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**A Quantile Regression Approach to Panel Data
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A Quantile Regression Approach to Panel Data Analysis of Health Care Expenditure in OECD Countries[§]

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Abstract

This article investigates the variation in the effects of various determinants on the per capita health care expenditure. A total of 28 OECD countries are studied over the period 1990-2012, employing an instrumental variable quantile regression method for a dynamic panel model with fixed effects. The results show that the determinants of per capita health care expenditure do vary with the distribution of the health care expenditure growth, while the change patterns are dissimilar. Specifically, the lagged health spending growth has a significantly positive effect, with an effect that decreases towards the higher quantiles of growth of per capita health care expenditure. Per capita GDP has a significantly positive effect, both the short and long run income elasticities are smaller than one, and health care is a necessity. The density of physicians only has a significant negative effect at the lower tail of the distribution. The elderly population has the reverse effect at the lower and upper tails, and this shows an upward trend with the increase in health expenditure growth. Life expectancy has an effect similar to the proportion of the old. Variable representing Baumol's model of "unbalanced growth" theory has a significantly positive effect, and the change pattern of its influence shows a marked upward trend. However, one component of "Baumol variable", labor productivity, only shows significant effect in the low half of the distribution. More attention needs to be paid to the influence of determinants in health expenditure study.

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JEL classification: C22, C23, I11

1 Introduction

Most of the literature on health care expenditure (HCE) in Organization for Economic Cooperation and Development (OECD) countries estimates the mean effect of determinants using ordinary least squares regressions. However, the effects of determinants may be different at different health care spending levels. Most studies in the literature have ignored this when estimating parameters in a standard linear regression, and have focused on average effects. In this article, we adopt a quantile regression method in order to investigate whether the effects of determinants change with the increase in health spending, since such heterogeneity could have important policy implications.

This paper builds on the existing studies in two ways. First, as was stated above, we focus on analyzing the changes in the effects of the determinants on per capita health care expenditure. The empirical literature on health expenditure in OECD countries has rarely considered this. To meet our aims, we use a balanced panel of data from 28 OECD countries over the period 1990-2012, and apply a quantile regression method for panel data with fixed effects. Moreover, recent studies have found that health care expenditure in a given year is conditioned on the previous year, indicating the existence of an “anchorage effect” (“expenditure inertia”, see Okunade and Suraratdecha, 2000; Lago-Peñas *et al.*, 2013; Blazquez-Fernandez *et al.*, 2014). We capture this kind of effect by including the lagged dependent variable in our models. Since a standard quantile regression to the dynamic panel data models with fixed effects is typically biased (Galvao, 2011). This study attempts to reduce the estimated bias by using the quantile regression dynamic panel data instrumental variables (QRPIV) method (Galvao, 2011).

Second, with respect to the determinants of per capita health care expenditure, explanatory variables other than the lagged dependent variable include not only the per capita Gross Domestic Product (GDP), the share of the population that is old, number of physicians per 1000 persons, the remaining life expectancy at age 65, which have all been used by knowledgeable scholars (see e.g. Gerdtham and Jönsson, 2000; Di Matteo, 2005; Blazquez-Fernandez *et al.*, 2014), but also the “Baumol variable” (Baumol’s (1967) model of “unbalanced growth”, defined as real wage growth minus productivity growth), which has been suggested as a theory-based determinant of HCE growth in the recent literature (see e.g. Hartwig, 2008; Bates and Santerre, 2013; Hartwig and Sturm, 2014). The core concepts under Baumol’s model of “unbalanced growth” are not complicated. First, Baumol divided the economy into two parts, a “progressive” and a “non-progressive” sector. Health care is included in “non-progressive” sector. And then, he assumed the growth in labor productivity can occur only in the “progressive” sector, while the wage rates in two

sectors are equal and rise in conjunction with productivity improvements in the “progressive” sector. When prices rise in proportion to costs, and the price elasticity is very low (such as health care), an increased shift of expenditure into the “non-progressive” sector will be revealed. Hartwig (2008) pointed out that Baumol’s theory can be tested if wage increases in excess of labor productivity growth (namely Baumol variable) drive the rise in health expenditure in a directly proportional way. We include “Baumol variable” as one of the determinants of health expenditure in this article, in order to provide some new results from quantile analysis.

To sum up, this paper differs from the existing studies of health care expenditure in two respects. First, we focus on the heterogeneity of the effects of determinants on per capita health care expenditure, and employ QRPIV method to examine health “expenditure inertia”. To the best of our knowledge, no existing study has explored health care expenditure from this point of view. Second, we pay more attention to the effects of “Baumol variable” on health spending, since the results from previous studies have told us nothing about the change pattern of its effect. We find that the effects of determinants do vary with an increase in health expenditure, and some interesting results (change patterns in the effects of the determinants) are revealed.

The remainder of the article is structured as follows. In Section 2, a review of the relevant literature is provided. Section 3 describes the data and the empirical quantile regression models for panel data that are used in this paper. Section 4 states and then discusses the main results and some discussion on the effect of determinants on the health expenditure growth. Section 5 provides concluding remarks.

2 Literature review

Previous researchers have usually grouped the literature on health expenditure into three different lines of inquiry (Narayan, 2006; Payne *et al.*, 2015). Based on recent developments in health care expenditure research, we categorize the related literature into four main types. The first type focuses on the determinants of health expenditure, with the aim of discovering the main explanatory variables and their influences (see e.g. Newhouse, 1977; Gerdtham *et al.*, 1992; Gerdtham, 1992; Hitiris and Posnett, 1992; Okunade and Suraratdecha, 2000; Sen, 2005; Baltagi and Moscone, 2010). These studies find that not only does income (or per capita GDP) have a strong influence on health care spending, but also so do some non-income variables, though the effects of such variables appear to be small. The most frequently identified non-income factors are the demographic dependency ratio (or the percentages of old people), the number of physicians, and the life expectancy. Recently, a few studies have used the “Baumol variable” as another explanatory variable in the regression, and have found it to have a significant effect on health spending. However, the most noteworthy finding is that, except for the income variable and “Baumol variable”, none of the factors that have been

found to influence the health care expenditure have conclusive influences, see the results in Table I.

