

厚生労働科学研究費補助金（政策科学総合研究事業（統計情報総合研究））  
研究報告書

空間統計を用いた医療資源の地理的分布の分析

研究協力者

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【研究要旨】

近年医療資源、特に人的資源である医師数の需給不均衡が社会問題となっており、これまでに医師の需要・供給両面からの調査研究がおこなわれてきた。医師の供給について診療科に着目した医師のキャリアパスと将来推計に関する研究では、今後総医師数は増え続けると予測されているが、喫緊の課題となっているのは医師をはじめとした各種医療資源の地域偏在である。今回の研究では、空間統計をベースとした基礎的な手法を行い、各医療資源の地域偏在に関する指標を算出し、現状を分析した。

平成 22 年度の医師歯科医師薬剤師調査、平成 23 年度の医療施設静態調査の二次データを用い、地域間の不平等度を示すための指標として、ジニ係数、空間的自己相関の指標として *moran* の I 統計量を、一次医療圏単位、二次医療圏単位で算出し、散布図にした。

ジニ係数については、どの医療資源も一次医療圏よりも二次医療圏のほうが低く、二次医療圏の不平等度のほうが低いという結果であった。特に地域に密着すべき、プライマリケアに関連性の強い医療資源に関しては、一次医療圏レベルでの不平等度を改善するべきであると考えられる。*moran* については、一次医療圏よりも二次医療圏のほうが低いもの、一次医療圏よりも二次医療圏のほうが高いもの、同様の傾向を示すもの、の 3 パターンが見られた。

一次医療圏と二次医療圏で各医療資源はジニ係数について同様の傾向が見られる一方で、空間的自己相関を示す *moran* は各医療資源でいくつかのパターンが存在した。量的な不平等度だけでなく、空間的な集積性にも着目し、医療資源の適正配置を考慮する必要が示唆された。

A. 研究目的

近年医療資源、特に人的資源である医師数の需給不均衡が社会問題となっており、これまでに医師の需要・供給両面からの調査研究がおこなわれてきた。平成 4 年度厚生科学研究費補助金による「新たな医師需給の予測に関する研究報告」では平成 12 年には約 15000 人、平成 27 年には約 19000

人の医師が過剰になると報告されており、1990 年代初頭までは医師過剰という風潮から医師需給不均衡は社会問題として表面化していなかった経緯がある。しかしその後、医師不足問題が深刻化していった背景から、文部科学省の「今後の医学部入学定員の在り方等に関する検討会」（2011 年 1 月 28 日）において、超高齢化社

会にどの医師が必要かということを含め、医師のキャリアパスを考慮すべきではないか、という点が重要課題として提起された。

これに関して、医師の供給について診療科に着目した医師のキャリアパスと将来推計に関する研究が行われてきた[1]。この研究では、医師・歯科医師・薬剤師調査のデータをもとに、診療科別医師数の将来推計を、多相生命表の原理を用いて行われている。多相生命表の原理を用いた医師数の将来推計は、各年次別の一年後にどの診療科になるかを表した移動確率を経験年数別・診療科別医師数に順次掛け合わせることで算定される。上記手法はその時点での条件が継続することを前提としているという点が方法論の限界として挙げられるが、各時点での状態間の変化をもとに将来推計をするためわずかな変化をも検知できる可能性があり、医師供給の全体像を把握することができると考えられている。上記研究によると、今後総医師数は増え続けると予測されている。また、2008年に医学部定員数増員を全国的に展開し医師養成数を増加させるという方針が明記された（安心と希望の医療確保ビジョン 2008年6月）政策的背景を鑑みても、総医師数は今後も増加傾向にあると想定される。

しかし医師数不足をめぐる状況で喫緊の課題となっているのは医師の診療科別の地域偏在である。医師総数を増やしても医師の地域偏在は改善されないという報告もある[2]。総医師数に関する政策のみならず、医師適正配置を目的とした政策が展開されるべきであり、そのためには、医師数をはじめとした医療資源がどのように地理的に偏在しているかを精緻に分析する必要がある。

今回の研究では、空間統計をベースとした基礎的な手法を行い、各医療資源の地域偏在に関する指標を算出し、現状を分析した。

## B. 研究方法

### 研究デザイン、使用データ

平成22年度の医師歯科医師薬剤師調査、平成23年度の医療施設静態調査の二次データを用い、横断的な分析を行った。

### 対象となる医師、医療資源

人口動態統計上死亡数の多い疾患と関連のある医療資源を今回の分析の対象とした。具体的には、急性期で最も死亡数の多い急性心筋梗塞、慢性期で死亡数の多い、腎不全、自殺、に着目した。これらに特に関連すると想定された医療資源として、以下の地理的な偏在について分析した。

#### ●医師（人口1000人当たり）

総医師数、循環器内科医（主たる診療科）、循環器内科専門医、腎臓内科医（主たる診療科）、腎臓専門医、透析専門医、精神科医（主たる診療科）

#### ●その他医療資源（人口1000人当たり）

心臓カテーテル施行施設数、冠動脈CT施設数、透析施設数、精神科在宅医療施設数、精神科救急医療施設数

### 使用する医療圏単位について

大きく分けて一次、二次、三次の医療圏があるが、医療資源の分布を考える際に、どの医療圏を解析単位として扱うかは重大な問題である。目安の一つとして、入院管理が必要か（二次医療圏）、プライマリケアなどの日常的な臨床と接点があるべきか（一次医療

圏)、という切り口が考えられる。今回は、一次医療圏と二次医療圏の両方の区分単位を用いて、各医療資源の分布を調べ、両医療圏単位での地理的な偏在の特性について分析した。

### 分析手法

地理的な偏在の程度を定量的に分析する指標として、以下の2つの方法が一般的な手法とされている。

#### a) 不平等度に関する指標

地域間の不平等度を示すための指標として、ジニ係数があげられる。ジニ係数は、値が1に近づくほど地域間の不平等の度合いが高く、0に近いほど地域間の平等の度合いが高いことを示す尺度として用いられる。

