Health Care is "a Necessity" or "a Luxury"? Evidences from Local Quantile Regressions

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Abstract

In this paper, local relationship between per capita health care expenditure (HCE hereafter) and GDP is investigated with local quantile regressions. The advantage of using local quantile regressions is the assumption of homogeneity on per capita HCE could be relaxed so the number of countries in a cross-sectional model can be enlarged. Per capita GDP and HCE of 151 countries in 2000 and 25 %, 50 % and 75 % quantile regressions are considered in this paper. To check significance of the relationship in local quantile regressions, significance tests for nonparametric regressions suggested by Racine (1997) and Aït-Sahalia et al. (2001) are implemented. The adequacy of of these tests are investigated with Monte Carlo simulations whose primary simulation results reveal these test are suggestive. Our empirical results show that per capita GDP has significant effect on per capita health expenditure. The sizes of effect are quite different among 25 %, 50 % and 75 % quantiles. Besides, the effects are found distinct among different ranges of per capita income. In other words, the per capita health care expenditures are heterskedastic. The conditional distribution of health care expenditure on per capita GDP is asymmetric and skewed to the left. For low per capita GDP countries, the effect of income on health expenditure is insignificant, which indicates the health care is a necessity. On the contrast, the effect becomes larger for the countries with high per capita GDPs, which implies the health care is a luxury in these countries.

1 Introduction

Whether health care is a luxury good, i.e., income elasticity of expenditures is above or below 1.0, has been debated for more than a decade. And the empirical results shown in literature are confusing and conflicting as well. Regressing per capita health care expenditure (HCE, hereafter) on per capita GDP of 13 OECD countries, Newhouse (1977) concludes the health care is a luxury good. However, Gerdttham and Jonsson (2000) finds the GDP elasticity of HCE is around slightly less than one from a cross-section model using data of OECD countries. Due to the disadvantages of cross-section models being faulted for small data sets and the implicit assumption of homogeniety of HCE across OECD countries, time series models with panel data have been studied recently by Gerdtham (1992), Hitiris and Posnett (1992), Gerdtham et al. (1992), Blomqvist and Carter (1997), Gerdtham and Löthgren (2000) and Okunade and Karakus (2001). Even the curse of sample size of cross-section data is overcome via using panel data set, the spurious regression could be resulted in the nonstationarity of time series data caused by the existence of unit roots, nonlinearity (i.e., structural changes and thresholds), outliers. Consequently, reliable empirical results from time series models are difficult to obtain. Therefore, models allow large cross-section data are required.

Instead of studying the global relation between HCE and GDP, the local relationship is investigated in this paper via using local quantile regression suggested by Yu and Jones (1998). The advantage of using quantile regression to study the local relation between HCE and GDP is the assumption of homogeneity of HCE could be relaxed. Consequently, the sample size of cross-section data under study is allowed enlarged. Thus, the per capita GDPs and per capita HCE of 151 countries in 2000 are considered in this paper. To check significance of the relationship in local quantile regressions, significance tests for nonparametric regressions suggested by Racine (1997) and Aït-Sahalia et al. (2001) are implemented. The adequacy of these tests is investigated with Monte Carlo simulations. Based on our primary simulation results, these test are suggestive. Our empirical results show that the per capita GDP has significant effect on per capita HCE. The sizes of effect are quite different among 25 %, 50 % and 75 % quantiles. Besides, the effects are also found distinct for different ranges of per capita GDP. For low per capita GDP countries, the effect of income on health expenditure is small, which indicates health care is a necessity in these countries. On the contrary, the effect becomes larger for the countries with high per capita GDPs, which implies health care is a luxury for them.

The remains of this paper are organized as follows. The basic concept of local linear quantile regressions are introduced in section 2. Section 3 demonstrates the significance tests in local linear regressions. Performance of the significance tests is investigated in section 4. An empirical study on the effect of per capita GDP on per capita HCE using local quantile regression is presented in section 5. Conclusions and suggestions are raised in the final section.

