Does income inequality affect the demand for health care? Evidence from Japan

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This paper examines the impact of income inequality on the demand for health care in Japan. The relationship between income inequality and the demand for health care is an extension of the theory of the relationship between income inequality and population health. We use the Gini coefficient, which is calculated from disposable income data, as a measure of income inequality. The structural error correction model (SECM) shows that the price, income, and inequality elasticities of the demand for health care are -0.56, 0.61, and 1.41, respectively. Hence, the demand for health care in Japan is more elastic with respect to income inequality. Furthermore, there is evidence in favor of Granger-causality from income inequality to real health care expenditure. We conclude that, in the case of Japan, greater income inequality leads to a greater demand for health care.

Keywords: Demand for health care; Income inequality; SECM; Cointegration

Contents

1. Introduction

1.1 Economic backgrounds

In recent years, a large number of studies have been conducted on the demand for health care (e.g., Blomqvist and Carter, 1997; Clemente et al., 2004; Freeman, 2003; Gerdtham and Löthgren, 2000; Hansen and King, 1996; Herwartz and Theilen, 2003; Narayan and Narayan, 2008a; Wang and Rettenmaier, 2007; Yu and Chu, 2007). The literature has focused on several determinants of the demand for health care, such as income level, population ageing, and environmental quality. It is important to note that these variables have a direct impact on health status. For example, aging leads to poor health, and therefore, elderly persons require more health care goods and services to maintain their health. In other words, it is reasonable to assume that the demand for health care depends on health status. Given that deterioration in health status leads to an increase in the demand for health care, variables that have a negative impact on health status are likely to be important determinants of the demand for health care. In view of this point, this paper aims to examine the importance of income inequality.

From a theoretical perspective, income inequality can be regarded as one of the determinants of population health. For example, given that individuals assess their well-being by comparing themselves to others who earn more than themselves, an increase in income inequality leads to a decrease in well-being and, consequently, an increase in chronic stress for some (e.g., Wilkinson, 1997). Hence, income inequality damages the health of the relatively poor people in the community.[1] Using survey data, some studies demonstrate that income inequality has a negative impact on individual well-being (e.g., Alesina et al. 2004), and it is widely accepted that well-being and health are strongly related to each other. Furthermore, the negative impact of income inequality has also been examined in the mental health literature. For example, Daly and Wilson (2009) focus on suicides, and show that income inequality affect mental health condition (i.e., suicide risk).

Several previous studies suggest that income inequality affects population health. This further implies that income inequality may increase the demand for health care at the aggregate level, since deterioration in health status leads to an increase in the demand for health care. In other words, the relationship between income inequality and the demand for health care is a simple extension of the theory of the relationship between income inequality and population health. It is likely that the demand for health care depends on health status. Hence, it is theoretically possible that income

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1 For a detailed survey on the relationship between income inequality and population health, see, for example, Lynch et al. (2004).

inequality affects the demand for health care.

To examine the adequacy of the abovementioned hypothesis, this paper focuses on Japan. There are good reasons for focusing on Japan. For example, income inequality in Japan has continued to increase since the 1980s (e.g., Förster and Mira d'Ercole, 2005). The share of non-regular workers reached a third of employees in 2003, and this labor market dualism created a large segment of the population with lower wages, short-term job experience, and limited opportunities to enhance their human capital. These facts have raised serious concerns about equity in Japan (e.g., OECD, 2008). Therefore, the use of Japanese data seems to provide good information on the importance of income inequality.

Although the ratio of health care expenditure (HCE) to GDP in Japan is lower than those in the other OECD countries such as the United States, the ratio in Japan is expected to increase remarkably in future because of rapidly aging population (e.g., Ministry of Health, Labour and Welfare, 2007).[2] In fact, Narayan (2007) finds strong evidence to suggest that per capita HCE in Japan converges to that in the United States. Furthermore, Narayan and Narayan (2008b) indicate that transitory shocks (demand shocks) have high explanatory power for the dynamics of per capita HCE in Japan. Therefore, if it is found that income inequality has a significant impact on the demand for health care, then this result can provide useful information for predicting the future dynamics of HCE in Japan. For these reasons, we focus on Japan in examining the adequacy of the abovementioned hypothesis.