#### b) 空間的偏在に関する指標

空間データの大きな特徴の一つに、空間的自己相関が挙げられる。空間的自己相関とは、距離が近いほど物事の性質が似る傾向にあるという性質である。データの全体的な空間的自己相関の有無に関する指標としては、moranのI統計量が知られている。moranの値が1に近いとき、正の自己相関の存在を示唆し、逆に-1に近いときは負の自己相関の存在を示唆する。

今回の研究では、これらの記述統計量をもとに、現状の医療資源の集積に関する考察を行った。ジニ係数をx軸に、グローバルmoran統計量をy軸とした散布図を作成した。

## C. 研究結果

### 1. 医師数に関して

図1が、各医師数の地理的偏在についてのジニ係数とmoranの散布図である。全体的に、一次医療圏よりも二次医療圏のほうがジニ係数は低く、二次医療圏の不平等度のほうが低い傾向が見られた。また、各医療圏でのジニ係数の順位はほぼ同じであった。総医師数、循環器内科医、循環器専門医では、一次医療圏でmoranが高いのに対し、二次医療圏でmoranが低く、精神科医では、一次医療圏でmoranが低いのに対し、二次医療圏でmoranが高いという結果であった。腎臓内科医師、透析専門医、腎臓内科専門医は両医療圏で同様のmoranを示していた。

### 2. その他医療資源について

図2が、各医療資源数の地理的偏在についてのジニ係数とmoranの散布図である。図1と同様、一次医療圏よりも二次医療圏のほうがジニ係数は低い傾向にあり、その順位はほぼ同じであった。

精神科在宅、精神科救急、透析施設では一次医療圏でmoranが低いのに対し、二次医療圏でmoranが高いという結果であった。心臓カテーテル施設、冠動脈CTに関しては、ほぼ同じmoranを示していた。

## D. 考察

ジニ係数については、どの医療資源も一次医療圏よりも二次医療圏のほうが低く、二次医療圏の不平等度のほうが低いという結果であった。入院過程関連した医療資源に関しては、二次医療圏単位で医療提供体制がもともと設定されているものもあるため、それが原因であると考えられる。一方で、精神科や精神科在宅医療施設などは、地

域に密着すべき、プライマリケアに関連性の強い医療資源であるため、一次医療圏レベルでの不平等度も改善すべきであると考えられる。

moran については、一次医療圏よりも二次医療圏のほうが低いもの、一次医療圏よりも二次医療圏のほうが高いもの、同様の傾向を示すもの、の3パターンが見られた。一次医療圏で moran が高いのに二次医療圏で moran が低いというのは、二次医療圏単位ではあまり空間的な自己相関がないが、二次医療圏の内部で医療資源が偏って存在しているということを意味する。そのため、この傾向を示した医療資源については、同じ二次医療圏に属していても、実質的にはアクセスに差が生じている可能性がある。二次医療圏を基準として医療資源の量を設定しているものに対しては、量だけでなく、アクセスへの距離なども考慮して提供体制を考える必要が示唆される。一次医療圏で moran が低い二次医療圏で moran が高いというのは、二次医療圏単位では空間的自己相関があるが、二次医療圏内部ではランダムに医療資源が散らばっているということを意味する。このような特徴を示した医療資源に関しては、同じ二次医療圏に属していれば、同様のアクセスを得られるかもしれないが、そもそも二次医療圏でクラスターが生じているため、その医療資源が多い地方、少ない地方が存在していることになる。このような特徴を示した医療資源に関しては、各地方で平等に医療資源が行

き届くような量的な調整が重要かもしれない。

#### E. 結論

一次医療圏と二次医療圏で各医療資源はジニ係数について同様の傾向が見られる一方で、空間的自己相関を示す moran は各医療資源でいくつかのパターンが存在した。量的な不平等度だけでなく、空間的な集積性にも着目し、医療資源の適正配置を考慮する必要が示唆された。

#### 【参考文献】

- [1] S. Koike et al, "Estimation of physician supply by specialty and the distribution impact of increasing female physicians in Japan." BMC Health Serv. Res., vol. 9, p. 180, Jan. 2009.
- [2] Y. Kobayashi et al, "Geographic distribution of physicians in Japan." Lancet, vol. 340, no. 8832, p. 1391, Dec. 1992.