2 Local Linear Quantile Regressions

In a regression analysis, the condition mean of a variable Y on other k variables $\boldsymbol{X}$, $E(Y|\boldsymbol{X}) = Q(\boldsymbol{X})$, is of interest. The conditional mean can either be specified "parametrically" as $E(Y|\boldsymbol{X}) = Q(\boldsymbol{X};\boldsymbol{\beta})$ in which $\boldsymbol{\beta}$ is the parameter vector or be specified "nonparametrically" as $E(Y|\boldsymbol{X}) = Q(\boldsymbol{X})$. In literature, parametric models are usually classified into linear and nonlinear ones. The conditional mean is said to be a linear parametric model if $Q(\boldsymbol{X};\boldsymbol{\beta}) = \boldsymbol{X}\boldsymbol{\beta}$ and a nonlinear parametric model if $Q(\boldsymbol{X};\boldsymbol{\beta})$ is a nonlinear function in $\boldsymbol{\beta}$. On the other hand, a nonparametric model is the one with no parametric functional form specified for the conditional mean $Q(\boldsymbol{X})$. Nonparametric regression analysis has been widely discussed in literature recently. In some circumstances, conditional quantile rather than conditional mean is of interest, such as VaR (value-at-risk) in finance.

Koenker and Bassett (1978) extend the concepts of population quantiles to the linear quantile regression in which the τth quantile relationship between response variable Y and explanatory variables $\boldsymbol{X}$ at $\boldsymbol{X} = \boldsymbol{x}$ is represented as

$$Q_\tau(Y|\boldsymbol{X} = \boldsymbol{x}) = \boldsymbol{x}\boldsymbol{\beta}_\tau.$$

It is ready to see

$$\tau = \int_{-\infty}^{\boldsymbol{x}\boldsymbol{\beta}_\tau} f_y(s|\boldsymbol{x})ds$$

where $f_y(\cdot)$ is the density function of Y. Then, a quantile regression model for a sample

$\{(y_t, \boldsymbol{x}_t'), t = 1, \ldots, T\}$ can be written as

$$y_t = \boldsymbol{x}_t^{'}\boldsymbol{\beta}_\tau + u_{t,\tau}, \qquad t = 1, \ldots, T,$$

where $\boldsymbol{x}_t$ is a $k \times 1$ vector of the tth sample observations of $\boldsymbol{X}^{'}$, $\boldsymbol{x}_{t1} \equiv 1$, and u_t is i.i.d. with distribution F. $Q_\tau(u_{t,\tau}|\boldsymbol{x}_t) = 0$ follows the above definitions immediately. In light of the fashion of sample quantile estimators, the sample point estimator $\hat{\boldsymbol{\beta}}_\tau$ of the linear quantile regression parameters, $\boldsymbol{\beta}_\tau$, is obtained by solving

$$\begin{aligned}
&\min_{\boldsymbol{\beta} \in \mathbf{R}^p} \frac{1}{T} \sum_{t=1}^{T} \rho_\tau(y_t - \boldsymbol{x}_t^{'}\boldsymbol{\beta}) \\
&= \min_{\boldsymbol{\beta} \in \mathbf{R}^p} \frac{1}{T} \sum_{t=1}^{T} \left[\tau - I(y_t - \boldsymbol{x}_t^{'}\boldsymbol{\beta} < 0)\right] (y_t - \boldsymbol{x}_t^{'}\boldsymbol{\beta}) \qquad (1) \\
&= \min_{\boldsymbol{\beta} \in \mathbf{R}^p} \frac{1}{T} \left[\sum_{t \in \{t: y_t \geq \boldsymbol{x}_t^{'}\boldsymbol{\beta}\}} \tau |y_t - \boldsymbol{x}_t^{'}\boldsymbol{\beta}| + \sum_{t \in \{t: y_t < \boldsymbol{x}_t^{'}\boldsymbol{\beta}\}} (1-\tau)|y_t - \boldsymbol{x}_t^{'}\boldsymbol{\beta}| \right]. \qquad (2)
\end{aligned}$$

