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Factor Decomposition of Inter-prefectural Health Care Expenditure Disparities in Japan

Masayoshi Hayashi
The University of Tokyo

Akiko Oyama
Dai-ichi Life Insurance Company

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Masayoshi Hayashi [a]

Akiko Oyama [b]

Abstract

Despite frequent discussions on regional variations in health care expenditure (HCE), few studies account for the sources of such regional disparities. This study bridges this gap in the literature by taking the following two steps. First, we explore the determinants of regional HCE in Japan, covering a data period that expands the scope of previous studies (i.e., the 2000s). Second, we decompose the variations in regional HCE into contributions explained by the HCE determinants examined in the first step, utilizing a regression-based decomposition method. In the regression analysis, we find that the effect of the number of hospital beds on per capita HCE is larger than that of the other determinants, except the proportion of the elderly population. In particular, a 1% increase in the number of hospital beds induces a .22–.43% increase in HCE, in line with Roemer's Law. The decomposition analysis also finds the salient effect of the number of hospital beds. In particular, this variable accounts for a large proportion of inequality (between 37.6% and 83.9%). This finding also corroborates Roemer's Law. Our results strongly suggest that the national policy in Japan of reducing hospital beds regionally has been an effective instrument for containing rapidly increasing HCE.

Keywords*: regional health care expenditure, regression-based inequality decomposition, Japan*

JEL Classification*:* I18, I14, H51, H73

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[a] Faculty and Graduate School of Economics, University of Tokyo, Japan.

[b] International Operations Division, Dai-ichi Life Insurance Company, Tokyo. Japan. Oyama was a research fellow at the Policy Research Institute, the Japanese Ministry of Finance when this research was conducted.

1. Introduction

Per capita health care expenditure (HCE) shows a large degree of regional variation in many countries such as Finland (Häkkinen and Luoma 1995), Japan (Kawanobe and Ganryu 1999, Tokita et al. 2000), Spain (Cantarero 2005, Costa-Font and Rico 2006, Costa-Font 2010), and the United States (Welch et al. 1993, Skinner and Fisher 1997, Culter and Sheiner 1999, Hay 2003, Thornton and Rice 2008). Studies of this topic typically develop arguments from both equity and efficiency perspectives. For instance, one of the most important objectives of health care policy is equitable access to health care services (HCSs) regionally (Hingstman and Boon 1989, Mangano 2010, Fang et al. 2010, Shinjo and Aramaki 2012). Although such an objective may suggest increasing HCE in low-spending regions, equalizing per capita HCE does not necessarily lead to equitable access to HCSs. For example, if there are regional disparities in health care needs that are covered by the relevant HCSs, there naturally are corresponding disparities in per capita HCE even in the presence of equitable access to HCSs. To evaluate regional equity in HCS provisions, therefore, we should explore factors that affect regional HCE.

Similarly, arguments based on an efficiency perspective may call for equalizing HCE, but this time by decreasing HCE in high-spending regions. For example, the US Congressional Budget Office (2008) argues that "[l]arge differences across the country in spending for the care of similar patients could indicate a health care system that is not as efficient as it could be, particularly if that higher spending does not produce commensurately better care or improved health outcomes." In this regard, reforms designed to increase efficiency in HCS provision could reduce geographic variations in HCE. However, a reduction in HCE in high-spending areas may not necessarily increase efficiency and may even result in worsening health outcomes. In addition, if health care needs differed regionally, we would observe similar differences in per capita HCE—even if regional efficiency levels were the same. To examine efficiency in regional HCS provisions, therefore, we would again need to explore the determinants of regional HCE.

This line of argumentation implies that the simple equalization of regional HCE leads to neither equitable nor efficient allocations of HCS provisions. Therefore, to understand how to control HCE equitably *and* efficiently, we must identify factors that affect HCE and then estimate the magnitudes of their effects for a number of reasons. First, finding such HCE determinants would help evaluate regional HCE from an equity perspective. For example, since the study published by Newhouse (1977), the literature has explored the effect of regional income on HCE (Parkin et al. 1987, Murillo et al. 1993, Boungnarasy 2011, Kumar 2013). To achieve equity, HCSs should be distributed regionally according to medical needs, not regional wealth. If regional income continues to explain a large part of regional HCE, even after controlling for the other factors that affect such expenditure, we suspect that wealthier regions have higher levels of HCSs than less wealthy regions do. As a result, to the extent that there exist regional disparities in income, we regard cross-regional disparities in HCE as inequitable or "unjust" (Costa-Font 2010).

Second, finding HCE determinants could also help assess HCE disparities from an efficiency perspective. For example, Culter and Sheiner (1999) and Skinner and Fisher (1997) evaluate regional Medicare spending in the United States, showing that such expenditure varies significantly (15–20% of total Medicare spending) even after controlling for needs-related "demand-side" determinants. To explain inefficiency, "supply-side" determinants may thus be important, such as the number of hospital beds (Culter and Sheiner 1999). Several Japanese studies suppose that if an excess supply of HCSs exists, physicians tend to take advantage of information asymmetry to provide "unnecessary" services to their patients (Izumida et al. 1998, Kawanobe and Ganryu 1999, Tokita et al., 2000). This is a modern representation of the classical Roemer's Law, which postulates that "a built bed is a filled bed" (Roemer 1961).

It may also be important to identify the contributions of such determinants to regional variations in HCE in order to evaluate regional HCE disparities. Despite the rich literature on regional HCE determinants, authors are yet to quantify how these each account for regional HCE variations. This gap in the literature is surprising, as we are naturally expected to be interested in the sources of regional *disparities*. In this study, therefore, we aim to bridge this gap by taking the following two steps. In the first step, we expand the body of knowledge on this topic (see Izumida et al. 1998, Kawanobe and Ganryu 1999, Tokita et al., 2000) by exploring the determinants of regional HCE in Japan. In particular, and in contrast to earlier studies, our analysis covers the decade of the 2000s, which allows us to compare how the results change over time. In the second step, which is more important in terms of the novelty of the current study, we decompose the variations in regional HCE into the contributions explained by each of the HCE determinants examined in the first step. In so doing, we utilize the regression-based decomposition method proposed by Morduch and Sicular (2002) and Fields (2003), which is based on the work by Shorrocks (1982). Although regional analyses have previously applied the regression-based decomposition method to examine regional income inequality (Tsui 2005, Yu and Tsui 2005, Heng 2008, Costa-Font 2010), no studies—to our best knowledge—have thus far applied this method to analyze regional HCE. Indeed, the current study is one of the first attempts to identify the degree to which a specific HCE determinant explains the overall disparities in regional HCE. In so doing, we also examine how the degree of each contribution changes over time.

The rest of the paper is structured as follows. Section 2 summarizes the current state of the public health system in Japan. Section 3 presents HCE determinant studies by using Japanese prefectural data. Section 4 explains the regression-based decomposition method and applies it to regional HCE in Japan. Section 5 concludes with a summary of our findings.

2. Institutional Background

2.1. The health care system in Japan

The coverage of the Japanese system of public health insurance is universal.[1] As summarized in **Table 1**, public health insurance consists of two schemes designed for different population groups. The first is an occupation-based scheme called the Employees' Health Insurance (EHI), which covers employees and their dependents. The EHI is an umbrella term for three main programs. The first is those managed by health insurance associations set up by large firms (a firm that has more than 700 employees is eligible to establish its own association-managed health insurance (AMHI)). In addition, multiple firms can together form a single association if their combined number of employees exceeds 3000. The second is the programs managed by the Japan Health

[1] Those who receive public assistance are excluded from the public insurance system. Technically, those who fail to pay contributions to their public health insurance are also excluded from social insurance, but they are eventually helped through public assistance.