#### F. 健康危険情報

なし

#### G. 研究発表

1. 論文発表等

なし

2. 学会発表等

なし

#### H. 知的財産権の出願・登録状況

なし

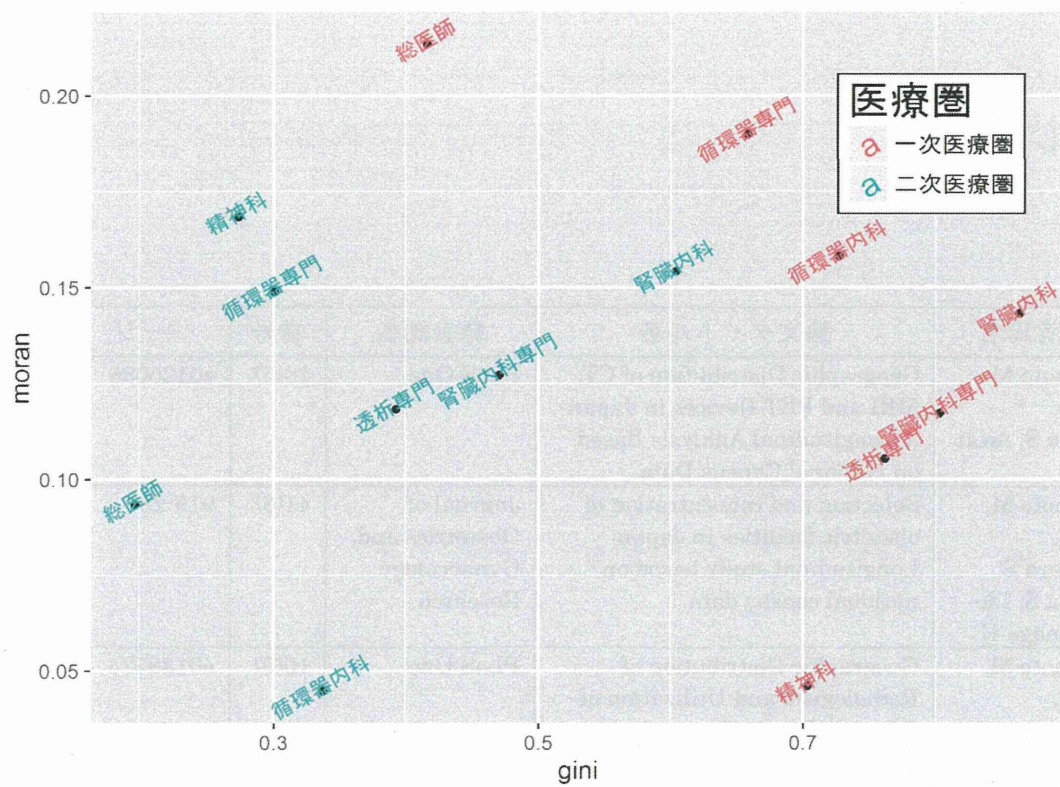


図 1:各医師数のジニ係数と moran

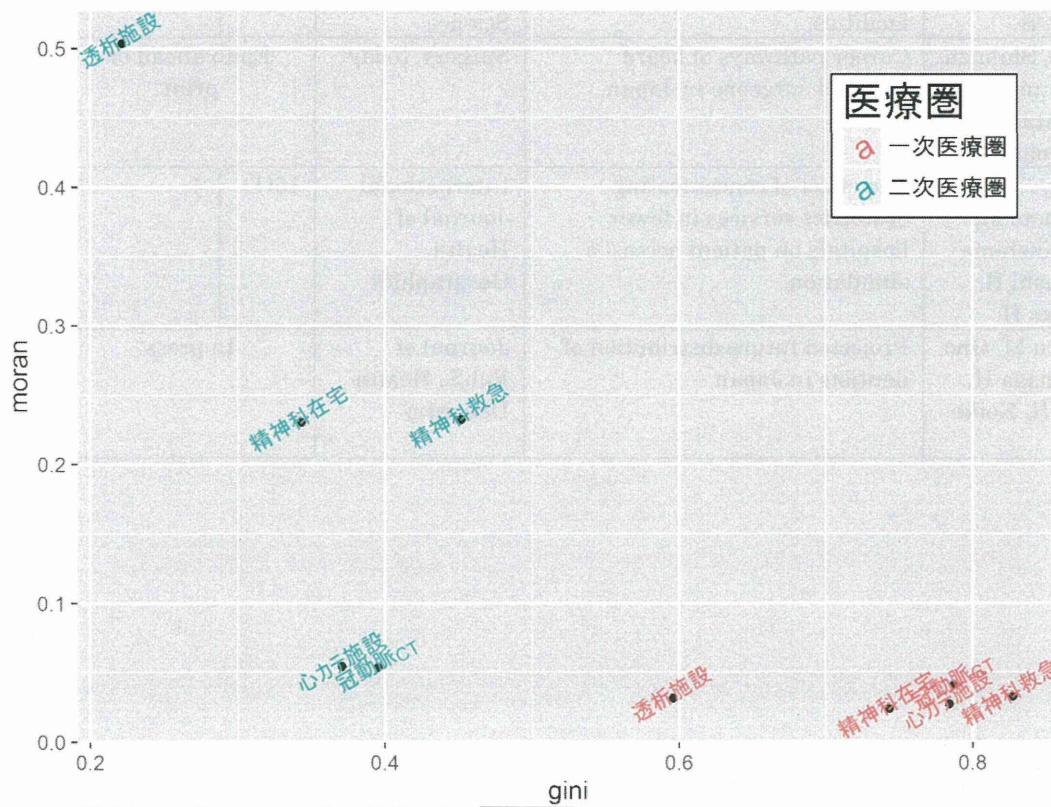


図 2:各医療資源のジニ係数と moran

### Ⅲ. 研究成果の刊行に関する一覧表

書籍

該当なし

雑誌

発表者氏名	論文タイトル名	発表誌名	巻号	ページ	出版年
Matsumoto M, Koike S, Kashima S, Awai K.	Geographic Distribution of CT, MRI and PET Devices in Japan: A Longitudinal Analysis Based on National Census Data.	PLoS One	10(5)	e0126036	2015
Matsumoto M, Koike S, Matsubara S, Kashima S, Ide H, Yasunaga H.	Selection and concentration of obstetric facilities in Japan: Longitudinal study based on national census data.	Journal of Obstetrics and Gynaecology Research	41(6)	919-25	2015
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RESEARCH ARTICLE

# Geographic Distribution of CT, MRI and PET Devices in Japan: A Longitudinal Analysis Based on National Census Data

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**Competing Interests:** The authors have declared that no competing interests exist.

## Abstract

### Background

Japan has the most CT and MRI scanners per unit population in the world; however, the geographic distribution of these technologies is currently unknown. Moreover, nothing is known of the cause-effect relationship between the number of diagnostic imaging devices and their geographic distribution.

### Methods

Data on the number of CT, MRI and PET devices and that of their utilizations in all 1829 municipalities of Japan was generated, based on the Static Survey of Medical Institutions conducted by the government. The inter-municipality equity of the number of devices or utilizations was evaluated with Gini coefficient.

### Results

Between 2005 and 2011, the number of CT, MRI and PET devices in Japan increased by 47% (8789 to 12945), 19% (5034 to 5990) and 70% (274 to 466), respectively. Gini coefficient of the number of devices was largest for PET and smallest for CT (p for PET-MRI difference <0.001; MRI-CT difference <0.001). For all three modalities, Gini coefficient steadily decreased (p for 2011-2005 difference: <0.001 for CT; 0.003 for MRI; and <0.001 for PET). The number of devices in old models (single-detector CT, MRI<1.5 tesla, and conventional PET) decreased, while that in new models (multi-detector CT, MRI≥1.5 tesla, and PET-CT) increased. Gini coefficient of the old models increased or remained unchanged (increase rate of 9%, 3%, and -1%; p for 2011-2008 difference <0.001, 0.072, and 0.562, respectively), while Gini coefficient of the new models decreased (-10%, -9%, and -10%; p for 2011-2008 difference <0.001, <0.001, and <0.001 respectively). Similar results were observed in terms of utilizations.