The k-dimensional $\hat{\boldsymbol{\beta}}_\tau$ constructs a sequences of hyperplanes which estimate the response variable over whole conditional distribution given different τ's. Through the regression quantiles, the combination of $\boldsymbol{x}_t$ and $\hat{\boldsymbol{\beta}}_\tau$, the conditional distribution of response variable can be explored. Furthermore, the optimization mechanism specified in (2) suggests a feasible way to sort the sample observations, whereas it is vague how to sort the observations in general parametric models. Other characteristics of regression quantiles are inherent robustness and equivariant properties, see Koenker and Bassett (1978) for more details. The estimation for linear quantile regression is suggested by Koenker and d'Orey (1987)and for nonlinear quantile regression is suggested by Koenker and Park (1996). The asymptotic distribution of quantile regression estimators in linear models with i.i.d. errors is derived by Koenker and Bassett (1978), with heteroskedastic errors by Koenker and Zhao (1996) and Zhao (1997), and with strong mixing errors by Fitzenberger (1997), respectively.

In stead of specifying the linear quantile relationship between Y and $\boldsymbol{X}$ "globally", the "local" linear quantile regression is considered by Yu and Jones (1998). The local linear fit is to approximate the unknown regression function $m_\tau(z)$ with a linear function, i.e., $m_\tau(z) = m_\tau(x) + m_\tau'(x)(z - x) \equiv a + b(z - x)$, for z is a neighborhood of x. Locally estimating $m_\tau(x)$ is equivalent to estimating a, and estimating $m_\tau'(x)$ is equivalent to estimating b. The local linear quantile estimators are obtained as

$$\arg\min_{a,b} \frac{1}{T}\sum_{t=1}^{T} \rho_\tau(y_t - a - b(x_t - x))K\left(\frac{x_t - x}{h_\tau}\right), \tag{3}$$

where $K(\cdot)$ is a kernel function and h_τ is the bandwidth of kernel or the smoothing parameter. It is clear that $\hat{a} = \hat{m}_\tau(x)$ is the fitted value of Y at $X = x$ and $\hat{b} = \hat{m}'_\tau(x)$ is the first derivative of Y on X at $X = x$. It is well known that the estimations are insensitive to the kernel function $K(\cdot)$ but very sensitive to the selection of bandwidth h. Yu and Jones (1998) suggest the automatic bandwidth selection as:

$$h_\tau = h_{\text{mean}} \times \left[\frac{\tau(1-\tau)}{\phi[\Phi^{-1}(\tau)]^2}\right]^{1/5},$$

where h_{mean} is the optimal bandwidth selection for regression mean estimation. Several data-driven bandwidth selectors have been introduced in literature, e.g., cross-validation method of Rudemo (1982) and Vieu (1995), generalized cross-validation method of Wahba (1977) and plug-in method of Ruppert et al. (1995). Hall and Johnstone (1992) point out that bandwidth selected by cross-validation methods may vary substantially. Jones et al. (1996) provid a complete survey for methods of bandwidth selection. In addition, the pre-asymptotic substitution selector proposed by Fan and Gijbels (1995) and the empirical-bias bandwidth selector (EBBS) by Ruppert (1997), are also useful alternatives.

In regression analyzes, checking the significance of X on Y is commonly required after estimation. To the best of our knowledge, there is not any test provided to check the significance of X on Y in local linear quantile regressions. In the next section, we extend the significance tests suggested by Racine (1997) and Aït-Sahalia (2001) for nonparametric regressions to local linear quantile regressions.

3 Significance Tests for Local linear Quantile Regressions

In this section, tests proposed by Racine (1997) and Aït-Sahalia (2001) for the nonparametric regressions are extended to construction of the significance tests for local linear quantile regressions.