Insurance Association (JHIA) for the employees (and their family members) of private firms that do not have their own AMHI programs.[2] The JHIA also manages the Seamen's Insurance, which covers mariners and their family members. The third is the programs managed by mutual aid associations such as those for local and national government employees as well as teachers and employees at private schools.

The second type of public health insurance is the National Health Insurance (NHI), which consists of region-based programs managed by municipalities to cover those of their residents excluded from the EHI. The insured typically include the self-employed, farmers, workers in smaller firms, the unemployed, and the elderly. Through municipal NHI programs, the Japanese system of public health insurance provides universal coverage. Since the NHI covers the health care costs of the retired,[3] a special financial arrangement has been made to lessen its financial burden. The Elderly Health Care Service (EHCS) was introduced in 1983 as a health care cost-sharing scheme for those aged 70 and over, to support public health insurance programs with higher proportions of elderly members, the NHI in particular. The 2008 reform then separated those aged 75 and above (called "old-old") from the EHCS and set up a different health care finance scheme for this segment of the population. The scheme, called the Heath Care Service for the Old-Old (HCSOO), is managed by a committee that represents all the municipalities in a prefecture. Those aged 75 years and over contribute premiums to this finance scheme, which differ among prefectures with reduced rates for low-income households. Meanwhile, the EHCS has been retained as a cost-sharing scheme among the public health insurance programs to cover the benefits for those aged between 65 and 74.

Table 1

The premium collection methods for the EHI and NHI are identical. In EHI programs, premiums are set as a fixed percentage of employees' earnings and shared equally by employers and their employees. In NHI programs, premiums are based on income level and the number of family members, and therefore they differ among

[2] The JHIA insurance was called the government-managed health insurance scheme before October 2008. These premiums consisted of special and basic rates. While the special rate used to finance the EHCS was uniform across the country, the basic rate differed by prefecture in order to reflect differences in medical expenditure, after adjusting for differences in age-composition and income factors.

[3] If the elderly are dependent family members of households whose heads are enrolled in the EHI, they are also covered by the EHI.

municipalities. However, the parameters that define actual contributions differ by individual program, even those within a given scheme. In other words, premium payments vary markedly, even among identical households across different public health insurance programs.

By contrast, the Japanese health system provides uniform benefits to all Japanese regardless of the programs to which they subscribe. All public health insurance programs cover a common range of standardized HCSs, and their coverage is quite wide. The insurance benefits include 70% of the medical costs (if patients are aged 75 or above, the benefits are 90% unless they earn more than a certain income threshold) and reimbursements of co-payments when medical costs are "catastrophic." Moreover, the medical costs that HCS providers are entitled to receive are nationally standardized in a fee schedule, which is set and reviewed by central government every other year. Since the fee schedule applies uniformly, patients can obtain standardized HCSs at identical prices (30% co-payment). Furthermore, patients are free to choose service providers of their liking regardless of having a referral or not.[4]

Providers, private or public, can start hospitals or clinics if they satisfy the criteria set by the central government. Doctors can choose to work in the private or public sectors in any part of the country. Providers are paid according to the fee schedules set by the central government if their services are covered by public health insurance. There are no differences in insurance coverage,[5] whether service providers are clinics or hospitals, or private or public. Finally, providers are reimbursed with insurance benefits for the bills they submit.

2.2. Distribution of prefectural per capita HCE

As mentioned in the Introduction, regional HCE varies widely in Japan. **Figure 1** shows per capita HCE for each of the 47 prefectures in Japan for 2010. This figure shows that Kochi spends the most with JPN¥ 378,472 (about US$ 3,785), while Saitama

[4] However, patients pay an initial installment fee (usually less than JPN¥10,000) when they choose to receive services at designated, usually large-scale, hospitals without a referral (which is usually issued by a clinic).

[5] Co-payments have been increased in a series of reforms. For those aged under 69 in the EHI, the rate was raised from 20% to 30% (NHI subscribers already faced a 30% rate). The premium base was also imposed on bonuses, thus applied to entire annual salaries. For high-income elderly aged above 70, the co-payment rate was raised from 10% to 20% in 2002, and again increased to 30% in 2006. In that year, the rate for those aged between 70 and 74 was also raised from 10% to 20%. The ceilings on co-payments were also raised, in line with personal earnings.

spends the least with JPN¥ 221,469 (about US$ 2,215). The difference is then JPN¥ 157,003 (about US$ 1,570), totaling about 71% of the latter's HCE. **Figure 2** shows the squared coefficient of variation for the log of per capita HCE, highlighting that disparities in per capita HCE steadily decreased throughout the 2000s.

The unit of analysis in our study is prefecture partly because comprehensive regional HCE data are only available on a prefectural basis. More importantly, however, prefectures are considered to be the appropriate unit of jurisdiction for analyzing health care policy in Japan. Since the late 1980s, prefectures have been required by the Medical Care Act (MCA) to design and implement the Regional Health Plan (RHP). The RHP mainly concerns the number of hospital beds, on which the central government has focused in order to control its growth. Before the enactment of the MCA, the creation of new hospitals had been approved as long as applications complied with the legal requirements. However, prefectures can now prohibit providers from increasing the number of hospital beds or opening new hospitals if the current number of beds is already considered to be larger than necessary.

Until April 2008, when the new MCA was implemented, the RHP placed little emphasis on how health care should be provided. The new MCA, however, requires the RHP to include detailed descriptions (and indicators), set by the national government, on health service resources and utilization, the outcomes of the major four diseases (cancer, stroke, acute myocardial infarction, and diabetes), and five areas of health care functions (ambulatory, disaster, rural, prenatal, and child health). In particular, prefectures are now required to articulate the 'disease-oriented' critical paths to facilitate "role sharing and effective integration" among different levels of providers and establish a "seamless" provision of health care over different stages (i.e., primary, secondary, tertiary, and home care). The RHP is also required to allocate treatment functions among health care providers in its prefecture and specify the roles of the provider in terms of disease-oriented critical paths.

3. Determinants of Regional HCE

3.1. Regression models

Given the importance of prefectures in health care provision in Japan, we use the prefectural data to analyze regional HCE. We first estimate an aggregate HCE function by using regional data, an approach that has a long tradition in health economics (Gerdtham and Jönsson 2000). The literature has explored sources of HCE variation by regressing per capita HCE on a set of variables, using data aggregated at either the national[6] or the regional level.[7] To estimate the HCE function, we use the following log-linear specification:

$$\log Y_i = \beta_0 + \sum_k \beta_k \log X_{k,i} + \varepsilon_i \tag{1}$$

where Y_i is per capita HCE in prefecture i. We consider J (possible) determinants, where $X_{j,i}$ is the j-th determinant with β_k being its coefficient, while ε_i is an error term, which may or may not contain unobserved heterogeneity (fixed effects). We first estimate (1) with a cross-section of prefectural data for every year from 1990 to 2010.

In cases where ε_i contains unobserved heterogeneity such that

$$\varepsilon_{it} = \mu_i + \theta_t + u_{it},$$

we estimate a panel data version of (1) by pooling a cross-section of prefectures over the subsets of or all the years from 1990 to 2010. In this case, the regression model will be

$$\log Y_{it} = \beta_0 + \sum_k \beta_k \log X_{k,it} + \mu_i + \theta_t + u_{it} \tag{2}$$

where μ_i is the unobserved heterogeneity (prefectural fixed effects), θ_t is the year-specific fixed effects, and u_{it} is the idiosyncratic error.