## Conclusions

The more abundant a modality, the more equal the modality's distribution. Any increase in the modality made its distribution more equal. The geographic distribution of the diagnostic imaging technology in Japan appears to be affected by spatial competition derived from a market force.

## Introduction

Japan currently has the most diagnostic imaging devices in the world. The number of computed tomography (CT) scanners per 100,000 population is 101, which is, by far, the largest among those of the Organisation for Economic Co-operation and Development (OECD) countries (Australia, with 44, is a distant second). The number of magnetic resonance imaging (MRI) scanners per 100,000 in Japan, which is 48, is also the largest among the OECD countries [1]. Despite this knowledge of device numbers, the geographic distribution of these technologies within the country is largely unknown. Few studies on their geographic distribution currently exist for any country, let alone Japan [2], despite the abundance of studies on the adoption of these technologies [3–7].

Theoretically competition shapes the distribution. In a free market, service suppliers pursue the maximization of profit. Hence, the geographic distribution of services is affected by this market force. This is the basis of the spatial competition model [8,9]. More specifically, spatial competition is an economic model in which the quantity of a service resource determines its distribution. In this model, when few service resources or suppliers exist, the distribution is skewed to cities with large populations in which the maximal profit is expected. However, an increase in service resources increases the competition for profit in the large cities. This can relocate the service resource towards smaller cities, with the result of improved equity in service distribution (the spatial competition effect) [8].

The spatial competition model is an attractive framework for considering the relationship between the amount of medical resources and its geographic distribution. However, the distribution of human resources for health, such as physicians, reportedly does not fit the prediction of this hypothesis. Even a substantial increase in the number of physicians did not improve the equity of the urban-rural distribution [10–12].

The distribution of material resources, such as diagnostic imaging devices, however, may be different from that of human resources, because, unlike humans, materials do not have the “preference for urban areas;” this preference is known to have a strong impact on human resource distribution [13–15]. The extent to which the spatial competition force influences the distribution of material resources, however, is currently unknown.

If spatial competition holds in diagnostic imaging devices, the devices would first be adopted in large cities. With an increase in numbers and subsequent competition in the large cities, they would then spread out to the smaller cities. In Japan, the first CT scanners were available in clinical practices in the 1970s; these were then followed by MRI scanners in the 1980s and positron-emission tomography (PET) scanners in the first decade of the 2000s [16,17]. Thus, PET can be regarded as being in the early state of adoption, MRI in the middle, and CT in the late stage. Thus, it is possible, in Japan, to test whether different modalities in different adoption stages illustrate different levels of equity in their distribution.

Japan is also well suited to testing the spatial competition hypothesis with regard to diagnostic imaging devices for other reasons. One of these reasons is that the entire population is

covered by public health insurance, while most medical institutions, whether they be private or public, are run by profits from their practice [18]. The fee schedule for diagnostic imaging services is the same across the nation and medical institutions profit from patients' out-of-pocket expenditures and reimbursements from public insurance. Although there are several types of insurers in Japan, the extent of services covered is uniform across the insurers. Thus there is no geographic inequity in the power to create demand for the imaging services. The second reason is because an extensive number of diagnostic imaging devices are traded every year, as the device market is large and mature in Japan. The third reason is that there is no regulation for medical institutions with regard to purchasing medical equipment [17]. As such, any hospital or clinic in any location can purchase or rent imaging devices if it can afford them. In this way, the national and local governments do not put a regional cap on the number of devices. For these reasons, it is assumed that the distribution of diagnostic imaging devices is more likely to be influenced by the market force and demand distribution in Japan, than in other countries.

Consequently, the primary purpose of this investigation is to illustrate the trend in the distribution of diagnostic imaging devices in Japan. The second purpose is to show that the geographic distribution of the devices follows a spatial competition model, by showing the association between the number of CT, MRI and PET scanners and their distributions in Japan.

## Materials and Methods

### Device data

Japan has three levels of government: municipal, prefectural and national. Data analyzed pertained to the number and use of CT, MRI and PET scanners in each of Japan's 1829 municipalities (city, town and village). The CT, MRI and PET were chosen because they are representative of current diagnostic imaging modalities, are commonly used for scanning the entire body, and vary greatly in the timing of being available and in the amount of devices available.

Unpublicized individual data were obtained from the Static Survey of Medical Institutions that was conducted in 2005, 2008 and 2011. Permission to use the data for research was obtained by the Ministry of Health, Labour and Welfare. The Static Survey of Medical Institutions is conducted by the Ministry every three years. All clinics and hospitals in Japan are required, by national law, to report their activities and resources in the survey; the capture rate of the data in the survey was estimated, based on childbirth data, to be 91.8% in 2005, 93.8% in 2008, and 92.3% in 2011 [19]. Data on the number of CT, MRI and PET scanners in each hospital or clinic on October 1 of the year was used. Data on the number of utilizations in September of each year for CT, MRI and PET was also used. CT was classified into multi- and single-detector CT in the 2008 and 2011 survey. MRI was classified into as with  $<1.5$  and  $\geq 1.5$  tesla; PET was classified as conventional PET and PET-CT in the 2008 and 2011 data. The information on the device versions was not available in the 2005 dataset. The 2011 survey did not cover all of the facilities in Fukushima and some of the facilities in Miyagi prefecture, because of the Great East Japan Earthquake. For this reason, data in these areas was deleted.

### Municipality data

The municipality population in 2012 was extracted from the Statistical Observations of Shi Ku, Machi, Mura 2013, which was published by the Statistics Bureau, Ministry of Internal Affairs and Communications [20]. The institution-based device data mentioned previously was connected to this municipality-based population data through the municipality code. Mergers

changed the number of municipalities in Japan between 2005 and 2011, and so the 2012 municipality classification was applied to the 2005, 2008 and 2011 data.