The second type of research examines whether or not health care expenditures are stationary in the time series dimension, and explores structural breaks in health spending series and the convergence of health care expenditures across countries (see e.g. Barros, 1998; Hitiris and Nixon, 2001; Okunade *et al.*, 2004; Narayan, 2006, 2007; Kerem *et al.*, 2008; Payne *et al.*, 2015). Most of the recent studies of this type have confirmed the convergence in per capita health care expenditures across developed countries, once we allow for breaks in health expenditures.

The third type of study has focused on the long run (cointegration) relationship between health care expenditure and its determinants, as well as on differences between the short- and long-run income elasticity (IE) of health care expenditure (see e.g. Blomqvist and Carter, 1997; Mccoskey and Selden, 1998; Okunade and Karakus, 2001; Chou, 2007; Baltagi and Moscone, 2010; Blazquez-Fernandez *et al.*, 2014). A number of studies have found that the presence or absence of stable relationships among variables in the regression models varies according to the sample countries and sample period. Consequently, an analysis testing the stationarity of the variables is often required prior to estimation.

The fourth type of research, which is recognized as having important policy implications across countries, focuses on the heterogeneous effects of health care expenditure determinants. Existing studies have used two main methods to explore this heterogeneity. One involves grouping sample countries according to either their level of economic development or the sample period, and then employing an empirical analysis for each group (see e.g. Okunade and Suraratdecha, 2000; Di Matteo, 2005; Chakroun, 2010; Farag *et al.*, 2012; Blazquez-Fernandez *et al.*, 2014). The other involves using nonparametric, semi-parametric or quantile regression methods to detect the varying effects of factors (see e.g. Di Matteo, 2003; Chen *et al.*, 2009; Liu *et al.*, 2011; Yu *et al.*, 2011; Chen *et al.*, 2014). Heterogeneity is confirmed without exception.

To some extent, our focus in this article is related to the fourth type. However, our study differs from those cited in several important aspects with respect to the heterogeneous effect of health care expenditure. First, we examine a more recent time period (1990-2012) and a larger range of OECD countries. Second, even though some previous research has used a quantile regression method to examine the heterogeneity in health care spending, to the best of our knowledge, none of them have noted the importance of “expenditure inertia” at the same time, and hence, none of them have considered the influence of the lagged dependent variable. However, health “expenditure inertia” is pervasive and strong (Okunade and Suraratdecha, 2000; Blazquez-Fernandez *et al.*, 2014), and the results produced if ignoring this effect will be less realistic. Therefore, we include a one-period-lagged dependent variable in the regression model, and as a consequence, this article employs a quantile regression method for dynamic panel data with fixed effects. Third, since recent studies have discerned that “Baumol variable” is an-

other key determinant of health spending, this paper uses the “Baumol variable” as one of the explanatory variables. Therefore, some studies on health spending have corroborated the significance influence of “Baumol variable”, while no study has examined the heterogeneous effect of it on health spending.

To certain extent, this study is original in employing the QRPIV method to examine the heterogeneous effects of the determinants of health care expenditure, taking into consideration health “expenditure inertia” and the influence of “Baumol variable”.

[Insert Table I here]

3 The data and model

Our analysis uses annual data for 28 OECD countries from 1990 to 2012, extracted from the OECD statistics. Based on the availability of annual data for every year, we exclude Chile, Iceland, Israel, New Zealand, the Slovak Republic and Turkey. We collect information on per capita health care expenditure (PHE) and per capita GDP (PGDP), estimated using the constant purchasing power parity rate (constant 2010 PPP) and constant prices (constant at 2010), with all amounts expressed in US dollars. The other variables that we consider include the number of physicians per 1000 persons (Phy), to represent health care resources; the proportion of the population aged 65 years and older (POP65); the remaining life expectancy at age 65 (averaged over both sexes) (LE65) in each country; and “Baumol variable” (Bau), which is defined as the difference between real wage growth and productivity growth. In addition, to explore the main driver of the effect of “Baumol variable”, we split it into two separate variables, namely per capita real wage (Wage) growth and real labor productivity (Prod) growth in the overall economy, and then estimate the influence of these two variables separately.

Considering I(1) for PHE and other variables, as suggested by the existing literature on health care expenditure, we estimate the growth rate of HCE instead of level. For the original values of PHE, PGDP, Phy, POP65 and LE65, we calculate log differences of these variables and express as dlPHE , dlPGDP , dlPhy , dlPOP65 and dlLE65 , separately. The “Baumol variable” is defined as the excess of log difference of per capita real wage (dlWage) over log difference of labor productivity (dlProd). The descriptive statistics are summarized in Table II.

[Insert Table II here]

[Insert Table III here]

To check for stationarity of the growth of PHE and other variables, Table III reports the results of panel unit root tests. The LLC test (Levin *et al.*, 2002) assumes that all panels have the same autoregressive parameter, while the IPS (Im *et al.*, 2003) test relaxes the assumption of a common autoregressive parameter and instead allows for each panel to have its own autoregressive root. However, the bias correction terms in the LLC test and the detrending bias in the IPS test result in a power loss (Breitung, 2001). Therefore, the same type of panel unit root tests should be performed using a Fisher statistic (Choi, 2001). Note that the null hypothesis of all tests is the presence of a unit root in a series. However, the alternatives differ. In the LLC test and Breitung tests, there is an affirmative alternative of stationarity, while the alternative hypothesis in the IPS, Fisher-ADF and Fisher-PP tests is that the fraction of panels that are stationary is non-zero. As we can see from Table III, the five types of statistics all provide strong evidence (at the 1% significance level) in support of the two log level variable series (PGDP and Prod) having unit roots. However, there is no matching result for the rest of the log level variable series. On the other hand, all of the first differences of variables are stationary, which indicates that all of the variables follow an I(1) process. To illustrate, as an example, Figures 1 and 2 present graphical depictions of the time trend of the natural logarithm of per capita health expenditure and its first log difference for 28 countries, with Figure 1 showing non-stationary series and Figure 2 seemingly stationary series. In summary, the results of panel unit root tests support the argument that there are long-run stable relationships among the variables.

