships in the middle range of physician densities than the ones in the two ends. As to the elderly population, a one percentage point increase in the share of the population aged 65 or above would link to a decrease of 2.68% in physician density on average, with the biggest negative impacts on the lower end of quantiles (−3.27%, −2.51%, −3.17% at the 5th, 25th, 50th percentiles respectively) but in an increasing trend with a positive impact (2.15%) at the 95th percentile. Such an increasing trend of physician density's responses to the share of the elderly population coincides with the fact that both the senior aged people and the highest physician density are located in the townships of metropolitan areas, like Taipei, New Taipei and Kaohsiung City, where public transportation is more convenient than other areas in Taiwan. Other than those high-physician-density metros, the areas with a more elderly population tend to have less access to physician care to meet their higher demand than their counterparts.

The physician density generally increases with median income. On average, the income elasticity of physician density is −0.2092 (insignificant). We though observe a positive income elasticity on the higher end of quantiles as 0.8269 at the 75th percentile and 0.8109 at the 95th percentile but a negative income elasticity (−0.6181) at the 5th percentile. This implies that income or ability to pay for medical services is more influential to physician allocation choice at the high but not the low end. This is a sensible result since medical procedures and medications that the National Health Insurance does not cover are more likely to deliver in the metropolitan areas where both income and physician densities are high.

Both medical centers and regional hospitals play an important role in attracting physicians to the townships with either medical center(s) and/or regional hospital(s). The average effect of having medical center(s) on physician density is 158.17% compared to the ones without while holding other things constant. The impacts are steady with an up tail on the high end for the quantiles from SIVQR regression (214.90% at the 95th percentile). The average marginal effect of having regional hospital(s) on physician density is 148.64% relative to the ones without. Unlike medical centers, the impacts of having regional hospital(s) are bigger at the lower end of quantiles, where 181.56% increase in physician density for the townships with compared to without regional hospitals at the 5th percentile. These results suggest that regional hospitals are more likely to improve physician allocation for the townships with low physician densities, while medical centers have larger

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clustering effects in the areas with already high physician densities. In terms of the land size of the township, an increase in land size leads to lower physician densities with a down tail at the higher end of quantiles and an up tail at the lower end of quantiles.

In addition to the variables reported in Table 3, we also control for year dummies and a constant term in all regression equations. In general, year dummies for the later years have relatively higher fixed effects than the other years (base year = 2010), consistent with the increasing trend of physician density between 2010 and 2018 in Taiwan. However, we find different patterns of those year fixed effects among quantiles, in which greater year fixed effects are observed for the lower percentiles than for the higher. Take the year dummy of 2018 as shown in chart (h) of Figure 4; the estimated fixed effects relative to the reference year 2010 are in a downward trend with quantiles. The results imply that there have been more improvements in the townships with limited physician services (lower physician density) than in the ones with rich medical resources over the years. Hence, despite the inequality represented by measures like the Gini coefficient getting worse as the total number of physicians increases (see Table 2), the allocation of physician services has moved towards the lower end, i.e., the neediest areas as suggested by our spatial quantile regression results. Such encouraging results could be misread by employing simple measures of inequality and thereby mislead into inappropriate policy decisions.

For further investigation on the allocational differences in physician services among townships, we also conduct spatial lag (2SLS) and smoothed IV quantile regression (SIVQR) with the spatially lagged dependent variable for the top-7 specialist density on the same set of explanatory variables. The top 7 specialists combined composite over 70% of physicians as a whole in Taiwan. In terms of its share to total physicians in townships, the shares of the top 7 specialists combined have a mean of 0.8366 and a standard deviation of 0.1692, ranging from 0.5742 at the 5th percentile, 0.6889 at the 25th percentile, 0.8750 at median, to 1 for the 66th percentile and above, i.e., one-third of townships having all physicians classified in those top 7 ranked specialties in our sample.

The estimation results reported in Table 4 show similar patterns of impacts compared to the ones for total physician density. The two-stage least squares (2SLS) estimate of spatial lag coefficient (ρ) is -0.0180, exhibiting a weakly (insignificantly) negative spatial autoregressive correlation, while the SQR estimates of ρ with significantly negative values for most quantiles.