### Statistical analysis

To obtain the transition of the number of devices, the number of devices and utilizations (performed cases) in the entire country in each year was calculated. To examine the geographic distribution of the devices, the municipalities ( $n = 1829$ ) were classified into three types: “metropolis”, “city”, and “town/village”. “Metropolis” includes all of the wards (*ku*) of the ordinance-designated cities (*seirei-shitei-toshi*) and 23 special wards of Tokyo ( $n = 193$ ). “City” includes the other cities (*shi*) ( $n = 752$ ); “town/village” includes towns (*cho*) and villages (*son*) ( $n = 884$ ). An ordinance-designated city (*seirei-shitei-toshi*) has a population greater than 500,000, which is expected to reach the 1,000,000 mark in the near future. A city (*shi*) has a population greater than 50,000. Consequently, the number of devices and their utilizations per 100,000 population in each municipality type was calculated using the data of the total number of devices or utilization and the total population in the group of municipalities.

To evaluate the inter-municipality equity of the number of devices per unit population, the Gini coefficient was calculated. The Gini coefficient is the most popular parameter of income equity. It has been used extensively in the health-related literature, in which the inter-community, or inter-facility equity of resources, have been evaluated [2,11,21–26]. In this study, we regard the imaging device as the “wealth” of the municipality and illustrate the disparity of wealth among the municipalities using the Gini coefficient. In the calculation of the Gini coefficient, all of the 1829 municipalities were ranked by the number of devices per 100,000 population. Each municipality was plotted onto the plane of coordinates with its x-axis being the cumulative proportion of the population and the y-axis being the cumulative proportion of the devices. The plotted line is the Lorenz curve; the Gini coefficient is the area between the Lorenz curve and the 45 degree line, which is divided by the triangle under the 45 degree line [11,24]. The Gini coefficient ranges from 0 (complete equity) to 1 (complete inequity), according to the variation in the number of devices per 100,000 population among the municipalities. A similar procedure was conducted for the number of utilizations. A significance test was conducted to examine the difference in the Gini coefficient between devices and between years. This was accomplished by calculating the bootstrapped standard errors for the Gini coefficient [27].

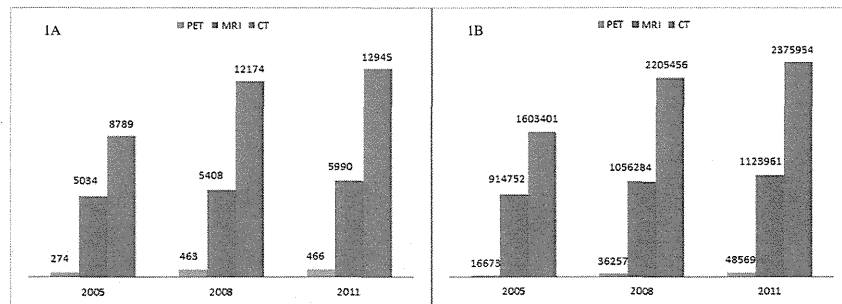
All but one of these statistical analyses were conducted using SPSS version 21 (IBM-SPSS Japan, Tokyo); the calculation of the Gini coefficients and the significance test for their differences were conducted with STATA software (version 12, College Station, TX, USA). All the maps shown in Results were created using ArcGIS version 10.0 (ESRI Japan Inc.).

### Ethics Statement

The Ethics Committee of the Graduate School of Medicine and Faculty of Medicine at the University of Tokyo has assessed and given permission for this study (assessment number 10128). The Ethics Committee for Epidemiological Research at Hiroshima University agreed to this permission (assessment number 838).

### Results

The transition of the number of devices and utilizations is shown in Fig 1. Between 2005 and 2011, the number of devices and utilizations in each modality increased. The increase in the devices and utilizations is largest in the PET (70 and 191%); this was followed by the CT (47% and 48%) and MRI (19% and 23% respectively). The transition of the number of devices, and that of utilizations for each subtype of modality, is illustrated in Table 1. The number of



**Fig 1. Number of devices (1A) and utilizations (1B) of CT, MRI and PET.** The number of utilizations is drawn from September of each year.

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devices, and that of utilizations for older models (i.e. single-detector CT, MRI < 1.5 tesla, and conventional PET), have decreased; those for newer models (i.e. multi-detector CT, MRI ≥ 1.5 tesla, and PET-CT) increased. This indicates that old models were increasingly replaced by newer ones.

Distributions of the number of devices and utilizations per 100,000 population among the municipalities in 2011 are shown in Fig 2. Disparity was observed in the distributions of all three modalities. In particular, PET was concentrated in some limited areas, while most of the municipalities did not possess it.