[Insert Figure 1 here]

[Insert Figure 2 here]

Based on the literature already cited on health care expenditure in OECD countries and Hausman test result, this paper considers a fixed effects panel data model.

First of all, we investigate the effects of varying determinants on the per capita health care expenditure growth by considering the following quantile regression model:

$$\min_{(\eta, \beta)} \sum_{k=1}^K \sum_{i=1}^N \sum_{t=1}^T w_k \rho_{\tau_k} (y_{it} - \eta_i - x'_{it} \beta(\tau_k)), \quad (1)$$

where $\rho_{\tau}(u) = u(\tau - I(u < 0))$, denotes the piecewise linear quantile loss function, y_{it} is the independent variable, η_i denotes the individual fixed effect, and x_{it} is a p -vector of covariates. K indicates the number of quantiles, so that K quantiles $\{\tau_1, \dots, \tau_k\}$ are estimated simultaneously. The weights w_k control the relative influence of the K quantiles $\{\tau_1, \dots, \tau_k\}$ on the estimation of the η_i . The choice of the weights is analogous

to the choice of discretely weighted L-statistics, and this paper adopts the Gaussian density weight function. When $K = 1$, the estimation of model (1) is simply equal to the estimate of a single quantile at a time. However, some researchers suggest that reweighting estimates at a few distinct quantiles is an important strategy for improving the efficiency of quantile regression estimates (e.g., Koenker, 2005). Hence, we let $K = 7$ and set $\{\tau_1, \dots, \tau_k\}$ to $\{0.05, 0.10, 0.25, 0.50, 0.75, 0.90, 0.95\}$ in the empirical estimation.

When applying quantile regression, one should keep in mind that the lag of the response variable y_{it-1} is included in x_{it} under the consideration of the “anchorage effect” of health spending. Writing in specific variables, $y_{it} = \text{dlPHE}_{it}$, $y_{it-1} = \text{dlPHE}_{it-1}$, $\tilde{x}'_{it} = (\text{dlPGDP}_{it}, \text{dlPhy}_{it}, \text{dlPOP65}_{it}, \text{dlLE65}_{it}, \text{Bau}_{it})$. When we examine the contributing factor for the effect of “Baumol variable”, we replace Bau_{it} with dlWage_{it} and dlProd_{it} . For the sake of simplicity, the following text omits the subscripts (except for the $t - 1$ subscript that is used to indicate the lag of the dependent variable).

In this regard, let $x_{it} = (y_{it-1}, \tilde{x}_{it})$; then, model (1) can be written as,

$$\min_{(\eta, \alpha, \beta)} \sum_{k=1}^K \sum_{i=1}^N \sum_{t=1}^T w_k \rho_{\tau_k} \left(y_{it} - \eta_i - \alpha(\tau_k) y_{it-1} - \tilde{x}'_{it} \tilde{\beta}(\tau_k) \right). \quad (2)$$

When lagged dependent variables are involved in quantile panel data models with fixed effects, some conventional quantile estimation methods suffer from bias effects like those in the ordinary least squares (OLS) case when the time dimension is modest (Galvao, 2011). We reduce the dynamic bias in the quantile regression fixed effect estimator by applying the instrumental variables (IV) quantile regression method with lagged regressors as instruments in this case. Specifically, we use dlPHE_{it-2} as the instrumental variable and estimate model (2) using the approach suggested by Galvao (2011). In addition, noting that the stationarity requirement is embedded in the estimation process, this article performs the empirical procedures in log differences. In a sense, we actually detect the varying effects of determinants on the growth of per capita health expenditure in the OECD countries. Moreover, returning to Figure 2, we notice that the growth of per capita health expenditures does not change around zero (the dashed line). Hence, strictly speaking, the growth of per capita health expenditure does not satisfy the assumption of covariance stationarity embedded in model (2). To meet this requirement, we demean the log difference series and then estimate the models in this article.

This study also estimates a linear panel data model for comparing the results of the different methods. This linear panel data model is expressed as

$$y_{it} = \eta_i + x'_{it} \beta + u_{it}, i = 1, \dots, N; t = 1, \dots, T. \quad (3)$$

When the dynamics of health expenditure are considered, model (3) can be rewritten as

follows:

$$y_{it} = \eta_i + \alpha y_{it-1} + \tilde{x}_{it}'\beta + u_{it}, i = 1, \dots, N; t = 1, \dots, T. \quad (4)$$

As has been mentioned, we use an IV method to attenuate the bias caused by the simple OLS method for model (4).

4 Results

4.1 Main specification

Table IV presents the results of models (2) and (4), with the corresponding graph being given in Figure 3. Model (2) is a quantile panel data model with fixed effects and lagged dependent variables, and the regression results indicate that, for all seven quantiles and linear model results, the lagged growth of per capita health care expenditure (dlPHE_{t-1}) at time $t - 1$ (except for non-significant results at the 0.90 and 0.95 quantiles) and the growth of per capita GDP (dlPGDP) at time t (except for non-significant results at the 0.05 and 0.10 quantiles) both have significantly positive influences on the growth of per capita health care expenditure, a finding which is in line with the results of some previous studies. For instance, Breyer *et al.* (2015) found that the lagged one-period health care expenditure growth has a significant positive effect on the current period growth for women in Germany over the period 1997-2009. A comprehensive study by Barros (1998) on the relationship between the growth of PGDP and the growth of PHE found a significantly positive correlation between them, similar to which we find in this article. This shows that, when we look at the influence of determinants on the growth (not the level) of per capita health expenditure, the positive effects of PGDP and health “expenditure inertia” that were confirmed in the level equations still hold.