To estimate either (1) or (2), we need to specify the regressors included in the model. We select determinants from those used by previous studies, based on the specific characteristics of the Japanese health system. First, the most popular choice is regional aggregate per capita income, the effect of which has been a prime focus since the publication of Newhouse (1977). Indeed, this variable is also important for our case since we are interested in how regional income inequality affects HCE. Note that some studies, including Newhouse (1977), consider *only* the effects of per capita income (see also Parkin et al. 1987, Murillo et al. 1993, Boungnarasy 2011, Kumar 2013). Moreover,

[6] See, for example, Newhouse (1977), Parkin et al. (1987), Gbesemete and Gerdtham (1992), Gerdtham (1992), Gerdtham et al. (1992), Hitiris and Posnett (1992), Murillo et al. (1993), Hansen and King (1996), Boungnarasy (2011), Blazquez-Fermandez et al. (2014), and Fan and Savedoff (2014).

[7] See, for example, Häkkinen and Luoma (1995), Freeman (2003), Cantarero (2005), Thornton and Rice (2008), and Wang (2009).

while international studies utilize GDP, regional studies employ a regional analogue of GDP. In this study, we employ **per capita prefectural income**, compiled by the Economic and Social Research Institute (2012).

Second, the literature has also considered the effects of demographic composition. Many studies have examined the effects of the proportion of the elderly population (Hitiris and Posnett 1992, Gerdtham 1992, Gerdtham et al. 1992, Hansen and King 1996, Häkkinen and Luoma 1995, Kawanobe and Ganryu 1999, Tokita et al. 2000, Freeman 2003, Cantarero 2005, Thornton and Rice 2008, Wang 2009, Blazquez-Fermandez et al. 2014, Fan and Savedoff 2014). In addition, some have assessed the impact of the proportion of the child population (Hansen and King 1996, Wang 2009, Blazquez-Fermandez et al. 2014). These factors are assumed to reflect the health care needs of different age groups, thereby influencing HCE. To allow for the diverse effects of different age groups, we thus use **the population shares of those aged 65 and above and those aged 15 or younger**.

Third, urbanization may affect regional HCE. On the one hand, the degree of urbanization could measure accessibility to health care (Kawanobe and Ganryu 1999, Thornton and Rice 2008). Since clinics and hospitals are likely to be located in densely populated areas, urban residents would find it easier on average to receive HCSs. On the other hand, urbanization may also be considered to be a proxy for the collection of environment factors that affect health status, such as pollution and congestion (Thornton and Rice 2008). To express the degree of urbanization in the Japanese case, we employ **the share of population that resides in "densely inhabited districts" in a given prefecture (i.e., urban residents)**.

Fourth, poverty may also be an important factor. Thornton and Rice (2008) allow for such effects by including as regressors in their regression models the share of population covered by Medicare and regional Gini coefficient values. Since analogous data for the latter are not readily available for our case, we only consider the effect of poverty by using as a proxy **the welfare ratio** (i.e., the share of households on welfare (social assistance recipients)) in each prefecture. In addition, since social assistance recipients do not have to pay co-payments when they receive HCSs, the welfare ratio may also proxy for price factors that increase demand for HCSs.

These four types of the five determinants may be considered to be demand-side factors. The last (but important) class of determinants, by contrast, is a supply-side factor. Such determinants concern the medical resources available in a given region. Of particular importance is Roemer's Law (Roemer 1961). Indeed, previous studies have considered the availability of medical beds to be an important determinant of HCE (Gerdtham et al. 1992, Cantarero 2005, Thornton and Rice 2008, Wang 2009). The Japanese literature typically associates the availability of hospital beds with an incentive for physicians to induce more demand for HCSs from potential patients (Kawanobe and Ganryu 1999, Tokita et al. 2000). In the same vein, several studies consider the effects on HCE of the available number of doctors and/or medical staff (Gerdtham et al. 1992, Kawanobe and Ganryu 1999, Tokita et al. 2000, Cantarero 2005, Thornton and Rice 2008, Wang 2009). Accordingly, we employ as proxies of available medical resources **the number of hospital beds** and **the number of doctors**, both normalized by regional population.

Table 2

Table 2 summarizes some of the determinants considered by previous studies. First, we do not include factors that are fixed regionally, such as the share of public sector HCE (Hitiris and Posnett 1992, Gerdtham 1992, Gerdtham et al. 1992, Hansen and King 1996, Blazquez-Fermandez et al. 2014, Fan and Savedoff 2014), since the health care system is usually uniform in a unitary country such as Japan. For a similar reason, we do not consider advancements in medical technology (Blazquez-Fermandez et al. 2014). Of course, these two factors may change over time, for which we could allow by considering fixed time effects in a panel data analysis. Second, although other factors could have been included in our models, given that we use a cross-section of 47 observations, adding more determinants may have complicated the model excessively and compromised the advantages of explanatory parsimony in the decomposition analysis presented in the next section.[8] **Table 3** provides the definitions as well as sources of the data used, and **Table 4** lists their summary statistics over time.

Tables 3 and 4

[8] Excluded factors include the relative prices of health services (Gerdtham 1992, Gerdtham et al. 1992, Murillo et al. 1993, Hansen and King 1996), female labor participation (Gerdtham et al. 1992, Wang 2009), inpatient share (Gerdtham et al. 1992, Häkkinen and Luoma 1995), the health status of the population (Thornton and Rice 2008), education level (Thornton and Rice 2008), and the availability of medical equipment and facilities such as CT scanners, ICUs, CCUs, and long-term care facilities (Tokita et al. 2000).

3.2. Estimation results

Table 5 presents the results of the estimation of (1). Note that since we take the logarithm of both the dependent and the explanatory variables, the estimated coefficients are free from a unit of measurement and interpreted as elasticities. The effects of the elderly population (proportion of those aged 65 and over), poverty (proportion of households on welfare), hospital beds (per population), and doctors (per population) are all statistically significant at the .01 level over time. The effect of the elderly population is the largest throughout the decade under study, ranging between .371 and .472, and increasing over time on average. This finding suggests that ageing raises HCE to a large extent. In addition, the effects of poverty increase from .042 in 2001 to .057 in 2010 with some fluctuations over time. The effects of hospital beds and doctors are also relatively large, with the former ranging from .218 to .250 and the latter from .148 to .240. These two variables may be related to supply-induced increases in HCE, with the effects of hospital beds particularly indicative of Roemer's Law. Less emphatic but still significant at standard levels is urbanization (share of population in densely inhabited areas), whose effect decreased from about .07 to .05 throughout the 2000s.

Table 5

As mentioned above, the effect of income on HCE has been of prime research interest. While previous studies, especially those that have explored international data, indicate that income elasticity is more than unity, our result based on Japanese prefectural data shows that the value is rather small. In particular, elasticity is at most .126, which is smaller than those estimated by existing studies, suggesting that income differences affect HCE little in the Japanese case. It is also interesting to see that elasticity declines, with some fluctuations, from .126 to less than .1 throughout the study period. When considered along with the increasing effect of poverty on HCE, this effect of income might be suggestive of an equity-oriented development of welfare policy after 2000. Lastly, the effects of the younger population (proportion of those aged 15 or under) are not significant.