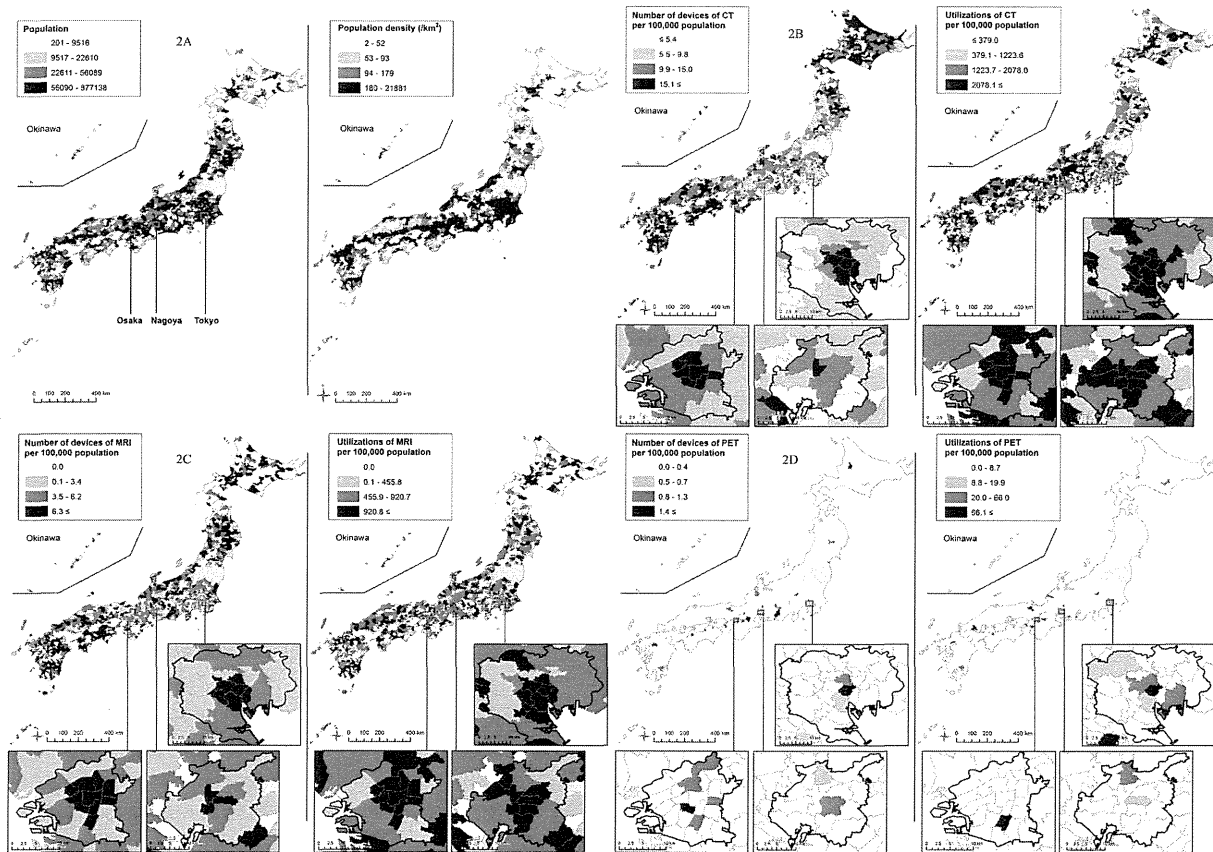
The transition of the number of devices and of utilizations per 100,000 population by municipality type is illustrated in Figs 3 and 4. CT scanners were widespread among the municipalities, but the distribution was biased toward smaller municipalities, such as towns and villages, rather than toward metropolises. In contrast, the number of MRI scanners was higher in larger municipalities. The distribution of PET scanners was even further skewed to larger municipalities. The rate of increase of PET scanners was larger in the larger municipalities, while the increase rates of the MRI and CT scanners were not largely different among the municipality types. Compared with the distributions of devices, those of utilizations of all the three modalities were biased toward larger municipalities, which can also be observed in Fig 2 (particularly in expanded metropolises). The rate of increase in PET utilizations was larger in the larger municipalities, while the increase rates of the MRI and CT utilizations were not so different among the municipality types. For both the number of devices and utilizations, disparity among the metropolis, city and village was larger in PET than in the CT or MRI.

The transition of the Gini coefficient for each modality is shown in Fig 5A (device) and 5B (utilization). Lorenz curves are shown as supporting information in S1 (device) and S2 Figs

**Table 1. Number of devices and utilizations classified by device version.**

		Number of devices			Number of utilizations		
		2008	2011	Change (%)	2008	2011	Change (%)
CT	Single-detector CT	6231	4598	-26.2	409647	190920	-53.4
	Multi-detector CT	5943	8347	40.5	1795809	2185034	21.7
MRI	MRI < 1.5 tesla	2635	2529	-4.0	316631	260950	-17.6
	MRI ≥ 1.5 tesla	2773	3461	24.8	739653	863011	16.7
PET	PET	199	117	-41.2	7085	6601	-6.8
	PET-CT	236	349	47.9	12850	41968	226.6

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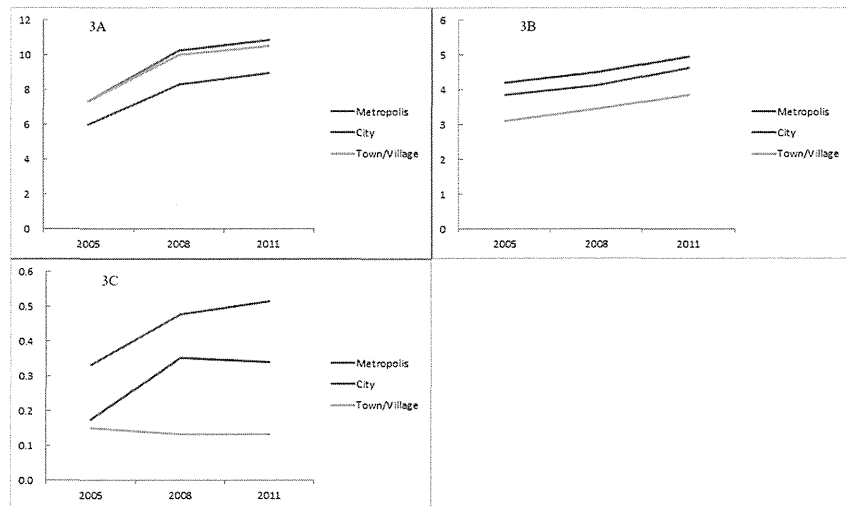


**Fig 2. Population, population density (2A), number of devices, and number of utilizations of CT (2B), MRI (2C) and PET (2D) in each municipality in 2011.** Quartile points of all values were used as cut-offs for color change except for PET in which quartile points of values excluding zero were used.