[Insert Table IV here]

[Insert Figure 3 here]

With respect to the influences of other determinants on the per capita health expenditure growth, Table IV reveals some interesting findings. First, we find that the coefficients of dlPhy , dlPOP65 and dlLE65 change signs across quantiles, and none of them has a significant effect on the growth of PHE in the corresponding linear model. Obviously, since the linear model focuses on the average effect, an effect that changes signs over the distribution is likely to show up as a non-significant effect on average. In this case, the results from the linear model may be misleading, meaning that the varying coefficient models are preferred.

Secondly, the coefficients of $dlPhy$ are only significant at the 0.05, 0.10, 0.25 and 0.50 quantiles. The growth in per capita health care expenditure decreases with the growth of Phy when the growth of PHE is low, while the growth of Phy has a non-significant influence on the growth of PHE at the high end of the distribution. In other words, on the supply side of health care, the growth of Phy will lead to a decline in the growth of PHE in areas with relatively low levels of growth of PHE , while having no significant effect on the growth of PHE in areas with high levels. This suggests that the government could control the growth of PHE in some areas by adopting a policy of increasing the number of physicians.

Thirdly, the coefficients of $dlPOP65$ are significant and negative at the 0.05, 0.10, and 0.25 quantiles, non-significant at the 0.50 and 0.75 quantiles, and significant and positive at the 0.90 and 0.95 quantiles. Figure 3 clearly shows that there is an increasing trend of effects from the low to high ends of the distribution. Increasing the percentage of people aged 65 and over will not always boost the per capita health spending, but tends to cut down the per capita health spending at the lower quantiles, while having a positive effect on the health expenditure at the high end. This result gives us a new understanding of the influence of aging on health expenditure. Actually, Table I shows that existing studies found no consistent result as to the direction of the effect of an increase in old people, possibly because almost all of the previous findings were obtained using linear models. One exception is Liu *et al.* (2011), who used a semiparametric panel varying coefficient model and found that the impacts of $POP65$ and other non-income variables on health care expenditure changed at different levels of economic development. To some extent, the findings of Liu *et al.* (2011) support our results.

Another interesting finding is that the coefficients of $dlLE65$ change from negative to positive across a range of quantiles, and there is also an increasing trend of effect as $dlPOP65$, with a similar change pattern being shown in Figure 3. That means that the absolute effect of an extension of lifespan is much bigger at the extreme quantiles (0.05, 0.10, 0.75, 0.90, 0.95), with an increase in remaining life expectancy at age 65 lessening the growth of PHE at the lower tail of the distribution, while increasing the pressure to control the health expenditure in areas with higher growths of PHE .

There are two opposing ideas about the possible influence of life expectancies on health expenditure in literature. On the one hand, some studies have found that individuals who are close to death generally receive intensive medical services (Lubitz and Prihoda, 1984; Lubitz and Riley, 1993). Thus, the proximity to death is a good predictor of health care expenditures, and an increase in longevity not matter much for the forecasting of health spending (Lubitz *et al.*, 2003; Shang and Goldman, 2008; Bjørner and Arnberg, 2012; Hyun *et al.*, 2015). This suggests that terminal health costs are postponed with the increase in life expectancy. If two countries have similar demographic structures but different life expectancies, the one with the higher life expectancy will probably spend less on health care, because it has fewer people who are near their deaths. On

the other hand, when people expect to live a longer life, they tend to spend more on health care; this is known as the “Eubie Blake effect” (Breyer *et al.*, 2015). These two sides of the argument suggest that the net effect of life expectancy on health expenditure will be a trade-off between these two effects. When the former dominates, there will be a negative relationship between life expectancy and health expenditure; otherwise, a positive relationship will appear. Combining those two opposing views, we think that these two kinds of effects exist simultaneously in society. When the “Eubie Blake effect” is bigger in absolute effect, the overall effect of life expectancy is positive; otherwise, the overall effect is negative. Considering the heterogeneity in the effect of the determinants, we find that the “Eubie Blake effect” is weak at the lower tail of the distribution of growth of PHE, with an increase in life expectancy decreasing the growth of per capita health care expenditure. At the higher tail of the distribution, though, this kind of effect becomes stronger and stronger, becoming the force with the largest absolute effect. To the best of our knowledge, our study is the first to obtain results that support both kinds of effects that have been found in past research. Further research should investigate the proportions of each kind of effect in an area. A good look at Table IV shows that the signs of the coefficients of $dIPOP65$ and $dLLE65$ at each quantile correspond, and their change patterns are similar, as Figure 3 shows. Obviously, this is not accidental result, since an increase in life expectancy will increase the proportion of older people in a society, *ceteris paribus*. In this regard, this feature provides further support for our previous findings.

In addition, last but not least, another interesting finding is that, for all seven quantiles and linear model result, the estimated coefficients on the “Baumol variable” are all positive and significant, which confirmed its robustness as in the recent literature. The estimates suggest that a 1 percentage points increase in “Baumol variable” raises the growth rate of per capita HCE by about 0.464 percentage points on the average. This is lower than the coefficient values found in Hartwig (2008), which were around 1, and in Hartwig and Sturm (2014), which were in the range of 0.7-0.9. And what is more we find there is a gradual increase in the estimated coefficients of “Baumol variable”, as is shown in Figure 3. In the areas with a rapid growth in per capita health expenditure, an increase in the gap between wage growth and labor productivity growth accelerates the growth of health spending. Existing studies have shown no results as to the change pattern of the effect of “Baumol variable”. Our findings indicate that, even though “Baumol variable” emerges as a robust and significant determinant of HCE growth, more attention needs to be paid to the varying influence of it.