We then pool the cross-section data over time and perform a panel regression using the second linear regression model (2). We examine three groups, namely the whole study period (2001–2010) and two subperiods (2001–2007 and 2008–2010), which correspond to different phases of the business cycle. **Table 6** presents the results. By pooling the data, we find somewhat different patterns in the coefficient estimates. Some of the variables that were statistically significant in the cross-section analysis become non-significant. First, per capita income is not significant for all three groups. Second, the proportion of the elderly population and number of doctors are only non-significant for the 2008–2010 subperiod. Third, the poverty variable is not significant for the whole study period and the 2001–2007 subperiod. While the reasons for the non-significance of these three variables are unclear, their variations may have reduced after controlling for the prefectural and year fixed effects. On the contrary, the proportion of the young population, the variable that was not statistically significant in all the cross-section estimations, is now significant for the whole study period and the 2001–2007 subperiod. Further, urbanization and the number of hospital beds are both significant for the three groups. In particular, the positive effect of hospital beds on HCE remains emphatically significant even after allowing for the two types of fixed effects. The hospital bed elasticity of HCE is now between .217 and .428, while the similar values for the year-by-year cross-section estimation are between .233 and .279.

Table 6

The result on hospital beds above shows that the case for Roemer's Law is quite robust. In fact, as shown in **Figure 3**, which lists the percentage changes in hospital beds (per million population) from 2001 to 2010, the RHP reduced the number of hospital beds during the study decade in most prefectures and was thus instrumental in containing rapidly expanding HCE.

Figure 3

4. Decomposition of Regional HCE Disparity

4.1 SFMS decomposition

In this section, we take advantage of the results of the regression analysis to characterize the contributions of these HCE determinants to regional disparities in per capita HCE in Japan. For this task, we employ the inequality decomposition method proposed by Fields (2003) and Morduch and Sicular (2002). Since this method is an extension of the inequality decomposition by Shorrocks (1982), we term it the SFMS (Shorrocks–Fields–Morduch–Sicular) method. While a number of studies have utilized the SFMS method to analyze regional disparities (Yu and Tsui 2005, Costa-Font 2010, Huang and Chen 2012), none has applied it to examine regional disparities in HCE.

The SFMS method starts by decomposing the dependent variable of the regression models (1 or 2), namely (the logarithm of) per capita HCE, by using the parameter estimates $\hat{\beta}_k$ and residuals $\hat{u}_i$ or $\hat{u}_{it}$ as follows. For the cross-section regression (1), we decompose the logarithm of per capita HCE as

$$y_i = \sum_k z_{k,i} + z_{0,i} \tag{3}$$

where $y_i \equiv \log Y_i$, $z_{k,i} \equiv \hat{\beta}_k \log X_{k,i}$, and $z_{0,i} \equiv \hat{\beta}_0 + \hat{u}_i$. The last term is the part of y_i unexplained by the determinants.[9] For panel regression (2), the analogue of (3) is

$$y_{it} = \sum_k z_{k,it} + z_{N,i} + z_{T,t} + z_{0,it} \tag{4}$$

where $y_{it} \equiv \log Y_{it}$, $z_{k,it} \equiv \hat{\beta}_k \log X_{k,it}$, $z_{N,i} \equiv \hat{\beta}_{0j} \cdot 1\{i = j\}$, $z_{T,t} \equiv \hat{\theta}_s \cdot 1\{s = t\}$, and $z_{0,it} \equiv \hat{\beta}_0 + \hat{u}_{it}$. Note that $\hat{\beta}_{0j}$ and $\hat{\theta}_s$ here are estimates of the prefectural and time fixed effects, $1\{\cdot\}$ is an index function, and $\hat{u}_{it}$ is the residual from the panel estimation of (2).

Second, we apply the inequality decomposition proposed by Shorrocks (1982) to (3) or (4) to obtain the proportional contribution $s_k(y)$ of the k-th determinant to an inequality measure of y, $I(y)$. As shown by Shorrocks (1982), the relevant class of $I(y)$ includes many of the major inequality indices defined over y, including variance, the squared coefficient of variation, the Gini index, and the Theil index. In the case of cross-section regression (1), the proportional contribution is given as

$$s_k(y) = \frac{\mathrm{cov}(z_k, y)}{\mathrm{var}(y)}, s_0(y) = \frac{\mathrm{cov}(z_0, y)}{\mathrm{var}(y)} \tag{5}$$

which adds up to unity over k and the residual

[9] In their original formation, Fields (2003) and Murdoch and Sicular (2002) treat the constant term ($\hat{\beta}_0$) and the residual term ($\hat{u}$) separately. Wan (2004) criticizes their use of these two terms, arguing that the contributions of $\hat{\beta}_0$ and $\hat{u}$ are not derived from "the natural rule of decomposition" of Shorrocks (1982). We can circumvent this critique by treating them together as a single variable $z_0 \equiv \hat{\beta}_0 + \hat{u}$ that, if they are OLS estimates, is a standard variable with its average $\hat{\beta}_0$. Note that the proportional contribution of z_0 is numerically identical to that of $\hat{u}$.

$$\sum_{k=1}^{K} s_k(y) + s_0(y) = 1.$$

For panel regression (2), the proportional contribution is calculated as

$$s_k(y) = \frac{\text{cov}(z_k, y)}{\text{var}(y)},$$

$$s_N(y) = \frac{\text{cov}(z_{N,t}, y)}{\text{var}(y)}, s_T(y) = \frac{\text{cov}(z_T, y)}{\text{var}(y)}, \text{ and } s_0(y) = \frac{\text{cov}(z_0, y)}{\text{var}(y)} \qquad (6)$$

which again adds up to unity:

$$\sum_{k=1}^{K} s_k(y) + s_N(y) + s_T(y) + s_0(y) = 1.$$

Note that the SFMS decomposition is not without criticism (Wan 2004, Cowell and Fiorio 2006). First, it only permits a regression model with a linear-in-parameter specification without interaction terms. Second, the class of inequality indices is defined over the specific form of the dependent variable in question. In our case, it is over y = log(Y), not Y = exp(y). Third, the decomposition has to include residuals, i.e., the part that is not explained by the observed determinants, which may then yield cases where such a part occupies a significant proportion. These shortcomings apply to the current study, as the decomposition method by Shorrocks (1982) presumes a simple summation in form of (3) or (4) for y. We regard these as acceptable trade-offs to make for taking advantage of Shorrocks' decomposition, which has its own advantages. In addition, we do not consider the third point to be a serious problem, since it is nonetheless informative to find the degree of the proportional contribution that is attributable to unknown factors, namely those elements other than the observed determinants. Finally, while we may well calculate standard errors for $s_k(y)$ (Murdock and Sicular 2002, Cowell and Fiorio 2006), we prefer to consider such an inference to be only suggestive and treat the decomposition result as descriptive one, as in Tsui (2005) and Costa-Font (2010).

4.2 Results

From the cross-section results for each year of the period 2001–2010, we can calculate the proportional contributions (5) of per capita income, the elderly population, the young population, urbanization, poverty, and the number of hospital beds/doctors to inequality (**Figure 4**). Note that while the proportion of the young population is not statistically significant throughout the period (see **Table 5**), we nonetheless include it in the decomposition analysis to ensure that the proportional contributions add up to unity. The same applies to the determinants that are not statistically significant in the results of the panel regressions in **Table 6**.

The results are summarized as follows. First, the number of hospital beds is by far the most influential factor that increases disparities in regional HCE, explaining from 45% to 49% of the regional variation. Next, the second highest contributing factor is the proportion of the elderly population, whose contributions were around 30% in the first half of the decade, with a declining influence in the latter half (31.1%→25.9%). The number of doctors is third most influential, with an increasing impact over the first three years of the period under study (16.7%→20.9%), followed by a period of stability around 21%, and then a hike to 25.8% in 2010, which is almost equal to the contribution of the elderly population in the same year. Fourth, poverty explains around 10% of the disparity with a gradual increase in its positive impact (8.4%→9.5%) from 2000 to 2005, then a small decrease (10.7%→9.3%) from 2007.