3.1 Racine's Test for Local quantile Regressions

Consider the local quantile regression function $y = m_\tau(x) + \epsilon$ between two random variables X and Y, where $m_\tau(x)$ is the τ-th quantile conditional on $X = x$. That is the conditional τ-quantile of Y on $X = x$ is $Q_\tau(Y|X = x) = m_\tau(x)$. Then X is said to have no influence on Y under the τ-th percentile of Y if $m_\tau(x) = Q_\tau(Y)$ where $Q_\tau(Y)$ is the unconditional quantile of Y. The Racine's significance test bases on the following intuition:

$$Q_\tau(Y|X) \perp X \Leftrightarrow \frac{\partial Q_\tau(Y|X)}{\partial X} = 0 \, a.s., \tag{4}$$

where $\perp$ denotes "orthogonal to" or "independent to". Then the null hypothesis can be represented as: $H_0 : \frac{\partial Q_\tau(Y|X)}{\partial X} = 0 \; for\, all\, x \in X$ against the alternative $H_A : \frac{\partial Q_\tau(Y|X)}{\partial X} \neq 0 \; for\, some\, x \in X$. Due to the variability of partial derivatives, the tests must be formulated to detect whether the partial derivatives equal to 0 over entire domain. Therefore, an aggregate measure of the derivatives over it's domain is necessary. Thus the null hypothesis is revised as:

$$H_0 : \lambda = E\iota' \left[\frac{\partial Q_\tau(Y|X)}{\partial X} \right]^2 = 0$$

against the alternative

$$H_A : \lambda = E\iota' \left[\frac{\partial Q_\tau(Y|X)}{\partial X} \right]^2 > 0,$$

where ι denotes a unit vector. It is clear that λ is an aggregation of squared derivatives of each x on $Q_\tau(Y|X = x)$. The null hypothesis is rejected when λ is larger than 0 significantly. Denote $\hat{m}'_\tau(x_t)$ as the estimated first derivatives of Y on X at $X = x_t$ from the sample observations $\{(y_t, x_t), t = 1, \dots, T\}$. The test statistic suggested by Racine (1997) is

$$\hat{\lambda}_T = \frac{1}{T} \sum_{t=1}^{T} \hat{m}'_\tau(x_t)^2.$$

In this paper, the following bootstrapping procedures are applied to obtain the null distribution of $\hat{\lambda}_T$ and then the critical values at significant level $1 - \alpha$:

1 . Given original bivariate sample data, $\{(y_t, x_t), t = 1, \dots, T\}$, estimate the unconditional quantile of Y, that is, $\hat{Q}_\tau(Y)$. As the null hypothesis is $Q_\tau(Y|X) \perp X$, $Q_\tau(Y|X) = Q_\tau(Y)$ is implied.

2 . Calculate the residuals $\hat{\varepsilon}_t = y_t - \hat{Q}_\tau(Y)$ for $t = 1, \dots, T$.

3 . Draw a "bootstrapped residual sample" from residuals $\{\varepsilon_t^*\}_{t=1}^T$ randomly *with replacement.*

4 . Generate a pseudo dependent variable y_t^* as $y_t^* = \hat{Q}_\tau(Y) + \varepsilon_t^*$, $t = 1, \dots, T$.

5 . Given the pseudo sample observations, $\{(x_t, y_t^*), t = 1, \dots, T\}$, the bootstrapped test statistic $\hat{\lambda}^*$ is calculated.

6 . Repeat steps 3–5 for B times, the bootstrapped $\hat{\lambda}_1^*, \hat{\lambda}_2^* \dots, \hat{\lambda}_B^*$ are calculated and then the empirical sampling distribution of the statistic under the null is obtained.

Denote $\lambda_{1-\alpha}^*$ as the empirical $(1-\alpha)$-th percentile of $\hat{\lambda}_1^*, \hat{\lambda}_2^*, \dots, \hat{\lambda}_B^*$ and $\hat{\lambda}_T$ as the test statistic calculated from the original sample observations $\{(x_t, y_t), t = 1, \dots, T\}$. Then, the null is rejected at significance level α when $\hat{\lambda}_T > \lambda_{1-\alpha}^*$.