[Insert Table V here]

To establish whether the effects of the determinants vary based on the per capita health expenditure growth, Table IV presents quantile regressions for $\tau = 0.05, 0.10, 0.25,$

0.50, 0.75, 0.90, 0.95. Chi-square statistics testing for the equality of the estimated coefficients at various quantiles are presented in Table V. For the lagged per capita health expenditure growth ΔPHE_{t-1} , Table V shows that, of the results for seven quantiles, nearly half of 21 pairs of quantiles are significantly different from each other. This indicates that the growth of health spending in the current period is affected less by its previous level in countries with high levels of per capita health expenditure growth than in those with low levels. Thus, there is a clear decrease in “health expenditure inertia” over the per capita health expenditure growth distribution. In other words, it is harder to change health spending in countries with lower levels of health expenditure growth than in those with higher levels.

For the per capita GDP growth, all of the pairs of quantiles are significantly different from each other, with the exception of the pairs $(\tau = 0.05, \tau = 0.10)$, $(\tau = 0.05, \tau = 0.25)$, $(\tau = 0.10, \tau = 0.25)$ and $(\tau = 0.90, \tau = 0.95)$. Combining these results with the analysis for ΔPHE_{t-1} , we find that the long run income elasticity varies over the distribution. It is easy to calculate and find that the long run elasticity is smaller than unity, our results support the view that health care is a necessity. The per capita health expenditure grows with an affordable way.

When considering the growth in the number of physicians per 1000 persons, 16 out of 21 pairs of quantiles are significantly different from each other. This confirms the heterogeneity of the influence of the supply side of health care expenditure. Countries with a lower growth of per capita health expenditure but a high level of health spending can control the growth of per capita health expenditure by adopting the policy of increasing the number of physicians.

For social ageing, the influence of the growth of percent population aged 65 and over (ΔPOP_{65}) on the per capita health expenditure growth differs significantly between quantiles. For a given percentage increase in the older population, the growth in per capita health expenditure is positive in countries with higher levels of health spending growth, but negative in countries with lower levels. This implies that the relationship between the growth of ageing population and the health expenditure is not constant, and that the influences of the old populations depend on the growth stage of the per capita health expenditure in a particular area.

The results of tests for the equality of the effect of the remaining life expectancy at various quantiles show that all of the quantile pairs are significantly different, except for the pair $(\tau = 0.05, \tau = 0.10)$. Similarly to the influence of the percentage of old people, the change pattern of the effect of ΔLE_{65} has an upward trend. The same extension of the expected lifespan induces a decrease in health spending in countries with a lower PHE growth, while bringing an increase in health spending in countries with a higher PHE growth, if all other factors are held constant. In this regard, health expenditure control under the situation of prolonged longevity is more difficult in countries with higher levels of growth of per capita health expenditure.

Another notable result shown in Table V is that 15 out of 21 pairs of quantiles are significantly different from each other for the “Baumol variable”. The effects of Baumol’s model of unbalanced growth on the per capita health expenditures growth are not equal in countries with different health care expenditures growth. The change pattern of the effect of the “Baumol variable” exhibits a steady upward trend. For the same expanding gap between wage growth and labor productivity growth, the positive effect of it on per capita health expenditure growth is much bigger in countries with high levels of per capita health expenditure growth than in those with low levels. In this situation, countries with higher levels of dIPHE will face more challenges in controlling health care spending.

To summarise, the influences of those determinants on the per capita health expenditure growth in OECD countries do vary with the distribution of the health spending growth. It is particularly important to distinguish these differences when considering health policy across countries. In addition, some variables (dlPhy, dlPOP65 and dlLE65) go undetected in the linear model since the influences of those variables change signs over the distribution of per capita health expenditure growth, carefully consideration for those variables should be needed when we care to take steps to restrain health expenditure growth.

4.2 Some more results from variable splitting

Not like the well-established finding about the positive correlation between HCE and GDP in the literatures since 1970s, or other widely discussed variables, such as old population percentage and life expectancy, “Baumol variable” has not been confirmed about its explanation for the rise in health care spending before the study of Hartwig (2008). In study, Hartwig defined “Baumol variable” as wage increases in excess of productivity growth, and split “Baumol variable” to test whether combining them together to one variable is legitimate before his final estimation. Inspired by this and our findings about the varying effect of “Baumol variable” on health expenditures growth, we split “Baumol variable” into two variables, namely per capita wage growth and labor productivity growth, and then re-estimate. The results are provided in Table VI, with the corresponding change pattern being shown in Figure 4. Table VII contains the results of Chi-square tests for the equality of the estimated coefficients across quantiles, as per Table V.

[Insert Table VI here]

[Insert Figure 4 here]

[Insert Table VII here]

Table VI shows that, apart from two component variables of “Baumol variable”, for each of the remaining determinant, the significance of the results estimated from models (2) and (4) is similar to that in Table IV. The change patterns corresponding to the influence of $dlPHE_{t-1}$, $dlPhy$, $dlPOP65$ and $dlLE65$ which pictured in Figure 4 are also similar to that depicted in Figure 3. For the Chi-square test results, once again, the results corresponding to $dlPHE_{t-1}$, $dlPhy$, $dlPOP65$ and $dlLE65$ presented in Table VII are consistent with our earlier results. Thus, our conclusions about the varying effect of these variables stated in the previous section do not hinge on the “Baumol variable” splitting.

Comparing the results in Tables IV and VI, and the other corresponding results in Figures 3 and 4, Tables V and VII, some noticeable results show up. Firstly, no statistical difference in the effect of $dlGDP$ is found between the quantiles after we split the “Baumol variable”. Secondly, and more striking, compared with the varying effect of “Baumol variable” shown in Table IV, the correlation between the components of “Baumol variable” and health expenditures growth is more varied. Except for the non-significant result at the 0.05 quantile, the coefficients of wage growth are all significant and positive. And 18 out of 21 pairs of quantiles are significantly different from each other, there is a significantly increasing trend of effect. For a given percentage increase in the wage growth, countries with high levels of per capita health spending growth suffer more strongly than those with low levels. However, the coefficients of the other component variable, productivity growth, are only significant and negative at the 0.05, 0.10, 0.25 and 0.50 quantiles. And the significant results are quite different from the non-significant results, while no significant difference is found in significant results, nor in non-significant results.