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(utilization). The Gini coefficient of the number of devices was largest in PET and smallest in CT for any year ( $p$  for PET-MRI difference in 2008:  $<0.001$ ;  $p$  for MRI-CT difference:  $<0.001$ ). This indicates greater equity in the distribution of CT scanners than that of MRI or PET scanners. For all three modalities, the Gini coefficient constantly decreased for the six years ( $p$  for 2011–2005 difference:  $<0.001$  in CT; 0.003 in MRI; and  $<0.001$  in PET). This means an increasingly equitable distribution in all modalities. The decrease was largest in CT (16%), followed by PET (12%) and MRI (4%). The Gini coefficient of the number of utilizations illustrated a similar trend. The Gini coefficient of utilizations was largest in PET, followed by MRI and CT ( $p$  for PET-MRI difference in 2008  $<0.001$ ,  $p$  for MRI-CT difference  $<0.001$ ). It did decrease ( $p$  for 2011–2005 difference  $<0.001$  for CT; 0.003 for MRI; and  $<0.001$  for PET) and its decrease was largest in CT (16%), followed by PET (9%) and MRI (4%).

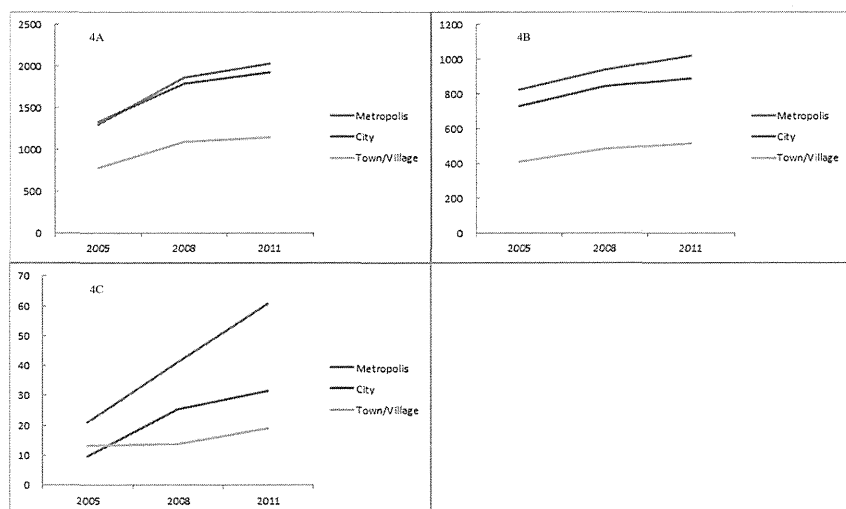
Fig 6 shows the transition of the Gini coefficient of each model with regard to the number of devices. Lorenz curves are shown as supporting information in S3 (old) and S4 (new models) Figs Both in the old and new models, the Gini coefficient was higher for the model whose number of devices was lower ( $p$  for difference between conventional PET and MRI  $<1.5$  tesla  $<0.001$ , that between MRI  $<1.5$  tesla and single-detector CT  $<0.001$ ; that between PET-CT and MRI  $\geq 1.5$  tesla  $<0.001$ , that between MRI  $\geq 1.5$  tesla and multi-detector CT  $<0.001$ ). For



**Fig 3. Number of devices of CT (3A), MRI (3B), and PET (3C) per 100,000 population, classified by municipality type.** "Metropolis" includes all the wards (*ku*) of the ordinance-designated cities (*seirei-shitei-toshi*), as well as 23 special wards of Tokyo ( $n = 193$ ). "City" includes the other cities (*shi*) ( $n = 752$ ); "town/village" includes towns (*cho*) and villages (*son*) ( $n = 884$ ).

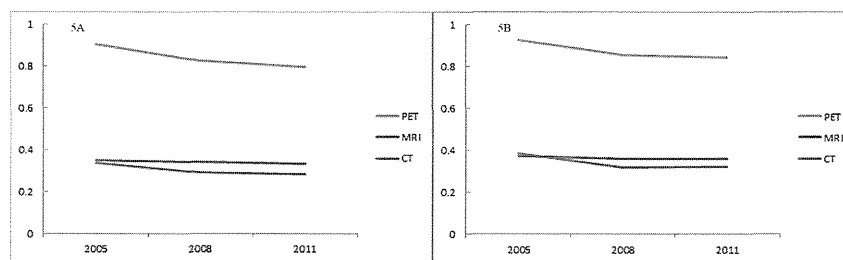
doi:10.1371/journal.pone.0126036.g003

the three years, the Gini coefficient of old models (single-detector CT, MRI < 1.5 tesla, and conventional PET) either increased or remained unchanged (increase rate 9%, 3%, and -1% respectively;  $p$  for 2011–2008 difference < 0.001, 0.072, and 0.562 respectively). In contrast, the Gini coefficient of new models (multi-detector CT, MRI  $\geq$  1.5 tesla, and PET-CT) decreased (increase rate -10%, -9%, and -10% respectively;  $p$  for 2011–2008 difference < 0.001, < 0.001, and < 0.001 respectively).



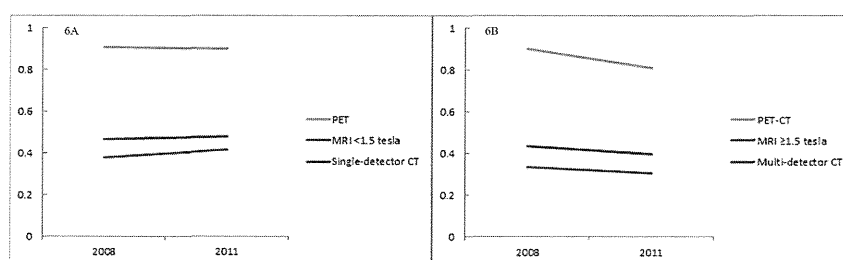
**Fig 4. Number of utilizations of CT (4A), MRI (4B), and PET (4C) per 100,000 population, classified by municipality type.**

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**Fig 5. Gini coefficient of the number of devices (5A) and utilizations (5B).**

doi:10.1371/journal.pone.0126036.g005



**Fig 6. Gini coefficient of the number of older devices (6A) and newer devices (6B).**

doi:10.1371/journal.pone.0126036.g006

## Discussion

The results of this study illustrated that there was substantial disparity in the geographic distribution of diagnostic imaging devices in Japan. The more abundant the modality, the more equal its distribution. Increasing the number of devices or utilizations improved the equity of the distribution. Old models, which decreased in number and were less used, showed an increasingly unequal distribution, while new models, which increased in number and were used more, were distributed more equally than before.