3.2 Aït-Sahalia's Test for Local Quantile Regressions

According to Aït-Sahalia et al. (2001), the null hypothesis of regressor X has no contribution to Y, that is,

$$H_0 : \Pr[m_\tau(x) = Q_\tau(Y)] = 1$$

against the alternative,

$$H_a : \Pr[m_\tau(x) = Q_\tau(Y)] < 1.$$

That is, the unconstrained estimator $m_\tau(x)$ and the constrained estimator $Q_\tau(Y)$ will be equal with probability one when the null is true, otherwise the probability will be less than one. Denote $\hat{m}_\tau(x_t)$ as the fitted value of Y given $X = x_t$ and $\hat{Q}_\tau(Y)$ as the sample quantile from the sample observations $\{(y_t, x_t), t = 1, \dots, T\}$. The test statistic suggested by Aït-Sahalia et al. (2001) is written as

$$\hat{\Gamma}_T = \frac{1}{T}\sum_{t=1}^{T}[\hat{m}_\tau(x_t) - \hat{Q}_\tau(Y)]^2.$$

Similarly, the following bootstrapping procedures are applied to obtain the null distribution of $\hat{\Gamma}_T$ and then the critical values with significant level $1-\alpha$:

1 . Given the original data set, the unrestricted and restricted regression functions are estimated respectively, i.e., $\hat{m}_\tau(x_t)$ and $\hat{Q}_\tau(Y)$. Then the test statistic $\hat{\Gamma}_T$ is calculated.

2 . Calculate the residuals under the null hypothesis: $\varepsilon_t = y_t - \hat{Q}_\tau(Y),\ t = 1, \ldots, T$. Then a pseudo sample is bootstrapped through $y_t^* = \hat{Q}_\tau(Y) + \varepsilon_t^*,\ t = 1, \ldots, T$, where ε^* are the bootstrapped residuals drawn randomly with replacement T times from the original residuals ε.

3 . Estimate the statistic $\hat{\Gamma}_T$ using the pseudo sample $\{y_t^*, x_t\}_{t=1}^T$ and denote as $\hat{\Gamma}_1^*$

4 . Repeat steps 2 and 3 for B times, then $\hat{\Gamma}_1^*, \ldots, \hat{\Gamma}_B^*$ are calculated and the empirical sampling distribution of the test statistic under the null could be constructed using $\hat{\Gamma}_1^*, \ldots, \hat{\Gamma}_B^*$.

Then the empirical sampling distribution of the test statistic is obtained. Since the test statistic $\hat{\Gamma}_T$ is the squared difference between $\hat{m}_\tau(x_t)$ and $\hat{Q}_\tau(Y)$, which is always positive, thus the one-sided test is considered. Denote $\hat{\Gamma}_{(1-\alpha)}^*$ as the $(1 - \alpha)$ sample percentile from $\hat{\Gamma}_1^*, \ldots, \hat{\Gamma}_B^*$. Then a test of size α can be conducted by comparing whether $\hat{\Gamma}_T > \hat{\Gamma}_{(1-\alpha)}^*$. If positive, H_0 is rejected, otherwise H_0 can't not be rejected.

4 Simulation Studies

To the best of our knowledge, there is no literature studying the significance tests in local quantile regressions yet. To check the adequacy of employing the tests suggested by Racine (1997) and Aït-Sahalia et al. (2001) to local quantile regressions, their performances are studied with simulations. In this section, linear and nonlinear DGPs are designed to evaluate the performances of the two tests respectively.

Our simulations focus on three conditional quantiles, $25\%, 50\%$, and 75%. Besides, the significance level is 5%, the sample size T is 100. For each simulation, 200 bootstrap resamplings and 200 replications are taken.

4.1 Linear DGP

In oder to evaluate the performances of these two tests under conventional linear models, a linear DGP is specified as,

$$y_t = 2 + x_t\beta_\tau + \epsilon_t, t = 1, \ldots, T,$$

where x_t and ε_t are i.i.d $N(0, 1)$. Under the null hypothesis, X has no contribution to Y, thus the null DGP specified $\beta_\tau = 0$. Then the ratio of the null hypothesis being rejected can be obtained, which is the size of the test. On the other hand, under the alternative, X has significant effect on Y, β_τ is specified to be 3. In our simulations, the bandwidth h is chosen according to the practical method suggested by Yu and Jones(1998) and the Gaussian kernel is taken in estimating local quantile regressions.