These results indicate that the growth of wage drives the rise in health expenditure growth in a dramatic way, whereas the growth of labor productivity can only restrain health care spending when per capita health expenditure growth is below a certain level. After the growth rate of HCE exceeds some certain level, Baumol’s model of “unbalanced growth” seems not well supported by the data, since only one of two components of “Baumol variable” has a significant effect on health spending growth. Thus, the combination of these two variables is illegitimate. One potential explanation is due to the definition of “Baumol variable” used in Hartwig (2008) and this study. To avoid problems surrounding productivity measurement in the health sector, we define “Baumol variable” in the same way as Hartwig (2008) did, which means that we define it as wage growth in excess of productivity growth in the overall economy, not just in the health sector. It is not hard to find that this definition is not exactly consistent with the Baumol’s (1967) model. To find more implications for the impact of Baumol’s model of “unbalanced growth” on health expenditure growth, improved definition of “Baumol variable” should be required in future.

5 Conclusions

Most of the research into the determinants of health expenditure has been restricted to mean-type analyses. We have investigated the influence of determinants over the entire range of health expenditures growth by considering 28 OECD countries, and used quantile regression techniques to examine changes in these influences on health spending at seven different quantiles: 0.05, 0.10, 0.25, 0.50, 0.75, 0.90 and 0.95. Specifically, we have considered the possibility of “expenditure inertia” by employing an instrumental variable quantile regression method for dynamic panel models with fixed effects. Additionally, given that few studies have examined the effect of “Baumol variable” on the growth of health care cost, we pay more attention on its effect.

Using a panel of 28 OECD countries over 23 years, a summary of our study’s findings is as follows. (a) Overall, the influence of the determinants (except for the growth of per capita GDP on health care when we split the “Baumol variable”) on the per capita health expenditure growth differs significantly at different quantiles, and the change patterns of the determinants are also dissimilar. (b) The health “expenditure inertia” is significant and strong, and decreases with the increase in per capita health spending growth. (c) Both the short- and long-run income elasticities of per capita health expenditure over the distribution are less than unity, indicating that health care is a necessity for the OECD countries. (d) The density of physicians has a significantly negative effect in the lower tail of health expenditures growth distribution. (e) An increase in the percentage of the population that is aged 65 and over has opposite effects on the lower and the upper tails of the distribution: an increase in the percentage will decrease the growth of health expenditure in countries with lower levels of growth in health spending, while increasing the growth of health spending in countries with higher growth rates. (f) The remaining life expectancy has a strong effect on health care, and the change pattern of its influence is similar to that of the proportion of the old. (g) The “Baumol variable” has a significantly positive effect, and the change pattern of its influence shows a clear upward trend. And more notably, one component of “Baumol variable”, labor productivity growth, only exhibits significantly negative effect in the lower half of the distribution, while the other component, wage growth, has significantly positive effect on the almost whole distribution.

Our findings have various implications for policy makers. Different policies are appropriate for controlling increases in health expenditure in different OECD countries, depending on the level of per capita health care expenditure growth. Countries with low levels do not need to worry too much, since increases in numbers of physicians and old people, and in life expectancies and labor productivity all lead to decreases in health expenditure growth. For countries with high levels, unfortunately, there is not much to do to restrain health care expenditure from rising. Our results suggest that, perhaps, one unprepossessing way is to subdue the growth of wage.

References

- Baltagi, B. H., Moscone, F., 2010. Health care expenditure and income in the OECD reconsidered: evidence from panel data. *Economic Modelling* **27**: 804-811.
- Barros, P., 1998. The black box of health care expenditure growth determinants. *Health Economics* **7**: 533-544.
- Bates, L. J., Santerre, R. E., 2013. Does the US health care sector suffer from Baumol's cost disease ? Evidence from the 50 states. *Journal of Health Economics* **32**: 386-391.
- Baumol, W. J., 1967. Macroeconomics of unbalanced growth: The anatomy of urban crisis. *The American Economic Review* **57**: 415-426.
- Bjørner, T. B., Arnberg, S., 2012. Terminal costs, improved life expectancy and future public health expenditure. *International Journal of Health Care Finance and Economics* **12**: 129-143.
- Blazquez-Fernandez, C., Cantarero, D., Perez, P., 2014. Disentangling the heterogeneous income elasticity and dynamics of health expenditure. *Applied Economics* **46**: 1839-1854.
- Blomqvist, A. G., Carter, R. A. L., 1997. Is health care really a luxury ? *Journal of Health Economics* **16**: 207-229.
- Breitung, J., 2001. The local power of some unit root tests for panel data. *Advances in Econometrics* **15**: 161-177.
- Breyer, F., Lorenz, N., Niebel, T., 2015. Health care expenditures and longevity: is there a Eubie Blake effect ? *The European Journal of Health Economics* **16**: 95-112.
- Chakroun, M., 2010. Health care expenditure and GDP: an international panel smooth transition approach. *International Journal of Economics* **4**: 189-200.
- Chen, J., Vargas-Bustamante, A., Mortensen, K., Thomas, S. B., 2014. Using quantile regression to examine health care expenditures during the great recession. *Health Services Research* **49**: 705-730.
- Chen, M., Lin, F., Chang, C., 2009. Relations between health care expenditure and income: an application of local quantile regressions. *Applied Economics Letters* **16**: 177-181.
- Choi, I., 2001. Unit root tests for panel data. *Journal of International Money and Finance* **20**: 249-272.
- Chou, W. L., 2007. Explaining China's regional health expenditures using LM-type unit root tests. *Journal of Health Economics* **26**: 682-698.
- Di Matteo, L., 2003. The income elasticity of health care spending. *The European Journal of Health Economics* **4**: 20-29.
- Di Matteo, L., 2005. The macro determinants of health expenditure in the United States and Canada: assessing the impact of income, age distribution and time. *Health Policy* **71**: 23-42.
- Farag, M., Nandakumar, A. K., Wallack, S., Hodgkin, D., Gaumer, G., Erbil, C., 2012. The income elasticity of health care spending in developing and developed countries. *International Journal of Health Care Finance and Economics* **12**: 145-162.
- Galvao, A. F., 2011. Quantile regression for dynamic panel data with fixed effects. *Journal of Econometrics* **164**: 142-157.
- Gerdtham, U. G., Jönsson, B., 2000. International comparisons of health expenditure: theory, data and econometric analysis. *Handbook of Health Economics* **1**: 11-53.
- Gerdtham, U. G., Sogaard, J., Andersen, F., Jönsson, B., 1992. An econometric analysis of health care expenditure: a cross-section study of the OECD countries. *Journal of Health Economics* **11**: 63-84.
- Gerdtham, U. G., 1992. Pooling international health care expenditure data. *Health Economics* **1**: 217-231.
- Hartwig, J., 2008. What drives health care expenditure ?—Baumol's model of 'unbalanced growth' revisited. *Journal of Health Economics* **27**: 603-623.
- Hartwig, J., Sturm, J., 2014. Robust determinants of health care expenditure growth. *Applied Economics* **46**: 4455-4474.
- Hitiris, T., Nixon, J., 2001. Convergence of health care expenditure in the EU countries. *Applied Economics Letters* **8**: 223-228.
- Hitiris, T., Posnett, J., 1992. The determinants and effects of health expenditure in developed countries. *Journal of Health Economics* **11**: 173-181.