1.2 Contributions and extensions

A contribution of this paper is that it examines the impact of income inequality on the demand for health care. In doing so, we extend the literature on the demand for health care in two ways. First, we estimate a model of the demand for health care in which real HCE is regressed on real income level, the health care price index, and the Gini coefficient. The most commonly used model in this literature is a bivariate one that consists of HCE and income level (e.g., Freeman, 2003; Gerdtham and Löthgren, 2000; Hansen and King, 1996; Newhouse, 1977). To examine the impact of income inequality, we follow the standard bivariate model and extend this model to a multivariate one by using the health care price index and the Gini coefficient. The inclusion of the health care price index in our model seems to be theoretically reasonable since the consumer demand theory usually assumes

2 For example, the aging ratio in Japan was 20.1 in 2005, and this figure was higher than those of most other countries such as France (16.3), Germany (18.8), the United Kingdom (16.1), and the United States (12.3).For example, the aging ratio in Japan was 20.1 in 2005, and this figure was higher than those of most other countries such as France (16.3), Germany (18.8), the United Kingdom (16.1), and the United States (12.3).

that the demand for a good depends on its own price. Furthermore, the inclusion of the Gini coefficient, which is a standard measure of income inequality (e.g., Förster and Mira d'Ercole, 2005), will serve our purpose.

Second, we use the structural error correction model (SECM: Boswijik, 1995) to estimate the model of the demand for health care. This is a time series technique and is applicable to statistical inference on cointegration parameters. The use of cointegration techniques is essential to the successful estimation of the model of the demand for health care, since health care data are likely to be integrated of order one (e.g., Hansen and King, 1996). Boswijik (1995) shows that the SECM method has superior properties in small samples and outperforms the other alternative methods such as the ordinary least squares (OLS) estimation, the fully modified OLS estimation (Phillips and Hansen, 1990), and the Johansen's maximum likelihood estimation (Johansen, 1988; Johansen and Juselius, 1990). Therefore, it is more advantageous to use the SECM method in cases with small samples as in the case of this study.

It is also important to note that the use of time series techniques does not require the assumption of homogeneity across countries. For example, Clemente et al. (2004) point out that the homogeneity assumption is quite restrictive in examining the demand for health care since consumer preferences and technologies in the health care industry are very different across countries. In addition, Blomqvist and Carter (1997) show that the hypothesis of a common income elasticity in the demand for health care is rejected for 18 OECD countries, and cast doubt on the validity of pooling health care data across countries. Herwartz and Theilen (2003) also obtain similar results. Hence, we prefer to use the SECM method rather than pooled and panel data techniques, which implicitly assume homogeneity across countries (e.g., Clemente et al., 2004).

There is, of course, a disadvantage in using time series techniques. Specifically, the unit root and cointegration tests based on time series data on health care may have lower power since sample sizes tend to be small (e.g., Wang and Rettenmaier, 2007).[3] To overcome this disadvantage, we use the bounds test for cointegration (Pesaran et al., 2001). Similar to the SECM method, the bounds test has superior properties in small samples and, therefore, seems to be better than the residual-based Engle-Granger test (Engle and Granger, 1987) and the vector autoregression (VAR)-based Johansen test (Johansen, 1988; Johansen and Juselius, 1990). The critical values for small sample sizes are reported in Narayan (2005). Furthermore, the bounds test does not require unit root tests in examining the existence of cointegration since it is applicable irrespective of whether the underlying regressors are

3 For example, most of the previous studies use annual data.

or (e.g., Pesaran et al., 2001). Hence, it is advantageous to use the bounds test for cointegration when using time series data with small sample sizes.

The organization of this paper is as follows. The next section briefly reviews some previous studies. Section 3 explains our methodologies. Section 4 details the data. Section 5 reports the empirical results. Section 6 provides some discussions. Section 7 presents the conclusion.

2. A brief review of some previous studies

There is a large amount of literature on the determinants of HCE. Therefore, it is impossible to review all the studies. In this section, we only review some previous studies that examine the determinants of HCE in the framework of cointegration, since cointegration techniques are widely utilized in recent applied studies that use time series and panel data.

Hansen and King (1996) examined the relationship between real per capita HCE and real per capita GDP, and used time series data for 20 OECD countries over the period 1960-1987. They found that GDP and HCE were not cointegrated for most of the countries. Furthermore, the same observation applied to the relationship between HCE, GDP, and non-income variables.