According to the spatial competition model, a scarce resource, such as PET, highly concentrates in large cities; this creates a very unequal distribution against the population. In contrast, the distribution of an abundant resource, such as CT, becomes fairly equal against the population. An increase in the amount of resources raises the equality of its distribution, while a decrease in resources, just like that of the old models of the devices, reduces the equality. All of these predictions were observed in the results. Thus, the results suggest that the relationship between the amount and the distribution of technology resources is influenced by spatial competition.

Among all of the types of service resources, the geographic distribution of physicians has been most extensively studied. In Japan, the number of physicians per unit population has increased by 70% over the past 30 years. That being said, the equity of their geographic distribution has remained unchanged [10–12,28–30]. A similar trend was observed in the United States [10,31]. The geographic distribution of physicians thus does not appear to follow the spatial competition model. Some of the proposed reasons for this are the physician's preference for urban areas and urban-rural imbalance of the physician's background [14,32,33]. Material resources do not have such elements. Thus, the distribution of diagnostic imaging devices is



supposed to be influenced more directly by market forces than that of human resources. Hospitals and clinics in Japan, whether located in urban or rural areas, can possess diagnostic imaging devices if there is sufficient demand and if the institutions can afford to rent or buy them. This factor would separate the distribution pattern between human and material resources.

As illustrated in Figs 3 and 4, the distribution of CT devices was skewed to rural municipalities, while that of CT utilizations was biased towards urban municipalities. This gap may be caused by the unique health care environment in Japan. Japanese health care is a combination of public and private institutions. The proportion of public institutions is higher in the rural areas, than in the urban areas [34]. Public medical institutions are run by profit from their practice, as well as with a local or national governmental budget. In addition, public and private medical institutions in rural areas can purchase equipment with the help of state subsidies. Thus, a rural medical institution is probably more likely to possess expensive diagnostic imaging devices than an urban institution if the expected profits gained from using the devices are the same [35]. This can increase the number of imaging devices in rural areas, particularly devices usable at primary care facilities, such as CT, while their utilizations are relatively small.

## Limitations

The financial protection policy for rural medical institutions potentially influenced the snapshot distribution of the devices in each year. This can lead to an overestimation of the spatial competition effect at each time point by biasing the distribution toward rural areas. In this sense, a comparison of the Gini coefficients among CT, MRI and PET at a certain time needs attention. However, the longitudinal change of the equity of the distribution, in response to the change in the amount of the devices, which is the primary reason for the existence of spatial competition, is not affected by this policy.

The rural protection policy could also be reflected in the distribution pattern of the subtypes of the modalities. As shown in the results, the number of new models of CT, MRI and PET increased and spread increasingly to small municipalities, while the number of old models decreased and their distributions gravitated towards large municipalities. This suggests that the replacement of old models with new ones, or the installation of new models in addition to conventional ones, are more common in rural than in urban areas in Japan.

MRI, and PET, in particular, cannot be placed in rural facilities without full-time radiologists, because the use of this equipment requires highly specialized knowledge. In Japan, most institutes with PET scanners only perform  $^{18}\text{F}$ -Fluorodeoxyglucose ( $^{18}\text{F}$ -FDG)-PET examinations and use  $^{18}\text{F}$ -FDG compounds delivered from commercially available PET laboratories. Because the half-life period of  $^{18}\text{F}$ -FDG is about 110 minutes, institutions using delivery  $^{18}\text{F}$ -FDG compounds must be located close to the PET laboratories. When comparing the equity of the distribution among CT, MRI and PET, both the spatial competition effect and these factors should be taken into account.

The number of utilizations in this study is for only one month, which is less reliable than the annual number. In addition, the CT data in the Static Survey of Medical Institutions in 2005 is not that of all types of CT, but only that of helical CT. Thus, it needs attention when 2005 CT data is compared with CT data in other years. However, by 2005, most of the conventional CT scanners were presumably replaced by the helical model in Japan. Thus, we consider that the difference between our data and the real number of CT scanners was small.

The nature of the Gini coefficients is also an issue. The Gini coefficient is most sensitive to the shape of the middle part of the Lorenz curve [21,36]. In our data, most municipalities did not possess PET. As such, the Lorenz curve of PET is a flat line in the low to middle part of the spectrum, rather than a true curve. In this situation, inequity illustrated by the Gini coefficient

may be overestimated, as compared with that of CT and MRI. In addition, the Gini coefficient can only be interpreted relatively, because there is no clear definition of a low or high value.

## Conclusions

A reasonable allocation of medical resources, based on the distribution of demand, is one focus of political interventions. The uneven distribution of human resources, such as physicians, is a worldwide problem. Consequently, numerous policies, sometimes using state power and a substantial budget, have been implemented to address this issue [33,37,38]. Although advanced medical equipment, such as MRI and PET, should be allowed to be concentrated in large cities because of its scarcity, devices which are regarded in Japan as tools for primary care, such as X-ray machines and CT, need to be distributed equally. The distribution of diagnostic imaging devices seems to be directly influenced by the invisible hand of the market, and thus is more likely to be optimized by an increase in numbers as compared with the distribution of human resource. Hence, we recommend, with regard to devices that need to be distributed fairly, that political priority be placed on securing resources in the right quantities, instead of in the allocation of resources.

## Supporting Information

**S1 Fig. Lorenz curves of the number of CT, MRI, and PET devices.**  
(TIF)

**S2 Fig. Lorenz curves of the number of CT, MRI, and PET utilizations.**  
(TIF)

**S3 Fig. Lorenz curves of the number of single-detector CT, MRI < 1.5 tesla, and conventional PET devices.**  
(TIF)

**S4 Fig. Lorenz curves of the number of multi-detector CT, MRI  $\geq$  1.5 tesla, and PET-CT devices.**  
(TIF)

## Author Contributions

Conceived and designed the experiments: MM SKo SKa KA. Analyzed the data: MM SKa.  
Wrote the paper: MM SKo SKa KA.

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