Lastly, the other three determinants (per capita income, the proportion of the young population, and urbanization) are shown to reduce disparity through their negative values of proportional contributions. Their absolute values are relatively small, however, with all in the range of −1% to 5.5%. Given that their coefficients in **Table 5** are all positive, this finding implies that they are inversely correlated with per capita HCE in all years of the study decade. Since these three determinants may be considered to reflect a strong regional economic climate, this result also suggests that per capita HCE is inversely correlated with economic strength.

Figure 4

Figure 5 illustrates the results from the panel regressions for the entire study period and two subperiods (2001–2010, 2001–2007, and 2008–2010). Note that pooling the time series and cross-section data allows us to obtain the proportional contributions of the two types of fixed effects, namely those of contemporaneous aggregate shocks and those of regional unobserved heterogeneity. As the former fixed effect measures annual aggregate shocks that are common to all regions, its proportional contribution is defined over the time series dimension of the pooled data. Its value changes as the time span changes: 16.3% for the whole period (2001–2010), 6.1% for the first subperiod (2001–2007), and 4.8% for the second subperiod (2008–2010). These changes reflect the changes in fee schedules for HCSs that are covered by public health insurance. As mentioned in Section 2, the coverage of public insurance is quite wide, and changes are made by the central government every other year. Indeed, there were rather large changes in the fee schedule during the 2000s.

On the contrary, the proportional contributions of regional unobserved heterogeneity are defined over the cross-section dimension of the pooled data. Such heterogeneity may include differences in regional preferences for HCSs that are constant over time. The values of its proportional contribution are quite large: 32.3% for the whole study period and 46.3% for the first subperiod. By contrast, the second subperiod has a value of –7.4%; however, the fixed effect is still shown to reduce regional disparities in HCE. Unfortunately, it is difficult to explain these changes in the two fixed effects over the three periods of the pooled data.

Figure 5 considers the determinants that were previously listed in **Figure 4**. Among the proportional contributions of such determinants, only some show similar results to those in **Figure 4**. First, the contribution of the numbers of hospital beds and doctors is again positive and large. In particular, the proportional contribution of hospital beds remains the largest. For the whole period and first subperiod, its values are 37.6% and 40.0%, respectively, which are slightly smaller than those in **Figure 4**. For the second subperiod, its value rises as high as 83%. The contribution of the number of doctors is similar (19.5%, 14.1%, and 15.2%, respectively), again slightly smaller than those in **Figure 4**. These reductions may be due to the inclusions of the two fixed effects above, which may have absorbed the variation in the cross-section data in **Figure 2**.

Second, the young population and urbanization variables again contribute to the reduction in per capita HCE, with similar contributions for the three groups. Nonetheless, while the proportional contributions of the young population (–2.4%, –2.1%, and –1.3%) are comparable with those in **Figure 4**, those of urbanization are now larger in absolute value (–9.8%, –13.8%, and –4.3%).

Third, the proportion of the elderly population now displays reduced proportional contributions, dropping as low as 9.8% for the whole period, 8.4% for the first subperiod, and .9% for the second subperiod. Poverty, on the contrary, moves in the opposite direction, with contributions of −2.2% for the whole period, −.1% for the first subperiod, and a big jump to 7.4% for the second subperiod. A possible reason for this large jump is the fact that the Japanese economy started to suffer from yet another severe economic recession in 2008, which ignited an increase in the poverty rate.

Lastly, the proportional contribution of income shows different patterns. While its contributions were negative in all periods of the cross-section analysis in **Figure 4**, they are now positive for the whole period and first subperiod. In addition, their values are quite small, with .007 for the whole period, .006 for the first subperiod, and −.013 for the second subperiod. These results confirm that income contributes little to regional disparities in HCE.

All these changes in proportional contributions may be due to the inclusions of the two fixed effects. In particular, for the determinants whose proportional contributions have reduced, the variations in their cross-section data may have contained much of either or both fixed effects.

Figure 5

5. Concluding Remarks

In this study, we explored the determinants of regional HCE in the first decade of the 21st century in Japan and decomposed the variations in regional HCE into the contributions explained by these HCE determinants, utilizing the so-called SFMS regression-based decomposition method. While the empirical analysis in this study yielded a variety of interesting results, two findings are of particular importance. First, income has little influence on regional HCE or the disparity in regional HCE, which has a favorable implication from an equity perspective. Indeed, a 1% increase in per capita regional income is associated with a .09–.13% rise in per capita HCE, considerably smaller than similar estimates in other studies. In addition, the effect of regional income becomes not statistically significant in the panel regression with the two types of fixed effects. A similar result is derived from the decomposition analysis. In particular, the proportional contributions of regional income are shown to be negative in all cases with the cross-section analysis, and in the case of the whole period with the panel analysis.

This finding suggests that income is inversely associated with variations in per capita HCE. However, its effects are rather small in the cross-section estimates (−6% to −3.8%) and even negligible in the panel data estimates (−1.3% to .07%). These results are nevertheless favorable in terms of equity since they strongly suggest that income differences do not affect HCE in Japan.

Second, supply-side factors, especially the number of hospital beds, influences regional HCE as well as the disparity in regional HCE, implying an efficiency loss in HCS provisions. We find that the effect of hospital beds on per capita HCE is larger than that of the other determinants, except the proportion of the elderly population in the cross-section estimation, and that this result is quite robust to including the two types of fixed effects. In particular, a 1% increase in per capita hospital beds induces a .22−.43% increase in per capita HCE, in line with Roemer's Law. Similarly, the decomposition analysis finds the salient contribution of the number of hospital beds to regional inequality in per capita HCE. In particular, the proportional contribution of the number of hospital beds ranges between 37.6% and 83.9%, again corroborating Roemer's Law. These results strongly suggest that the traditional RHP policy of reducing hospital beds during the 2000s in Japan was an effective instrument for containing rapidly increasing HCE.

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Table 1. Public health insurance in Japan (as of March 31, 2013)

<table>
<tr><th colspan="3">Institutional Type</th><th>Insurer (#insurers)</th><th>Coverage</th></tr>
<tr><td rowspan="6">Employees Health Insurance (EHI)</td><td colspan="2">Japan Health Insurance Association (JHIA)-managed</td><td>JHI (1)</td><td>35 million</td></tr>
<tr><td colspan="2">Association-managed</td><td>EHI associations (about 1400)</td><td>29 million</td></tr>
<tr><td colspan="2">Seamen’s Health Insurance</td><td>JHIA (1)</td><td>.13 million</td></tr>
<tr><td rowspan="3">Mutual Aid Association</td><td>Central Government Employees</td><td>Mutual aid associations (20)</td><td rowspan="3">9 million</td></tr>
<tr><td>Local Government Employees</td><td>Mutual aid associations (64)</td></tr>
<tr><td>Private School Teachers and Employees</td><td>Private School Teachers and Employees Association (1)</td></tr>
<tr><td colspan="3" rowspan="2">National Health Insurance (NHI)</td><td>Municipalities (about 1700)</td><td rowspan="2">38 million</td></tr>
<tr><td>NHI associations (165)</td></tr>
<tr><td colspan="3">Health Care Services for the Old-Old (NCSOO)</td><td>Prefecture-wise committees (47)</td><td>15 million</td></tr>
</table>

Table 2. HCE determinants

	Income	Elderly	Child	Urbanization	Poverty	Beds	Staff/ doctors
Newhouse (1977)	○						
Parkin et al. (1987)	○						
Hitiris and Posnett (1992)	○	○					
Gerdtham (1992)	○	○					
Gerdtham et al. (1992)	○	○					○
Murillo et al. (1993)	○						
Hansen and King (1996)	○	○	○				
Häkkinen and Luoma (1995)	○	○					
Kawanobe and Ganryu (1999)	○	○		○	○	○	○
Tokita et al. (2000)	○	○				○	○
Freeman (2003)	○	○					
Cantarero (2005)	○	○				○	○
Thornton and Rice (2008)	○	○		○	○	○	○
Wang (2009)	○	○	○	○		○	○
Boungnarasy (2011)	○						
Kumar (2013)	○						
Blazquez-Fermandez et al. (2014)	○	○	○				
Fan and Savedoff (2014)	○	○					