Gerdtham and Löthgren (2000) focused on the existence of cointegration between per capita HCE and per capita GDP, and used data for 21 OECD countries over the period 1960-1997. Using both time series and panel data techniques, they found that HCE and GDP were cointegrated. The panel data techniques that they used provided more robust results for the cointegrating relationship between HCE and GDP.

Blomqvist and Carter (1997) examined the poolability of data on real per capita HCE and real per capita GDP for 18 OECD countries over the period 1960-1991. Using time series techniques, they found that HCE and GDP were cointegrated for each of the countries. In a pooled system, the estimated income elasticity of the demand for health care was 0.976 and was significant. However, they also found that the hypotheses of both a common income elasticity and a common trend coefficient were rejected for these countries.

Herwartz and Theilen (2003) examined the determinants of HCE and used data for 19 OECD countries over the period 1960-1997. They used a model in which real per capita HCE was regressed on real per capita income, the proportion of the population over the age of 65, and a linear deterministic trend. They found that these variables were cointegrated for most of the countries. Although the hypothesis of homogeneity across these countries was supported for the period 1960-1981, it was rejected for the full sample period.

Karatzas (2000) examined the determinants of per capita real HCE for the United States over the period 1962-1989 and used economic factors, demographic factors, and health stock as explanatory variables. Using time series data, he found that per capita real income, income distribution, and the number of nurses have a significant positive impact on per capita real HCE, while the health care price index and the number of hospital beds have a significant negative impact on per capita real HCE.

Freeman (2003) examined the income elasticity of the demand for health care and used panel data for 50 U.S. states over the period 1966-1998. He found that HCE and disposable personal income were cointegrated. The estimated income elasticity was approximately 0.8 and was significantly smaller than 1, suggesting that health care was a necessary good.

Yu and Chu (2007) used the demand and supply approach to examine the income elasticity of the demand for health care. Using time series data for Taiwan over the period 1964-2001, they found that real HCE, real income, real wage, and population were cointegrated, and health care was a necessary good.

Clemente et al. (2004) examined the stability of the relationship between per capita HCE and per capita GDP for each of the 22 OECD countries over the period 1960-1997. They found that HCE and GDP were cointegrated with structural breaks for more than 70% of the countries. However, they also found that both estimated income elasticities and their break periods were different across these countries. Wang and Rettenmaier (2007) obtained similar results for 50 U.S. states.

Narayan and Narayan (2008a) examined the relationship between per capita HCE and environmental quality, and used panel data for 8 OECD countries over the period 1980-1999. They found that HCE, income, carbon monoxide emissions, sulfur oxide emissions, and nitrogen oxide omissions were cointegrated. In the long-run, HCE was elastic with respect to income, while it was inelastic with respect to carbon monoxide emissions and sulfur oxide emissions.

3. Methodologies

3.1 Model specification

Since the seminal work of Newhouse (1977), many studies have specified HCE as a function of income level. This bivariate specification has been extended by several recent studies in order to examine the other explanatory factors of the demand for health care (e.g., Narayan and Narayan, 2008a). Along these lines, we include income level in our regression model and adjust the basic bivariate specification with the health care price index and the Gini coefficient. Consequently, we suppose the following model:

$$\ln H_t = \beta_0 + \beta_1 \ln P_t + \beta_2 \ln Y_t + \beta_3 \ln G_t + e_t , \tag{1}$$

where $\ln H_t$ denotes logged real HCE; $\ln P_t$, logged health care price index; $\ln Y_t$, logged real income level; $\ln G_t$, logged Gini coefficient; e_t, an error term; and β_0, β_1, β_2, and β_3, the parameters to be estimated.

In this paper, we use the Gini coefficient as a measure of income inequality. As mentioned in Section 1, the theory suggests that an increase in income inequality leads to an increase in the demand for health care. Hence, the Gini coefficient is expected to be positively related to real HCE (i.e., $\beta_3 > 0$), since a higher Gini coefficient means higher income inequality.

In the consumer demand theory, the demand for a good is usually assumed to be a decreasing function of its own price (in other words, the demand curve for a good has a negative slope). Hence, the health care price index is expected to be negatively related to real HCE (i.e., $\beta_1 < 0$).