As the results showed in Table 1, two tests perform quite well under linear DGP. The empirical sizes under three quantiles are smaller than the specified nominal size 5 %. Besides, the empirical powers under three quantiles are all quite close to 1.

Table 1. Reject frequency of tests in DGP: $y_t = 2 + x_t\beta_\tau + \epsilon_t$

	Size	Power
Racine's Test		
$\tau = 25$ %	0.035	0.995
$\tau = 50$ %	0.040	0.995
$\tau = 75$ %	0.055	1.000
Aït-Sahalia's Test		
$\tau = 25$ %	0.055	0.940
$\tau = 50$ %	0.050	0.935
$\tau = 75$ %	0.015	0.875

4.2 Nonlinear DGP

It is well known that nonparametric methods are specified in estimating nonlinear models. Thus it is interesting for us to design a nonlinear DGP to evaluate the performances of these two tests. The nonlinear DGP is specified as,

$$y_t = 2 + sin(x_t\beta_\tau) + \epsilon_t,$$

where, x_t and ϵ_t are i.i.d. $N(0, 1)$. The empirical sizes and powers are presented in Table 2. Similarly, the simulated results indicate these two tests perform quite well under nonlinear DGP.

Table 2. Reject frequency of tests in DGP:
$y_t = 2 + sin(x_t\beta_\tau) + \epsilon_t$

	Size	Power
Racine's Test		
$\tau = 25$ %	0.020	0.990
$\tau = 50$ %	0.020	0.990
$\tau = 75$ %	0.035	0.985
Aït-Sahalia's Test		
$\tau = 25$ %	0.015	0.910
$\tau = 50$ %	0.025	0.935
$\tau = 75$ %	0.020	0.820

To summary, significance tests suggested by Racine (1997) and Aït-Sahalia et al. (2001) are supported by our simulations for local quantile regressions.

5 Empirical Studies for Health Care Expenditure

To answer whether health care is "a necessity" or "a luxury", most of empirical studies are restricted to OECD countries to avoid the problem of heterogeneity in health care data. In this paper, we study the relationship between the HCE and per capita GDP comprehensively over 151 countries in 2000. As different local quantiles are employed in this paper, the curse of heterogeneity in health care data can be avoided. That is, a local quantile regression is considered to study the impact of per capita GDP on HCE. To investigate the significance of per capita GDP on HCE, tests of Racine (1997) and Aït-Sahalia et al. (2001) discussed above are implemented. Testing results are presented in Table 3.

Table 3. Significance Testing Results of regressing per capita HCE on GDP

	Test Statistic	Critical Value	Conclusion
Racine's Test			
$\tau = 25$ %	0.0032045494	0.00011670343	reject H_0
$\tau = 50$ %	0.0044326355	0.00042350174	reject H_0
$\tau = 75$ %	0.0056384925	0.0042760529	reject H_0
Aït-Sahalia's Test			
$\tau = 25$ %	585309.31	26646.703	reject H_0
$\tau = 50$ %	730986.85	34605.482	reject H_0
$\tau = 75$ %	839407.18	202131.22	reject H_0

From Table 3, the relationships between per capita HCE and GDP are all significant for quantiles 25 %, 50 % and 75 %. Therefore, we conclude there exists significant relationship between per capita GDP and HCE.