Table 3. Data

Variable	Definition	Sources
Y	Per capita HCE (1000 yen)	*Estimates of National HCE*
$X_{1,.}$	Per capita regional income (1000 yen)	*Provincial Accounts*
$X_{2,.}$	Proportion of those aged 65 and older	*Population Census*
$X_{3,.}$	Proportion of those aged below 15 (percent)	
$X_{4,.}$	Proportion of those who live in densely inhabited districts (percent)	
$X_{5,.}$	Proportion of whose who receive public assistance benefits (percent)	
$X_{6,.}$	Number of hospital beds per 1000 population (beds)	*Survey of Medical Institutions*
$X_{7,.}$	Number of doctors per 1000 population (persons)	

Table 4. Summary statistics

		2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Per capita HCE (000 yen)	mean	248	246	251	256	264	264	272	277	287	298
	s.d.	32	32	31	32	33	32	34	34	35	36
	min.	176	175	180	184	191	192	199	203	212	221
	max.	307	308	315	318	331	332	344	353	365	378
Per capita income (000 yen)	mean	2,820	2,794	2,812	2,826	2,820	2,850	2,856	2,680	2,587	2,655
	s.d.	429	433	451	459	494	494	487	434	369	362
	min.	2,116	2,080	2,095	2,066	2,066	2,071	2,060	2,009	2,039	2,025
	max.	4,977	4,892	4,996	4,999	5,175	5,232	5,165	4,784	4,395	4,306
Proportion of population ≧65 (percent)	mean	19.8	20.3	20.8	21.2	21.8	22.4	23.0	23.6	24.2	24.4
	s.d.	2.9	2.9	2.9	2.8	2.8	2.7	2.7	2.6	2.6	2.6
	min.	13.5	14.2	14.9	15.5	16.1	16.5	16.9	17.2	17.5	17.3
	max.	25.5	26.1	26.5	26.8	27.1	27.5	28.1	28.5	29.0	29.5
Proportion of population <15 (percent)	mean	14.7	14.5	14.3	14.1	14.0	13.8	13.7	13.5	13.3	13.3
	s.d.	1.1	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
	min.	11.8	11.9	11.9	11.9	11.3	11.5	11.6	11.5	11.2	11.2
	max.	19.7	19.4	19.0	18.7	18.7	18.3	18.0	17.9	17.7	17.7
Proportion of urban population (percent)	mean	50.3	50.3	50.3	50.4	50.8	50.9	50.9	51.0	51.1	51.7
	s.d.	18.6	18.4	18.3	18.1	18.8	18.6	18.5	18.3	18.2	18.9
	min.	24.9	25.0	25.1	25.3	24.2	24.3	24.5	24.7	24.9	25.0
	max.	97.2	96.3	95.5	95.5	98.0	97.0	96.0	95.4	95.3	98.2
Proportion of households on public welfare	mean	1.5	1.6	1.7	1.7	1.8	1.8	1.8	1.9	2.1	2.3
	s.d.	0.7	0.7	0.8	0.8	0.8	0.9	0.9	0.9	0.9	1.0
	min.	0.5	0.5	0.5	0.6	0.6	0.6	0.6	0.6	0.6	0.7
	max.	3.0	3.3	3.6	3.8	4.0	4.1	4.2	4.3	4.8	5.2
Hospital beds (per 1000 population)	mean	16.6	16.5	16.3	16.3	16.2	16.1	16.0	15.9	15.8	15.7
	s.d.	4.7	4.6	4.6	4.5	4.5	4.4	4.4	4.4	4.4	4.4
	min.	9.4	9.3	9.2	9.2	9.1	9.0	8.8	8.7	8.6	8.5
	max.	28.6	27.8	27.7	27.4	27.0	26.8	26.8	27.0	27.0	26.9
Doctors (per 1000 population)	mean	2.1	2.1	2.1	2.2	2.2	2.2	2.2	2.3	2.3	2.3
	s.d.	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4
	min.	1.2	1.3	1.3	1.3	1.3	1.4	1.4	1.5	1.5	1.5
	max.	2.7	2.8	2.8	2.8	2.8	2.9	2.9	3.0	3.0	3.0

Table 5. Estimation results: Cross-section data

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Per capita income (000 yen)	0.126**	0.117**	0.091	0.109**	0.099*	0.117**	0.104**	0.091*	0.088*	0.096**
	(0.068)	(0.060)	(0.055)	(0.047)	(0.051)	(0.054)	(0.051)	(0.050)	(0.052)	(0.050)
Proportion of population ≧65 (percent)	0.371***	0.391***	0.379***	0.405***	0.402***	0.443***	0.429***	0.450***	0.445***	0.472***
	(0.062)	(0.068)	(0.079)	(0.080)	(0.078)	(0.088)	(0.092)	(0.101)	(0.102)	(0.081)
Proportion of population <15 (percent)	0.012	0.042	0.033	0.070	0.096	0.142	0.140	0.146	0.144	0.216*
	(0.117)	(0.115)	(0.129)	(0.125)	(0.119)	(0.135)	(0.132)	(0.140)	(0.136)	(0.120)
Proportion of urban population (percent)	0.072***	0.074***	0.062**	0.061**	0.057**	0.060**	0.052**	0.050**	0.050**	0.057**
	(0.023)	(0.023)	(0.024)	(0.024)	(0.025)	(0.024)	(0.023)	(0.023)	(0.023)	(0.024)
Proportion of households on welfare (per 1000 persons)	0.042***	0.042***	0.045***	0.048***	0.049***	0.048***	0.055***	0.053***	0.053***	0.057***
	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.015)	(0.016)	(0.016)	(0.016)
Hospital beds (per 1000 population)	0.250***	0.243***	0.222***	0.225***	0.227***	0.235***	0.236***	0.229***	0.233***	0.218***
	(0.036)	(0.036)	(0.036)	(0.036)	(0.035)	(0.037)	(0.038)	(0.036)	(0.035)	(0.034)
Doctors (per 1000 population)	0.148***	0.163***	0.178***	0.174***	0.188***	0.181***	0.179***	0.191***	0.191***	0.240***
	(0.047)	(0.042)	(0.042)	(0.035)	(0.035)	(0.040)	(0.042)	(0.040)	(0.040)	(0.040)
Constant	2.240**	2.151**	2.526**	2.204**	2.245**	1.808*	2.003**	2.064**	2.118**	1.772**
	(0.944)	(0.906)	(0.929)	(0.825)	(0.869)	(0.959)	(0.918)	(0.953)	(0.941)	(0.818)
Adjusted R^2	0.943	0.946	0.945	0.944	0.948	0.947	0.948	0.946	0.946	0.946