3.2 Structural error correction model

To obtain the parameter estimates in equation (1), we use the SECM method. The error correction model in structural form (i.e., SECM) is specified as

$$\Delta \ln H_t = \omega + \phi_0 \ln H_{t-1} + \phi_1 \ln P_{t-1} + \phi_2 \ln Y_{t-1} + \phi_3 \ln G_{t-1} + \sum_{i=1}^{j} \psi_{0i} \Delta \ln H_{t-i}$$
$$+ \sum_{i=0}^{j} \psi_{1i} \Delta \ln P_{t-i} + \sum_{i=0}^{j} \psi_{2i} \Delta \ln Y_{t-i} + \sum_{i=0}^{j} \psi_{3i} \Delta \ln G_{t-i} + u_t, \qquad (2)$$

where Δ denotes a lag operator; u_t, an error term; and ω, $\phi_0,\cdots,\phi_3$, and $\psi_{01},\cdots,\psi_{3j}$, the parameters to be estimated. The estimates of the cointegrating parameters β_1, β_2, and β_3 are given by ϕ_1/ϕ_0, ϕ_2/ϕ_0, and ϕ_3/ϕ_0, respectively, and the restriction on β_1, β_2, and β_3 can be examined by the likelihood ratio (LR) test (e.g., Boswijik, 1995).

It is important to note that the use of the SECM method requires the following three assumptions: (i) $\ln H_t$, $\ln P_t$, $\ln Y_t$, and $\ln G_t$ are integrated of order one; (ii) they are cointegrated with one cointegrating vector; and (iii) $\ln P_t$, $\ln Y_t$, and $\ln G_t$ are weakly exogenous for the cointegrating vector (e.g., Boswijik, 1995).[4] Under these assumptions, the efficient inference on the cointegrating vector can be conducted by analyzing only equation (2).

3.3 Bounds test for cointegration

The bounds test for cointegration also starts from the estimation of equation (2). The null hypothesis of no cointegration can be examined by the joint significance test for the lagged level

4 The validity of these assumptions is examined empirically in Section 6.

variables $\ln H_{t-1}$, $\ln P_{t-1}$, $\ln Y_{t-1}$, and $\ln G_{t-1}$ in equation (2). More specifically, the null and alternative hypotheses are given by

$$\mathrm{H}_0: \ \phi_0 = \phi_1 = \phi_2 = \phi_3 = 0,$$
$$\mathrm{H}_1: \ \phi_0 \neq 0, \ \text{or} \ \phi_1 \neq 0, \ \text{or} \ \phi_2 \neq 0, \ \text{or} \ \phi_3 \neq 0.$$

We can use the standard F-statistic to examine these hypotheses. The *F*-statistic has a non-standard distribution under the null hypothesis, and the asymptotic critical values are reported in Pesaran et al. (2001). However, Narayan (2005) and Narayan and Narayan (2005) point out that these critical values cannot be used in cases with small samples as in the case of this study because they are generated for large sample sizes. Therefore, we use appropriate critical values tabulated in Narayan (2005), who report a new set of critical values for sample sizes ranging from 30-80 observations.

If the computed *F*-statistic falls outside the critical value bounds, a conclusive decision can be made without knowing the order of integration of the variables. For example, if the computed *F*-statistic is higher than the upper bound, then the null hypothesis of no cointegration is rejected.

4. Data

This paper uses annual Japanese data. The sample period is chosen as 1970-2009 because of data availability.[5] The data consist of total medical care expenditure, the medical care price index, disposable income, the corporate goods price index, and the Gini coefficient. The data sources are the websites of the Statistics Bureau and the Bank of Japan.

In this paper, we use total medical care expenditure as a measure of HCE. This data consists of expenditure on medicines, health fortification (foods used for health maintenance and improvement, such as nutritional supplements, and similar to ordinary medicine which come in the form of pills, capsules, granule, powder, grain, liquid (extract), etc.), medical supplies and appliances, and medical services.

In this study, only data on the annual averages of monthly income per household are available to calculate the Gini coefficient over the long period. Therefore, the Gini coefficient is calculated from data on the annual averages of monthly disposable income per household by annual income quintile group. To ensure consistency of data, we use data on total medical care expenditure and disposable income per household.