- Hyun, K. R., Kang, S., Lee, S., 2015. Population aging and healthcare expenditure in Korea. *Health Economics*. Published online in Wiley Online Library. DOI: 10.1002/hec.3209.
- Im, K. S., Pesaran, M. H., Shin, Y., 2003. Testing for unit roots in heterogeneous panels. *Journal of Econometrics* **115**: 53-74.
- Kerem, K., Püss, T., Viies, M., Maldre, R., 2008. Health and convergence of health care expenditure in EU. *International Business & Economics Research Journal* **7**: 29-44.
- Koenker, R., 2005. *Quantile regression*. Cambridge University Press: New York.
- Lago-Peñas, S., Cantarero-Prieto, D., Blázquez-Fernández, C., 2013. On the relationship between GDP and health care expenditure: a new look. *Economic Modelling* **32**: 124-129.
- Levin, A., Lin, C. F., Chu, C. S. J., 2002. Unit root tests in panel data: asymptotic and finite-sample properties. *Journal of Econometrics* **108**: 1-24.
- Liu, D., Li, R., Wang, Z., 2011. Testing for structural breaks in panel varying coefficient models: with an application to OECD health expenditure. *Empirical Economics* **40**: 95-118.
- Lubitz, J., Cai, L., Kramarow, E., Lentzner, H., 2003. Health, life expectancy, and health care spending among the elderly. *The New England Journal of Medicine* **349**: 1048-1055.
- Lubitz, J., Prihoda, R., 1984. The use and costs of Medicare services in the last 2 years of life. *Health Care Financing Review* **5**: 117-131.
- Lubitz, J., Riley, G. F., 1993. Trends in Medicare payments in the last year of life. *The New England Journal of Medicine* **328**: 1092-1096.
- McCoskey, S. K., Selden, T. M., 1998. Health care expenditures and GDP: panel data unit root test results. *Journal of Health Economics* **17**: 369-376.
- Narayan, P. K., 2006. Examining structural breaks and growth rates in international health expenditures. *Journal of Health Economics* **25**: 877-890.
- Narayan, P. K., 2007. Do health expenditures 'catch-up' ? Evidence from OECD countries. *Health Economics* **16**: 993-1008.
- Newhouse, J. P., 1977. Medical-care expenditure: a cross-national survey. *Journal of Human Resources* **12**: 115-125.
- Okunade, A. A., Karakus, M. C., 2001. Unit root and cointegration tests: timeseries versus panel estimates for international health expenditure models. *Applied Economics* **33**: 1131-1137.
- Okunade, A. A., Karakus, M. C., Okeke, C., 2004. Determinants of health expenditure growth of the OECD countries: jackknife resampling plan estimates. *Health Care Management Science* **7**: 173-183.
- Okunade, A. A., Suraratdecha, C., 2000. Health care expenditure inertia in the OECD countries: a heterogeneous analysis. *Health Care Management Science* **3**: 31-42.
- Payne, J. E., Anderson, S., Lee, J., Cho, M. H., 2015. Do per capita health care expenditures converge among OECD countries ? Evidence from unit root tests with level and trend-shifts. *Applied Economics* **47**: 1-14.
- Sen, A., 2005. Is health care a luxury ? New evidence from OECD data. *International Journal of Health Care Finance and Economics* **5**: 147-164.
- Shang, B., Goldman, D., 2008. Does age or life expectancy better predict health care expenditures ? *Health Economics* **17**: 487-501.
- Yu, T. H. K., Wang, D. H. M., Chang, L. Y., 2011. Examining the heterogeneous effect of healthcare expenditure determinants. *International Journal of Behavioural and Healthcare Research* **2**: 205-213.