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Table 4: Spatial lag and smoothed IV quantile regression, ln (top-7 specialists per 1,000 population)

	(1)	(2)	(3)	(4)	(5)	(6)
		Smoothed Instrument Variable Quantile Regression				
VARIABLES	2SLS	0.05	0.25	0.50	0.75	0.95
Spatial dependence (ρ)	−0.0180	−0.1327	−0.6534***	−0.4976***	−0.4779**	−0.9519***
	(0.1848)	(0.2058)	(0.1353)	(0.1601)	(0.2158)	(0.2097)
% Aged 0–14	0.0200	0.0041	0.0539***	0.0350***	0.0594***	0.0402**
	(0.0199)	(0.0185)	(0.0091)	(0.0124)	(0.0084)	(0.0177)
% Aged ≥ 65	−0.0197*	−0.0350**	−0.0227***	−0.0236***	−0.0066	0.0106
	(0.0101)	(0.0137)	(0.0048)	(0.0061)	(0.0066)	(0.0146)
ln (income)	−0.2617	−0.4660	0.2728**	0.3467	0.6456***	0.7484***
	(0.2903)	(0.2903)	(0.1177)	(0.3364)	(0.2221)	(0.2405)
Medical center	1.4336***	1.2679***	1.0943***	1.1955***	1.2041***	1.8532***
	(0.0934)	(0.0727)	(0.0367)	(0.0686)	(0.2941)	(0.1381)
Regional hospital	1.2281***	1.4308***	1.0067***	0.9398***	0.9196***	1.0417***
	(0.0800)	(0.1063)	(0.0177)	(0.0334)	(0.0497)	(0.0834)
ln (area)	0.0272	0.0616*	−0.0531***	−0.0639***	−0.0864***	−0.1149***
	(0.0509)	(0.0373)	(0.0201)	(0.0217)	(0.0302)	(0.0329)
d_2018	0.2242**	0.2718***	0.3058***	0.2172***	0.2219**	0.1354*
	(0.0894)	(0.0638)	(0.0429)	(0.0710)	(0.0962)	(0.0784)
other control variables	constant term and year dummies (d_2011 – d_2017) included but not reported					
Observations	3,249	3,249	3,249	3,249	3,249	3,249
R-squared	0.2074					

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Column (1) reports the estimates from spatial lag (2SLS) regression. Columns (2) — (6) are the estimates from the smoothed IV quantile regression at the specified quantile. Bootstrapped standard errors are in parentheses.

Table 5: Spatial dependence estimates conditional to various quantiles

	ln (Physicians/1,000 p)		ln (Top-7 Specialists/1,000 p)	
Quantile	Spatial dependence (ρ)	se	Spatial dependence (ρ)	se
2SLS	−0.1801	(0.1938)	−0.0180	(0.1848)
0.05	−0.2515	(0.1730)	−0.1327	(0.2058)
0.10	−0.3226**	(0.1432)	−0.3164**	(0.1554)
0.15	−0.4105**	(0.1883)	−0.5278***	(0.1846)
0.20	−0.3015	(0.2352)	−0.6544***	(0.1524)
0.25	−0.1782	(0.1561)	−0.6534***	(0.1353)
0.30	−0.1685	(0.1425)	−0.6166***	(0.1121)
0.35	−0.1778	(0.1444)	−0.5533***	(0.1196)
0.40	−0.2373	(0.1723)	−0.5371***	(0.1562)
0.45	−0.2793	(0.1801)	−0.5434***	(0.1579)
0.50	−0.3001*	(0.1634)	−0.4976***	(0.1601)
0.55	−0.3449***	(0.1259)	−0.4783***	(0.1482)
0.60	−0.3910***	(0.1494)	−0.4702***	(0.1425)
0.65	−0.4188**	(0.1847)	−0.4938***	(0.1581)
0.70	−0.4029**	(0.1814)	−0.4924***	(0.1595)
0.75	−0.4000	(0.3046)	−0.4779**	(0.2158)
0.80	−0.5219*	(0.2818)	−0.5302***	(0.2042)
0.85	−0.5417**	(0.2265)	−0.6515***	(0.1639)
0.90	−0.7610***	(0.1822)	−0.7365***	(0.1271)
0.95	−1.1713***	(0.1320)	−0.9519***	(0.2097)

Note: Robust (2SLS) and Bootstrapped standard errors (SIVQR) are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Demographic composition-wise, the share of the younger population has positive impact on the top 7 specialist density, while the share of the elderly population exhibits an increasing trend in which negative effects are observed at the lower quantiles and positive impacts at the 95th percentile (insignificant). Similarly, the income elasticities of top-7 specialist density are −0.2617 in the spatial lag (2SLS) regression, the lowest at the 5th percentile's negative elasticity (−0.4660) and topped at the 95th percentile's positive one (0.7484) in the quantile regressions. That is, income induces clustering effects on physician allocation choice at the higher quantiles but

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not the lower. Scale-wise, the impacts of medical centers and regional hospitals on top-7 specialist density are smaller than the ones on physician density. The same applies to the coefficient estimates of land size elasticity in comparison between the two equations.