To obtain real variables, total medical care expenditure and disposable income are divided by the medical care price index and the corporate goods price index. Medical care expenditure, the medical

5 The data on the medical care price index for Japan is available from 1970.

care price index, disposable income, and the corporate goods price index are the annual averages of monthly data. To increase the sample size, we use the data for two-or-more-person workers' households.

5. Empirical Results

5.1 Cointegration tests

We begin by examining the existence of cointegration among the variables since the bounds test for cointegration is applicable without knowing the order of integration of the variables.[6] In this paper, we assume that equation (2) includes an unrestricted intercept. The lag length of equation (2) is 2 and is selected by the Akaike information criterion (AIC).[7]

Table 1 Bounds test for cointegration

(A) Cointegration test

Test	Statistic	5% critical value bounds: Lower bound	5% critical value bounds: Upper bound
Bounds F-test	7.3290**	3.548	4.803

(B) Diagnostic tests for equation (2)

Tests	Statistics	p-values
Serial correlation LM test	4.3539	0.1134
ARCH LM test	0.6086	0.7376
Ramsey RESET	0.8030	0.6693
Jarque-Bera normality test	0.8259	0.6617

For the bounds F-test, the critical values for the sample size of 40 are used and are tabulated in Narayan (2005). The lag length of equation (2) is 2 and is selected by the AIC. The serial correlation LM test is the Lagrange multiplier (LM) test for the null hypothesis of no residual autocorrelation up to order 2. The ARCH LM test is the LM test for the null hypothesis of no autoregressive conditional heteroskedasticity (ARCH) up to order 2. The Ramsey RESET is the specification error test for the regression with the second and third powers of the fitted values. The Jarque-Bera normality test is the test for the null hypothesis of residual normality. ** and * indicate significance at the 1% and 5% levels, respectively.

6 Although unit root tests are not a prerequisite for the bounds test, we find that all the variables are integrated of order one. The unit root test results are reported in Section 6.

7 If we use the general-to-specific approach developed by Hendry et al. (1984), the following results remain essentially unchanged. Although the results are not reported, they are available from the author upon request.

The cointegration test result for equation (2) is reported in Table 1. The computed F-statistic is higher than the upper bound critical value of 4.803 at the 5% level. Therefore, the null hypothesis of no cointegration is rejected at the 5% level, suggesting that real HCE and its determinants are cointegrated. This result is consistent with recent studies such as Blomqvist and Carter (1997) and Gerdtham and Löthgren (2000).

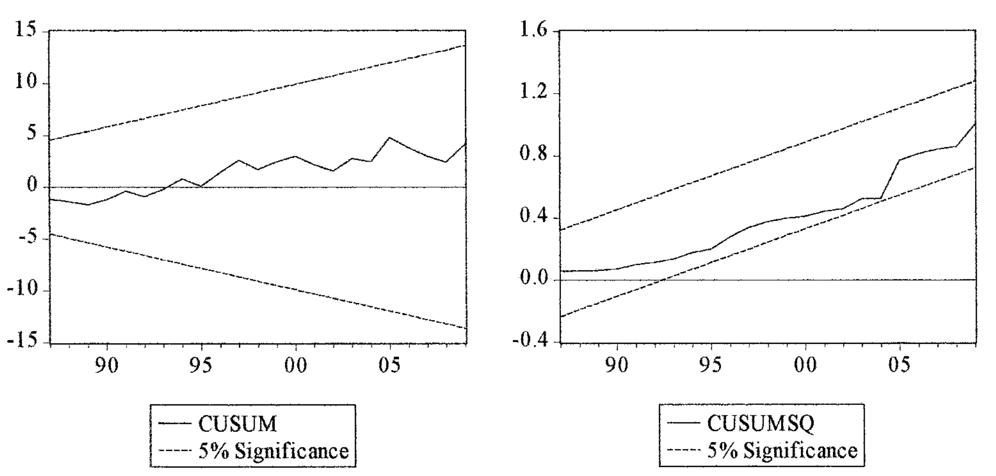
The diagnostic test results for equation (2) are also reported in Table 1. There is no evidence in favor of residual autocorrelation, conditional heteroskedasticity, model misspecification, and residual non-normality. Therefore, our cointegration test result based on equation (2) is appropriate since equation (2) is found to be successfully estimated.