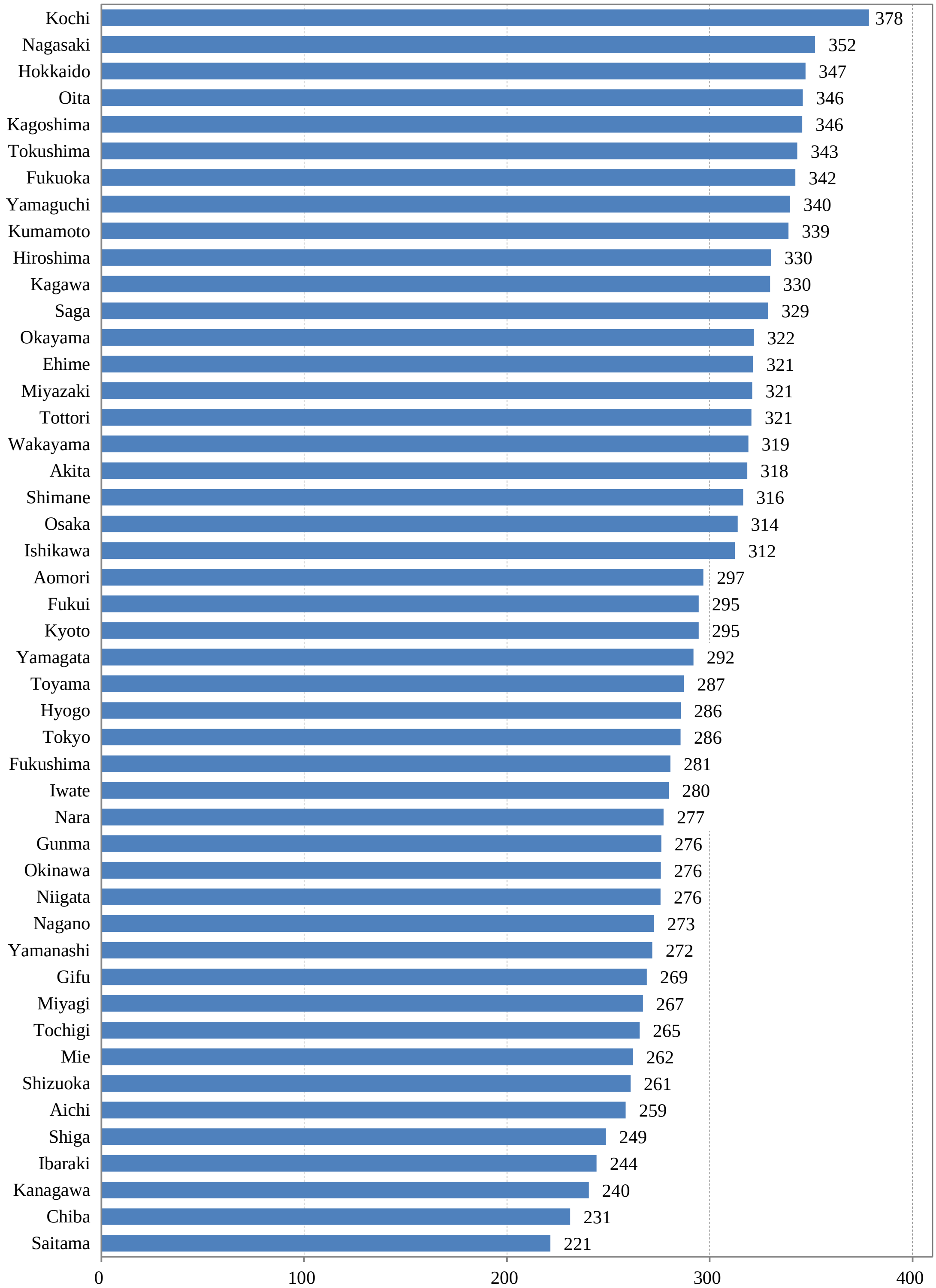
Notes: (i) ***: $p < .01$; **: $.01 \le p < .05$; *: $.05 \le p < .10$. (ii) Sample size is 47. (iii) Robust standard errors are in parentheses. (iv) Estimates are OLS.

Table 6. Estimation results: Pooled data

	2001–2010	2001–2007	2008–2010
Per capita income (000 yen)	0.029 (0.022)	–0.017 (0.026)	–0.014 (0.021)
Proportion of population ≧65 (percent)	0.124*** (0.023)	0.105*** (0.032)	0.016 (0.089)
Proportion of population <15 (percent)	0.115*** (0.039)	0.121** (0.056)	0.079 (0.063)
Proportion of urban population (percent)	0.174*** (0.044)	0.203*** (0.057)	0.066* (0.039)
Proportion of households on public welfare (percent)	–0.011 (0.012)	0.001 (0.017)	0.040* (0.020)
Hospital beds (per 1000 population)	0.236*** (0.033)	0.217*** (0.040)	0.428*** (0.139)
Doctors (per 1000 population)	0.188*** (0.036)	0.127*** (0.042)	0.145 (0.093)
Prefecture Effects	○	○	○
Year Effects	○	○	○
Adjusted R^2	0.999	0.999	0.999
$N \times T$	470 (47×10)	329 (47×7)	141 (47×3)

Notes: (i) ***: $p \leq .01$; **: $.01 < p \leq .05$; *: $.05 < p \leq .10$. (ii) Robust standard errors are in parentheses. (iii) Estimates are OLS.

Figure 1. Prefectural per capita HCE in 2010 (000 yen).



Source: Estimates of National Medical Care Expenditure, National Health Insurance Annual Report 2010, and Treasury Liability of Public Assistance Result Report, Ministry of Health, Labour and Welfare.

Figure 2. Changes in the squared coefficient of variation for prefectural per capita HCE during the 2000s.

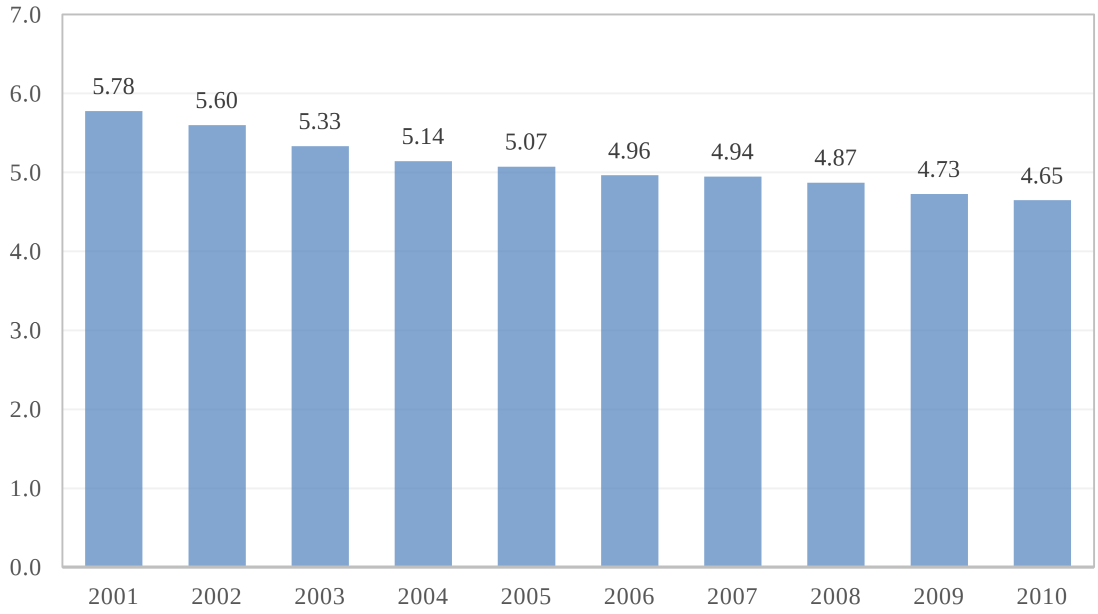


Figure 3. Percentage changes in hospital beds per million population between 2001 and 2010.