Similar patterns were revealed in the coefficient estimates from year dummies among quantiles regarding the allocation of top-7 specialists as in the one of total physicians. That is, the year fixed effects of the year 2018 compared to the base year 2010 are positive and greater in the lower quantiles than in the higher. It again provides evidence that physician services in terms of the top 7 ranked specialists have been allocated to the needier areas over the years in Taiwan.

Figure 5 depicts the estimated direct and indirect marginal effects of the "medical center" and "regional hospital" dummy variables on the log of physician density and top-7 specialist density from quantile regressions. In general, the indirect effects, representing the "spatial spillover effects," are related to the degree of spatial dependence measured by the coefficient ρ. Since there exhibits a negative spatial lag autocorrelation in physician density, the indirect effects are negative, implying that the direct effects (i.e., the estimated coefficients as reported in Table 3 and Table 4) are greater than the total effects. The direct effects of having medical center(s) compared to without get to as high as 214.9% more physicians per 1,000 population at the 95th percentile. Still, they are offset by the indirect effects so that the total effects remain as a steady trend among quantiles. Unlike medical center's effects, the direct effects of having regional hospital(s) on physician density and top-7 specialist density are bigger at the lower end of quantiles. In particular, the larger direct effects and total effects of having regional hospital(s) than having medical center(s) on physician density are observed at the lower end of quantiles (5th — 15th).

5.2 Spatial lag tobit and censored quantile regression results: specialist density (SD) equations

We conduct spatial lag Tobit regression (SAR-Tobit) on individual specialist density for the top 7 specialties to explore the differences in spatial dependence and the impacts of various drivers among the specialties.[11] Also, the

[11] Here the spatial lag Tobit regression (SAR-Tobit) is done with a nonlinear parametric estimation approach. Instead of treating the spatially lagged dependent term as an endogenous

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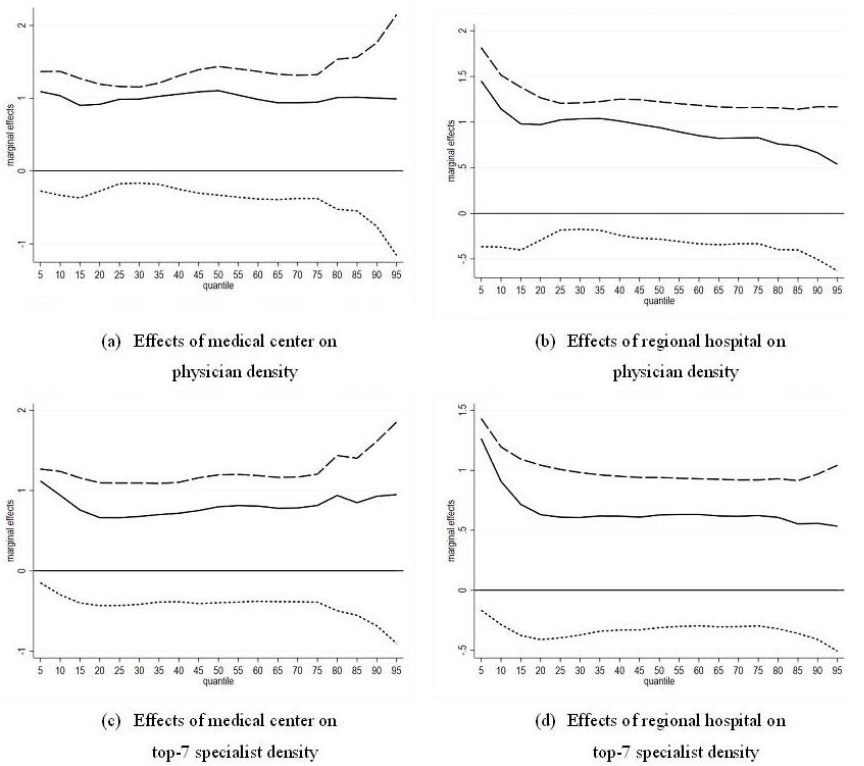