5.2 Estimation of demand equation for health care

Prior to proceeding to the estimation of the demand equation for health care, we examine the parameter stability of the SECM in equation (2).[8] As mentioned in Section 3, the estimates of the cointegrating parameters β_1, β_2, and β_3 in equation (1) are obtained from the parameters of the SECM in equation (2). Therefore, the parameter stability of the SECM can be regarded as indicative of the parameter stability of the demand equation for health care.

To examine the parameter stability of the SECM, we follow Narayan and Peng (2007) and Razafimahera and Hamori (2005) who use the cumulative sum of recursive residuals (CUSUM) and

Figure 1 CUSUM and CUSUMSQ tests for parameter stability



8 For the SECM in equation (2), there is no significant evidence to suggest residual autocorrelation, conditional heteroskedasticity, model misspecification, and residual non-normality. The results are reported in Table 1.

the CUSUM of squares (CUSUMSQ) tests. The results are reported in Figure 1. The plots of both the CUSUM and the CUSUMSQ statistics stay inside the 5% significance lines. Hence, there is no significant evidence to suggest the parameter instability of the SECM.

Table 2 Estimation results of the demand equation for health care

Parameters	Estimates	LR statistics
β_1 (Price elasticity)	-0.5590*	6.2114
β_2 (Income elasticity)	0.6120**	13.1425
β_3 (Inequality elasticity)	1.4057**	8.3891

** and * indicate significance at the 1% and 5% levels, respectively.

The cointegrating parameters of equation (1) estimated by the SECM method are reported in Table 2. Our main findings can be summarized as follows. First, we find that the health care price index, income level, and income inequality are significantly related to real HCE. Therefore, these explanatory variables are the important determinants of the demand for health care in Japan.

Second, we find that the health care price index has a negative impact on real HCE. This result is consistent with the consumer demand theory in which the demand curve for a good is assumed to have a negative slope. The price elasticity of the demand for health care (β_1) is -0.56, suggesting that a 1% rise in health care price decreases real HCE by 0.54%. Therefore, the demand for health care in Japan is inelastic with respect to its own price. This result is consistent with Yu and Chu (2007).

Third, we find that income level has a positive impact on real HCE. This result is consistent with most previous studies. Hence, we can then examine another important question, namely, whether health care is a necessary or a luxury good. This is still a matter of debate in the literature on the demand for health care (e.g., Clemente et al., 2004; Freeman, 2003; Yu and Chu, 2007). We find that the income elasticity of the demand for health care (β_2) is 0.61. Hence, health care in Japan can be regarded as a necessary good. This result is consistent with Freeman (2003) and Yu and Chu (2007).

Finally, we find that the Gini coefficient has a positive impact on real HCE, and this result is statistically significant at the 5% level. Hence, there is evidence in favor of our hypothesis that an increase in income inequality leads to an increase in the demand for health care. It is also found that the inequality elasticity of the demand for health care (β_3) is 1.41 and is larger in absolute value than the price and income elasticities. This result implies that the impact of income inequality on the demand for health care is larger in magnitude than the impacts of income level and own price.

5.3 Granger-causality tests

We are now certain that income inequality in Japan affects the demand for health care. To understand this relationship in more detail, we next examine Granger-causality between income inequality and real HCE. For this purpose, we use the following error correction model (ECM):

$$\Delta \ln H_t = \mu_0 + \alpha_0 EC_{t-1} + \sum_{i=1}^{k} \gamma_{0i} \Delta \ln H_{t-i} + \sum_{i=1}^{k} \gamma_{1i} \Delta \ln P_{t-i} + \sum_{i=1}^{k} \gamma_{2i} \Delta \ln Y_{t-1} + \sum_{i=1}^{k} \gamma_{3i} \Delta \ln G_{t-i} + \varepsilon_{0t}, \tag{3}$$

where ε_{0t} denotes an error term, and μ_0, α_0, and $\gamma_{01} \cdots$, γ_{3k} denote the parameters to be estimated. The error correction term EC_t is defined as

$$EC_t = \ln H_t - \beta_1 \ln P_t - \beta_2 \ln Y_t - \beta_3 \ln G_t . \tag{4}$$