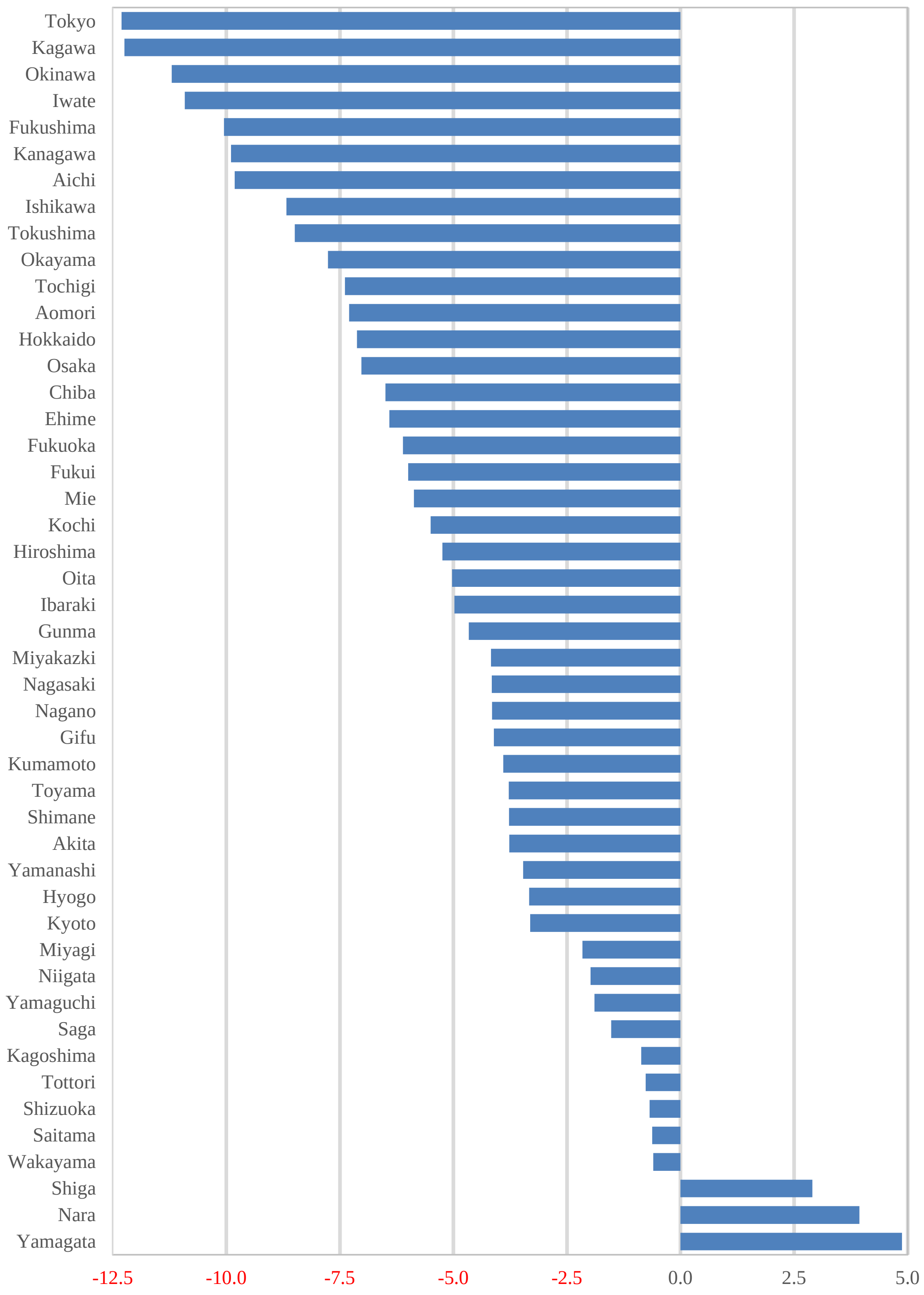


Figure 4. Factor decomposition: Cross-section data.

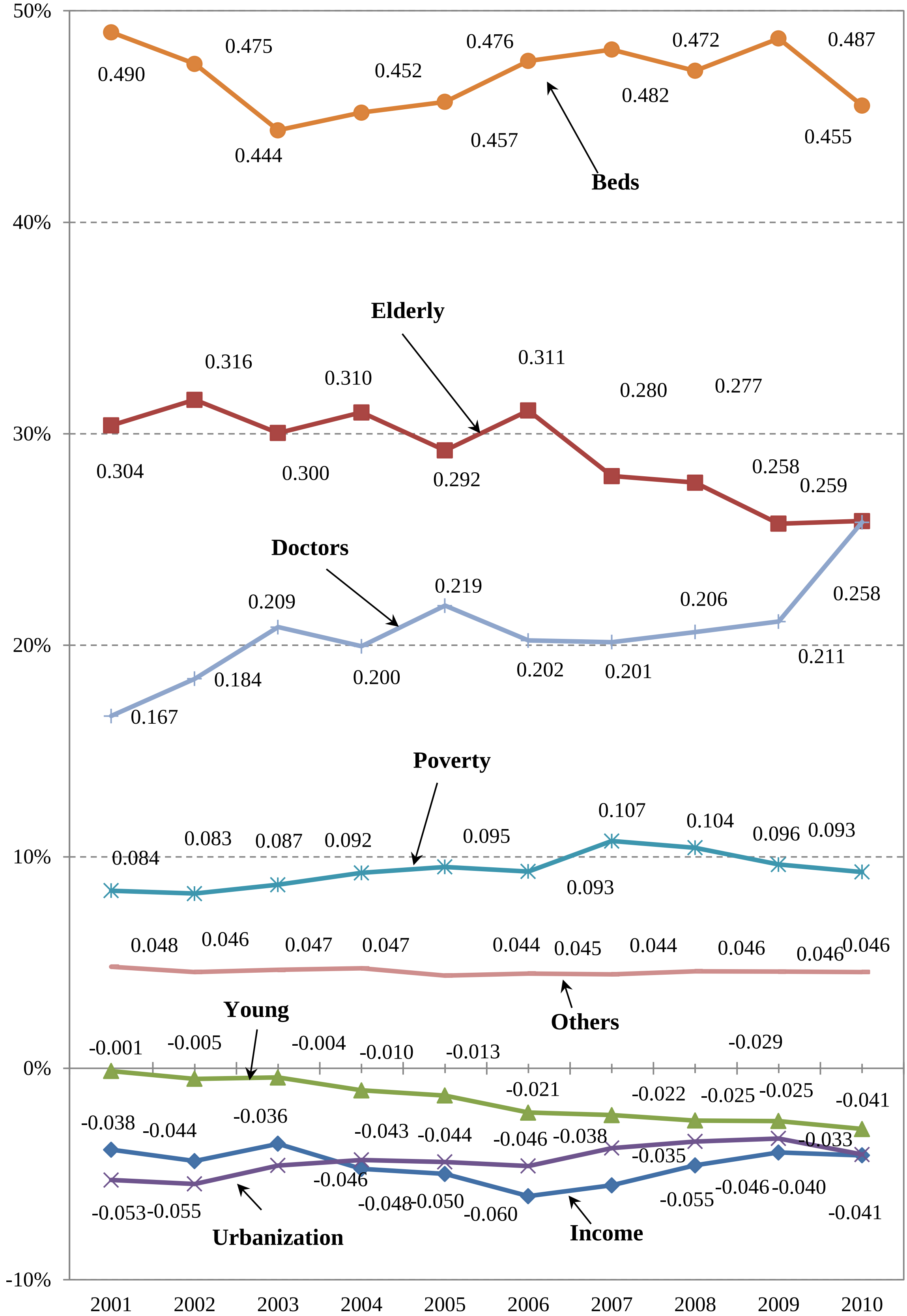


Figure 5. Factor decomposition: Pooled data.