Figure 5: Total, direct and indirect effects of medical center and regional hospital

Note: The solid line depicts the total effect, the dash line indicates the direct marginal effect, and the dot lines indicate the indirect marginal effect of medical center and regional hospital for the 5th — 95th percentiles on physician density (a, b) and on top-7 specialist density (c, d).

spatial censored quantile IV (CQIV) regression method, proposed by Chernozhukov, Fernández-Val, and Kowalski (2015), is applied to be coupled with an instrumented spatially lagged dependent term to explore the differences in the driving mechanism among various quantiles. The choice of

explanatory variable and then being estimated with the IV-Tobit approach, the estimation of SAR-Tobit is done with the transformed equation: $y = (\mathbf{I} - \rho\mathbf{W})^{-1}\mathbf{X}\beta + u$, where $u \equiv (\mathbf{I} - \rho\mathbf{W})^{-1}\varepsilon$ assumed to be a random error term with a zero mean. It is estimated in a maximum likelihood approach involving a nonlinear parametric form.

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Table 6: Spatial lag Tobit and CQIV estimates, ln (specialists per 1,000 population)

VARIABLES		(1) internal medicine	(2) general medicine	(3) family medicine	(4) surgery	(5) pediatrics	(6) gynecology	(7) ENT
Spatial dependence (ρ)		−0.291***	0.242***	−0.203***	−0.344***	−0.139***	−0.126***	−0.007
	0.25	0.075	0.511***	−0.599**	—	—	—	—
	0.50	−0.515***	0.306***	−0.370***	0.189	0.518**	0.067	0.426*
	0.75	−0.406***	0.085	−0.349***	−0.426***	−0.204***	−0.522***	−0.665***
	0.95	−0.451***	−0.366	−0.784***	−0.415***	−0.279***	−0.221***	−0.100***
% Aged 0–14		0.028***	0.019***	0.048***	0.013	0.067***	0.008	0.021**
	0.25	−0.017	0.032***	0.080***	—	—	—	—
	0.50	0.070***	0.011	0.048***	0.100	−0.196*	0.058	−0.006
	0.75	0.060***	0.012	0.062***	0.047*	0.072***	0.237***	0.160**
	0.95	0.015	0.014	0.077***	0.038*	0.051***	−0.007	0.016
% Aged ≥ 65		0.013**	0.009**	0.028***	0.041***	0.006	0.065***	0.024***
	0.25	−0.045	0.013**	−0.038	—	—	—	—
	0.50	−0.054*	0.011*	0.015	−0.043	−0.551***	0.004	−0.225
	0.75	−0.009	0.016*	0.031***	−0.012	−0.108***	−0.455***	−0.598***
	0.95	0.022*	−0.012	0.032**	0.010	−0.039***	0.019	−0.031*

Table 7: Spatial lag Tobit and CQIV estimates, ln (specialists per 1,000 population) (Continued)

VARIABLES	(1) internal medicine	(2) general medicine	(3) family medicine	(4) surgery	(5) pediatrics	(6) gynecology	(7) ENT
ln (income)	0.766***	−0.123	−0.112	0.213	0.439***	0.806***	−0.020
0.25	0.636	−0.674***	1.551**	—	—	—	—
0.50	2.263***	−0.123	0.544***	0.547	4.547**	0.583	4.006
0.75	2.595***	0.139	0.227	2.455***	0.983***	7.513***	4.988***
0.95	1.210***	0.346	−0.044	−0.414	1.149***	1.123***	0.389
Medical center	1.509***	0.732***	0.628***	1.719***	1.149***	1.019***	0.952***
0.25	1.676**	0.580***	0.791***	—	—	—	—
0.50	1.692***	0.780***	0.560***	9.601***	2.862***	10.85***	6.329*
0.75	1.405***	1.066***	0.491***	1.768***	1.168***	1.246***	1.923***
0.95	2.345***	1.152***	0.564***	2.96***	1.962***	1.869***	1.423***
Regional hospital	1.343***	0.041	0.431***	1.089***	0.697***	0.726***	0.614***
0.25	11.547***	0.199***	0.652***	—	—	—	—
0.50	1.659***	0.046	0.445***	10.103***	4.361***	10.944***	7.261**
0.75	1.483***	−0.004	0.372***	1.341***	1.052***	2.294***	2.436***
0.95	1.438***	0.477***	0.404***	1.386***	0.646***	0.863***	0.954***