Table 3 Estimation results of the ECM

(A) Adjustment coefficient		
Parameter	Estimate	t-statistic
α_0	-0.4128**	-5.0210
(B) Short-run causality		
Null hypothesis	Wald statistics	p-values
$\Delta \ln P_t$ does not Granger-cause $\Delta \ln H_t$	8.1596*	0.0169
$\Delta \ln Y_t$ does not Granger-cause $\Delta \ln H_t$	0.5883	0.7452
$\Delta \ln G_t$ does not Granger-cause $\Delta \ln H_t$	10.6899**	0.0048
(C) Diagnostic tests for the ECM		
Tests	Statistics	p-values
Serial correlation LM test	3.3341	0.1888
ARCH LM test	1.5134	0.4692
Ramsey RESET	2.6063	0.2717
Jarque-Bera normality test	2.3075	0.3154

The lag length of the ECM is 2 and is selected by the AIC. For details of the diagnostic tests, see the notes to Table 1. ** and * indicate significance at the 1% and 5% levels, respectively.

We focus on short-run Granger-causality. For example, the existence of short-run causality from income inequality to real HCE can be examined by the joint significance test for $\Delta \ln G_{t-1}, \cdots, \Delta \ln G_{t-k}$ in equation (3). The lag length of the ECM in equation (3) is 2 and is selected by the AIC.

The causality test results are reported in Table 3. The null hypothesis that $\Delta \ln G_t$ does not Granger-cause $\Delta \ln H_t$ is rejected at the 5% level, suggesting that income inequality Granger-causes real HCE. Therefore, there is additional evidence that income inequality in Japan affects the demand for health care.

It is also found that the health care price index Granger-causes real HCE, whereas income level does not Granger-cause real HCE. From these results, it seems reasonable to suppose that the demand for health care in Japan is more strongly affected by income inequality than income level. In this respect, the causality test results are consistent with the estimation results of equation (1).

The adjustment coefficient α_0 is negative and is significant at the 1% level. This result means that equation (1) can be regarded as indicative of attainable long-run equilibrium. Furthermore, all the diagnostic tests show the adequacy of the ECM. Therefore, the causality test results seem to be appropriate.

6. Discussions

From the above results, our hypothesis about the relationship between income inequality and the demand for health care seems to be empirically supported for Japan. In this section, we aim to check the robustness of the results by using the vector error correction model (VECM: Johansen, 1988; Johansen and Juselius, 1990).

Before estimating the VECM, it is necessary to check stationarity in each of the variables included in equation (1) and the number of cointegrating vectors. Using the unit root tests developed by Ng and Perron (2001), we find that all the variables are integrated of order one. To examine the number of cointegrating vectors, we use the trace and maximum eigenvalue tests developed by Johansen (1988) and Johansen and Juselius (1990). We find that the variables are cointegrated with one cointegrating vector. Furthermore, the Durbin-Hausman test (Choi, 1994), which is a residual-based test for cointegration and is more powerful in finite samples than the other residual-based tests for cointegration, also indicates that real HCE and its determinants are cointegrated.[9] Accordingly, these results are consistent with the result obtained from the bounds test.

Since it is found that the variables are cointegrated with one cointegrating vector, we can now examine the following VECM:

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9 Although these unit root and cointegration test results are not reported, they are available from the author upon request.

$$\Delta z_t = \mu + \alpha\beta' z_{t-1} + \sum_{i=1}^{k} \Gamma_i \Delta z_{t-1} + \varepsilon_t \,, \tag{5}$$

where $z_t = (\ln H_t, \ln P_t, \ln Y_t, \ln G_t)'$, $\alpha = (\alpha_0, \alpha_1, \alpha_2, \alpha_3)'$, and $\beta = (1, -\beta_1, -\beta_2, -\beta_3)'$. ε_t denotes a vector of error terms; μ, a vector of constant terms; and $\Gamma_1, \cdots, \Gamma_k$, parameter matrices of autoregressive terms. The lag length of the VECM in equation (5) is 2 and is selected by the LR test.