The estimation results of local quantile regressions are plotted in Figure 1. Several findings can be obtained from Figure 1. First, it is obvious that the effects of per capita GDP on heath expenditure are all positive for different considered quantiles. However, the effects are different among different quantiles. For countries with low per capita GDP, the slopes of estimated local quantile regressions of 25 %, 50 % and 75 % are positive but small. This indicates the impact of per capita GDP on HCE is small and the heath care is "a necessity" in these countries. However, the slopes become larger for countries with high per capita income, typically higher than \$ 20,000. In other words, health care becomes "a luxury" for countries with per capita GDP higher than \$ 20,000. Health care is in-between "a necessity" and "a luxury" for countries with middle level of per capital GDP. Second, the heterogeneity is obviously observed in per capita HCE. The variance of per capita HCE is small for countries with low per capita GDP but becomes larger for countries with high per capita GDP. This confirms the necessity of restricting the sample observations to OECD countries for holding the homogeneity of HCE when the conditional mean is considered. Third, the conditional distribution of per capita HCE on GDP is skewed to the right since the difference between 25 % and 50 % is smaller than the one between 50 % and 75 %. Besides, the skewness is reducing as the per capita GDP getting larger.

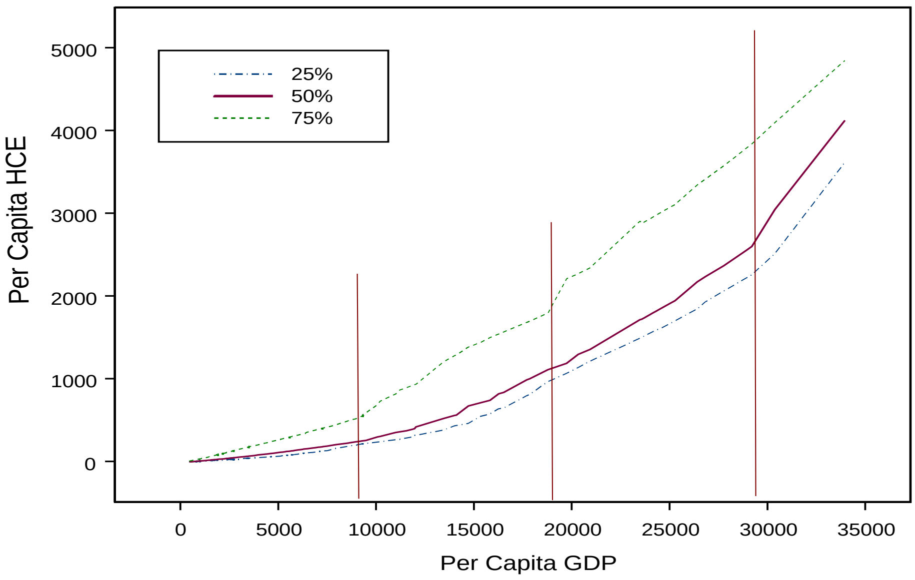

Figure 1: *Estimated Local Quantile Regressions of HCE on GDP*

6 Some Conclusions

It is debatable to conclude whether health care is “a necessity” or “a lexury”. Most of empirical studies are restricted to OECD countries to hold the homogeneity of health care expenditure data and to do the least square estimation for the linear conditional mean function. In stead of taking OECD countries as sample observations and estimating conditional linear conditional mean, 151 countries in 2000 are taken as our sample observations and 25 %, 50 % and 75 % local quantile regressions are estimated. To investigate the performance of significance tests suggested by Racine (1997) and Aït-Sahalia et al. (2001) for local quantile regressions, simulations are conducted. Applicability of these two tests are supported by our simulation results. To the best of our knowledge, this is the first study on the significance test for local quantile regressions.

Three main findings are obtained from our empirical study. First, the effect of per capita GDP on HCE is small for countries with low per capita GDP. On the other hand, the effect becomes larger for countries with high per capita GDP. Therefore, health care is “a necessity” for countries with low per capita GDP is concluded. However, it becomes “a luxury” for countries with high per capita GDP. Second, heterogeneity does exist in the per capita GDP data. This confirms the necessity of restricting the sample observations for OECD countries to hold the homogeneity of HCE hold for estimating the conditional mean. Third, the conditional distribution of per capita HCE on GDP is asymmetric and skewed to the right. The asymmetricity is reducing as the per capita GDP getting larger.

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