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Table 8: Spatial lag Tobit and CQIV estimates, ln (specialists per 1,000 population) (Continued)

VARIABLES		(1) internal medicine	(2) general medicine	(3) family medicine	(4) surgery	(5) pediatrics	(6) gynecology	(7) ENT
ln (area)		−0.184***	0.059***	0.015	−0.176***	−0.181***	−0.252***	−0.189***
	0.25	−0.218	−0.025	−0.266**	—	—	—	—
	0.50	−0.572***	0.047*	−0.035	−0.451	−1.391***	−0.08	−0.744
	0.75	−0.324***	0.087**	−0.013	−0.433***	−0.500***	−1.462***	−1.664***
	0.95	−0.189***	0.113***	−0.069**	−0.258***	−0.197***	−0.391***	−0.368***
d_2018		0.182**	0.188***	0.218***	−0.056	0.320***	−0.335***	0.077
	0.25	−0.078	0.311***	0.080	—	—	—	—
	0.50	0.317**	0.091	0.125**	0.439	0.751	0.116	0.153
	0.75	0.099	0.039	0.271***	−0.133	0.849***	1.077*	1.970***
	0.95	0.036	0.084	0.166	0.301*	0.326***	−0.249**	0.200
Other control variables		constant term and year dummies (d_2011 – d_2017) included but not reported						
Total observations		3,249	3,249	3,249	3,249	3,249	3,249	3,249
Left-censored obs.		995	180	520	1,532	1,549	1,767	1,722

Note: The gray shaded rows report the coefficient estimates of spatial lag Tobit regression (SAR-Tobit). The other rows are the coefficient estimates of censored IV quantile regression (CQIV) with spatial lag variables at quantiles of 0.25, 0.50, 0.75, 0.95. Due to the left-censored dependent variable, some equations (column (4) — (7)) fail to produce estimates (denoted as —) at the quantile of 0.25. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

instrumental variables for the spatially lagged dependent variable in the CQIV regression follows the previous one, i.e., the second- and third-order lags of the medical center dummy, based on the three criteria, including the Wu-Hausman specification test and Sargan-Hansen over-identification test, and partial R^2 ruling out weak instruments. Table 6 presents the coefficient estimates from seven specialty density (SD) equations. There exhibit vibrant variations in the driving mechanism for individual specialist density among the seven specialties.[12]

First, based on the spatial lag (SAR-Tobit) model measuring the conditional mean behaviors, negative spatial lag correlations are observed in most specialties except in general medicine. The spatial dependence estimate is 0.242 for the general medicine equation, which is the highest among the top-7 specialties, implying the development of clusters where similar values of specialist density in general medicine are concentrated. That is, the healthcare service provided by general medicine practitioners exhibits regional clustering. Based on chart (2) of Figure 2, clusters of high specialist density in general medicine are observed in middle-northern mountain areas and in the southern mountain areas. Also, clusters of low physician density in general medicine are observed in the townships around Hsinchu and Miaoli County and in the townships around Yunlin and Chiayi County. The observed spatial patterns of physician allocation are likely to be associated with the government-sponsored medical education program and its requirement to serve in medically deficient areas, as a large proportion of physicians in general medicine are new medical graduates who are in their post-graduate year (PGY) or are resident but have not received their specialist qualifications.[13] The specialist densities in internal medicine, fam-

[12]As in Table 6, the estimates from the spatial lag Tobit (SAR-Tobit generally fall in the ranges between the ones from various conditional quantiles of the CQIV model despite the two presenting generally different pictures of estimated results. It is worth noting that the estimates from the IV-Tobit approach are quite sensitive to the choice of instrumental variables, while the SAR-Tobit approach exhibits robust estimates; hence, SAR-Tobit estimates are adopted as the base to compare with the CQIV estimates. A Hausman specification test is conducted to compare the SAR-Tobit and the CQIV estimates at each quantile. The test result generally rejects the null hypothesis that the normality and homoskedasticity assumptions are required by the SAR-Tobit to hold. Such differences between the two regression approaches are also found in literature, for instance, Kowalski (2016).