Table 4 Estimation results of the VECM

(A) Long-run relationship		
Parameters	Estimates	LR statistics
β_1 (Price elasticity)	-0.4889*	-5.5840
β_2 (Income elasticity)	0.6333**	15.6010
β_3 (Inequality elasticity)	1.1540**	7.0366
(B) Adjustment coefficients		
Parameters	Estimates	LR statistics
α_0	-0.4638**	19.1606
α_1	0.0384	0.2890
α_2	0.0767	0.8042
α_3	-0.0428	0.5559
(C) Short-run causality		
Null hypothesis	Wald statistics	*p*-values
$\Delta\ln P_t$ does not Granger-cause $\Delta\ln H_t$	6.8296*	0.0329
$\Delta\ln Y_t$ does not Granger-cause $\Delta\ln H_t$	1.0969	0.5779
$\Delta\ln G_t$ does not Granger-cause $\Delta\ln H_t$	10.4844**	0.0053
(D) Diagnostic tests for the ECM (5)		
Tests	Statistics	*p*-values
Multivariate LM test for serial correlation	16.6727	0.4071
Multivariate Jarque-Bera normality test	13.8835	0.0849

The multivariate LM test for serial correlation is the LM test for the null hypothesis of no residual autocorrelation at order 1. For the multivariate Jarque-Bera normality test, we use the Cholesky factor of the residual covariance matrix. ** and * indicate significance at the 1% and 5% levels, respectively.

The estimation results of the VECM are reported in Table 4.[10] The estimated price, income, and inequality elasticities of the demand for health care are -0.49, 0.63, and 1.15, respectively, and they are statistically significant at conventional levels. These results are similar to the estimation results of the elasticities obtained from the SECM method. Therefore, our estimation results of the elasticities are robust.

The adjustment coefficient α_0 is negative and is significant at the 1% level. This result is consistent with the result obtained from the ECM in equation (3). On the other hand, the other adjustment coefficients α_1, α_2, and α_3 are insignificant. This result indicates that $\ln P_t$, $\ln Y_t$, and $\ln G_t$ are weakly exogenous for the cointegrating vector β (e.g., Johansen, 1995). Consequently, we find that all the assumptions of the SECM method discussed in Section 3 are valid.

Furthermore, the causality test results for the VECM show that $\Delta \ln G_t$ and $\Delta \ln P_t$ Granger-cause $\Delta \ln H_t$, but $\Delta \ln Y_t$ does not Granger-cause $\Delta \ln H_t$. Hence, we find that the causality test results are robust.

The diagnostic tests for the VECM show no significant evidence of residual autocorrelation and non-normality. Hence, it appears that the results obtained from the VECM are appropriate.

At this point, we can reasonably state that our results are generally robust. Hence, there is good evidence to suggest that income inequality in Japan affects the demand for health care.

7. Conclusion

This paper examines the relationship between income inequality and the demand for health care. Given that the demand for health care depends on the health condition, income inequality can affect the demand for health care. This is a simple extension of the theory of the relationship between income inequality and population health. A large number of studies have been conducted on the impact of income level on the demand for health care. However, the impact of income inequality on the demand for health care has not been fully examined. Hence, we distinguish our work from the extant literature by using the model of the demand for health care in which real HCE is regressed on the Gini coefficient as well as real income level and the health care price index.

Having firmly established the cointegration relationship among the variables in Japan, we obtain the following results: (i) income inequality has a significant positive impact on the demand for health care; (ii) the inequality elasticity of the demand for health care is larger in absolute value than the

10 If we use the t-statistics instead of the LR statistics, the test results remain unchanged. Although the results are not reported, they are available from the author upon request.

income and price elasticities; and (iii) income inequality Granger-causes real HCE. Using the SECM and the VECM methods, we find that these results are robust. On these grounds, we conclude that, in the case of Japan, greater income inequality leads to a greater demand for health care.

Finally, let us discuss the policy implications for Japan. Since 1970, medical care expenditure in Japan has continued to increase. Our results suggest that this upward trend is partly caused by an increase in income inequality. In fact, the Gini coefficient in Japan also tends to increase after the mid-1980s (e.g., Förster and Mira d'Ercole, 2005). This observation implicitly suggests that individuals in lower income groups require more health care goods and services to maintain their health. Hence, the health care policy for individuals in the lowest income group is likely to play an important role in improving and maintaining population health in Japan.

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