[13]According to the Principles of Government Sponsored Physician Distribution Service (Department of Health, Executive Yuan), government-sponsored medical graduates are re-

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ily medicine, surgery, pediatrics, and gynecology exhibit various degrees of negative spatial autoregressive correlation, i.e., dissimilar values of specialist density (H-L or L-H combination) in these specialties are more often observed in neighboring townships than in a random distribution spatially. It implies that the accessibility of specialist care in these specialties is locally clustered, i.e., specialists can extend their healthcare services to neighboring townships, or their existing healthcare services restrict the formation of new services in the area nearby.

As to demographic compositions, an increase in the share of the young population or the share of the elderly population induces more specialist density in all seven specialties (the young population on gynecologists and the elderly population on pediatricians are insignificant). The income elasticities of specialist density in internal medicine, pediatrics, and gynecology are positive but less than one, ranging between 0.439 and 0.806. Compared to the ones without, the townships with medical center(s) have from 62.8% more specialist density (in family medicine) to 171.9% more (in surgery). The townships with regional hospital(s) have 43.1% more specialist density (in family medicine) to 134.3% more (in internal medicine) in comparison to the ones without. Those results suggest that medical center(s) and/or regional hospital(s) have smaller clustering effects on some specialist densities than on total physician densities. Similarly, the land size effects on specialist density are generally negative, except for specialists in general medicine.

The results based on the CQIV regression model with the spatial-lagged dependent variable exhibit a different picture compared to the spatial lag Tobit estimates. First, in surgery, pediatrics, gynecology, and ENT SD equations, the quantile estimates of spatial dependence (ρ) are most in smaller scales with few positive ones at the lower quantiles and many in the negative zone. Especially for higher quantiles, negative spatial lag autocorrelations are observed. This indicates that a high value of specialist density in one township tends to go with a low value of specialist density in its neighboring township(s) in a high-low cross-checkered pattern implying a local (single township) rather than regional (multiple townships) clustering.

As to the demographic compositions in age, positive effects of increases in share of the young population or of the elderly population are observed in

quired to serve in some specific fields and specific geographic areas, including non-municipal government-affiliated health centers or clinics in low densely populated areas, for several years after they have completed the residency training.

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some of the quantile regression estimates, for instance, the ones in the equation of SD in family medicine. However, it is still within the expectation that most specialist services do not move along with the aged population, especially the specialties of pediatrics, gynecology, and ENT. The quantile estimates of income elasticity fall in the positive zone up to 7.513 (the 75th percentile in the SD equation of gynecology), while negative estimates are mostly small and statistically insignificant. The sign of quantile estimates for the medical center and regional hospital dummies are all positive, the same as the ones based on conditional means. However, the patterns of those hospital impact on specialist services vary by specialty and by quantile. For specialist density in internal medicine and general medicine, greater impacts of having medical center(s) are observed at higher quantiles. In contrast, the bigger ones are found at the median in other SD equations. As to the impacts of having regional hospital(s), there are bigger ones at the lower end than the upper end of quantiles, implying that regional hospitals generate more help to the needy areas than those with abundant resources. Consistent with the mean regression results, townships with bigger land sizes tend to have fewer specialists per 1,000 population for all quantiles and specialties except for general medicine.

The year fixed effects revealed by the year dummy of 2018 vary by specialties. Based on conditional means, specialist density in internal medicine, general medicine, family medicine, or pediatrics has increased since 2010. However, based on the conditional quantiles, growing trends are observed in specialty density at higher percentiles but not at lower quantiles. Unlike allocation in total physicians or top 7 specialists combined, the movement toward the lower end of quantiles over time only happens in general medicine. Hence, the allocational improvements are more likely as a mixture of physician care services rather than in a particular specialty individually.

6 Conclusion

As one of the structural barriers to access to health care, the low physician density in Taiwan has improved over the recent decade. However, physician distribution among the population may worsen and overcloud the improvement. On the one hand, similar to the literature, we find that the inequality represented by measures like the Gini coefficient shows no improvement as the total number of physicians increases based on the data between 2010 and 2018 in Taiwan. However, on the other hand, the allocation of physi-

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cian services has moved toward the needier areas, as suggested by our spatial quantile regression results. Such encouraging results that the access to health care is in fact further improved could be misread by employing simple measures of inequality.

In this study, we conduct various models, including SAR, SAR-Tobit, smoothed IV, and censored IV quantile regressions with a spatial dependence term to evaluate the distributional differences in determinants to physician density and specialist densities. We find that ability to pay for medical service is more influential to physician allocation choice at the high end but not the low end since medical procedures and medications that the National Health Insurance does not cover are more likely to deliver in the metropolitan areas where both income and physician densities are high. An increase in the share of the elderly population would lead to an increase in the physician density on the high end of quantiles but a decrease on the low end of quantiles. These two facts spell the challenge of addressing the issues faced by the needier population in the access to health care, especially for an aging population like Taiwan. Regional hospitals are more likely to be a policy resort to improve physician allocation for the townships with low physician densities. At the same time, medical centers have larger clustering effects in the areas with already high physician densities. We also find a negative spatial dependency in the higher ends of conditional quantiles, implying that similar values of physician density are less concentrated than in a random distribution.

The results of spatial quantile regression of specialist density for the top 7 ranked specialties individually also suggest that factors are heterogeneously associated with physician supply among quantiles and spatial dependency plays an important role. Unlike allocation in total physicians or top 7 specialists combined, we do not find movements of specific specialist services to the lower end of quantiles over time. It implies that the allocational improvements are more likely to be a mixture of physician services rather than individually in a particular specialty. Below are some policy implications from the findings for the top 7 specialties worth noting.

Since a large proportion of surgeons and gynecologists serve in hospitals, their location choices highly depend on the location of hospitals. Thus, their responses to medical centers and regional hospitals are similar at each quantile. Compared to surgeons, gynecologists are more likely to serve in a clinic setting and respond to patients' age and income with their location choices. On the contrary, internists and family medicine physicians have

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negative spatial autocorrelation at most quantiles. Namely, an area with high physician density is more likely to neighbor a low-density area and, therefore, in a high-low cross-checkered pattern. Such a local clustering represents an encouraging implication. That is, people living in medically deficient regions can go to nearby places to access specialty care provided the pattern of spatial dependence. Our results also show a matching of population needs and specialist allocation choice as the share of the youth population has positive impacts on having family medicine doctors at all quantiles. In contrast, income i.e., ability to pay, has positive impacts on having internists in the middle and high quantiles. Internists, especially those with a subspecialty in internal medicine, are more likely to serve in the hospital, and therefore medical centers and regional hospitals have larger impacts on having internists than on having family medicine specialists.

The results in pediatrics and ENT share several aspects in common. Their spatial autocorrelations are negative in high quantiles but positive in low quantiles. This implies that these specialists are clustered in low-density areas (L-L) rather than in high-density areas. Such a distribution is concerning because residents in many medically deficient townships cannot access these specialist care unless going for a long distance. The share of the young population increases for pediatricians only at high quantiles, but the share of the elderly population decreases for both pediatricians and ENT doctors at all quantiles. As an alarming sign, the results imply that the elderly population could lack specialty care services to fulfill their higher demand for internal medicine, family medicine, pediatrics, and ENT as population aging advances.

General practitioners in Taiwan are unique in that a large proportion of physicians in general medicine are new medical graduates who are in their post-graduate training years or are in residency but have yet to receive their specialist qualifications. In either case, they are working in teaching hospitals, which are usually large hospitals such as medical centers or regional hospitals, or in underserved areas, such as the mountain townships, which thanks to Taiwan's government-sponsored medical education and physician training program. Therefore, we see negative autocorrelation only at very high quantiles and positive autocorrelation at all other quantiles. While the government-sponsored physician training program has made great contributions in balancing physician care resources among areas, providing enough incentives for the participants to stay long in underserved areas remains challenging.

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台灣醫師分佈剖析: 空間分量迴歸分析

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近年來醫學系的擴張已顯著提升台灣醫師總量。文獻顯示增加醫師總量未必改善吉尼係數或其他指標衡量的醫師分配不均度。然而本文使用分量迴歸模型結合空間滯後效果顯示, 台灣自 2010 年起醫師總數增加對低分量的鄉鎮醫師密度改善程度較大。即便吉尼係數顯示不均程度加重, 研究結果顯示醫師分佈已移往醫療相對匱乏地區, 因此改善了此地區的醫療可近性。總體看來, 老年人口比、所得中位數、擁有醫學中心對高分量醫師密度有較大的正向影響。相反的擁有區域醫院則對低分量有較大的正向影響。這顯示區域醫院對改善醫師服務的分配不均有較大的政策意義。

關鍵詞: 醫師分佈, 替代變數分量迴歸, 空間相依度 , 空間滯後模型
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