Table I: A summary of previous related studies

Reference	Cross sections	Time period	Methodology	health inertia IE	short run IE	long run IE	old	Phy	LE65	Baumol variable
Newhouse (1977)	13 developed countries	1972	Cross section	No		1.15-1.31	No	No	No	No
Gerdtham <i>et al.</i> (1992)	19 OECD countries	1987	Cross section	No		1.33-1.44	+	-	No	No
Gerdtham (1992)	22 OECD countries	1972-1987	Panel data	No		0.74-1.58	+	No	No	No
Hitaris and Posnett (1992)	20 OECD countries	1960-1987	Panel data	No		1.01-1.16	+	No	No	No
Okumade and Suraratdecha (2000)	21 OECD countries	1960-1993	Time series	Yes	-0.94-2.39	-1.24-3.01	No	+	No	No
Sen (2005)	15 OECD countries	1990-1998	Panel data	No		0.21-0.51	Non-significant	+/Non-significant	No	No
Chakroun (2010)	17 OECD countries	1975-2003	Panel data	No		0.64-0.90	+	No	No	No
Baltagi and Moscone (2010)	20 OECD countries	1971-2004	Panel data	No		0.446-0.899	+	No	No	No
Semiparametric										
Liu <i>et al.</i> (2011)	22 OECD countries	1960-2002	panel varying coefficient model	No		1.139-1.371	-/+	No	No	No
Yu <i>et al.</i> (2011)	24 OECD countries and Taiwan	1992-2007	Quantile regression	No		1.20-1.47	+	+/ -	No	No
Farag <i>et al.</i> (2012)	173 countries	1995-2006	Panel data	No		0.83-0.90	+	+	+	No
Blazquez-Fernandez <i>et al.</i> (2014)	14 OECD countries	1971-2009	Panel data	Yes	0.18-0.20	0.87-1.12	Non-significant	No	No	No
Blazquez-Fernandez <i>et al.</i> (2014)	14 OECD countries	1971-2009	Panel data	No		0.87-0.94	+	No	No	No
Breyer <i>et al.</i> (2015)	German	1997-2009	"Pseudo-panel"	Yes			+	No	+	No
Hartwig (2008)	19 OECD countries	1971-2003	Panel data	No		0.30-0.70	No	No	No	+
Bates and Santerre (2013)	United States	1980-2009	Panel data	No		smaller than one	+	No	No	+
Hartwig and Sturm (2014)	33 OECD countries	1970-2010	Panel data	No		0.15-0.80	Non-significant	Non-significant	Non-significant	+

Notes: (1) The definitions of "IE", "Phy", and "LE65" are provided in Section 3. Either "No" or "Yes" indicates that the corresponding studies do not or do consider the specific variable, respectively. "+", "-", and "Non-significant" indicate that the estimated coefficient is statistically significantly positive, statistically significantly negative and non-significant, respectively. "/" in a result indicates that the corresponding findings vary with the regression model and the estimated technology, or at different quantiles.

(2) Since some of the studies used different definitions for the demographic structure, we use "old" in the Table I to refer to the variables related to the percentages of the old populations in the relevant studies. Specifically, Gerdtham *et al.* (1992), Gerdtham (1992) and Baltagi and Moscone (2010) defined "old" as the population aged 65 and over divided by the population aged 15-64, Breyer *et al.* (2015) captured the effect of age using a set of dummy variables for each age. All of the other studies listed in Table I use the same definitions for "old" as we use for "POP65" in this article.

(3) Gerdtham *et al.* (1992) also considered the share of the population who live in towns, the female participation ratio and various other explanatory variables. Gerdtham (1992) also considered inflation and the share of government expenditure on health care in his model. Sen (2005) also considered infant mortality rates per 100,000 population and the average length of patient stays in hospitals. Sen (2005) and Blazquez-Fernandez *et al.* (2014) also included the trend as an explanatory variable. Chakroun (2010) adopted a panel smooth threshold regression model, and did not include the variables old, young and Phy in the model simultaneously. In addition, Chakroun (2010) also chose life expectancy as the threshold variable. Baltagi and Moscone (2010) and Liu *et al.* (2011) also included the young population and the share of government expenditure in their models. Farag *et al.* (2012) also considered various other explanatory variables, such as government effectiveness, voice and accountability, GINI index, percentage of births attended by a skilled attendant over the time period, and the primary school net enrollment ratio. Breyer *et al.* (2015) also included the percentage of young population, mortality rate, a set of dummy variables for each cohort and a set of dummy variables for each year as explanatory variables. Bates and Santerre (2013) also included growth of the unemployment rate, growth of the union membership rate and growth of the poverty rate in their models. Hartwig and Sturm (2014) examined 38 explanatory variables suggested in the literature and found up to eight robust drivers in the linear model analysis.

Table II: Summary statistics

	Mean	Std.Dev.	Min.	Max.		Mean	Std.Dev.	Min.	Max.
	In original value					In log difference			
PHE	2348.983	1181.991	385.878	7394.987	dlPHE	0.031	0.039	-0.129	0.292
PGDP	28631.39	10659.92	7500	69256.6	dlPGDP	0.018	0.031	-0.157	0.136
Phy	2.886	0.823	0.97	6.167	dlPhy	0.015	0.036	-0.289	0.210
POP65	14.639	3.124	4.4	24.1	dlPOP65	0.012	0.012	-0.028	0.054
LE65	17.846	1.622	13.65	21.55	dlLE65	0.008	0.012	-0.048	0.079
Wage	35379.73	11655.31	9580	59188	dlWage	0.013	0.022	-0.078	0.158
Prod	70985.09	21267.01	21000	129692.4	dlProd	0.016	0.022	-0.066	0.111
					Bau	-0.003	0.025	-0.091	0.147

Notes: Bau is short for “Baumol variable”, and is defined as dlWage minus dlProd.

Table III: Panel unit root test

	LLC	IPS	Breitung	Fisher-ADF	Fisher-PP
Log levels					
PHE	-2.178**	0.953	4.881	39.946	46.028
PGDP	3.131	6.304	6.973	30.020	19.035
Phy	-2.747***	-0.279	2.699	47.148	89.021***
POP65	7.783	14.905	12.481	84.983***	82.357**
LE65	-8.655***	-5.720***	-1.627*	64.046	201.434***
Wage	0.134	3.506	3.618	84.344***	41.262
Prod	-1.268	1.968	5.475	17.120	11.731
Log differences					
dlPHE	-13.376***	-11.081***	-8.065***	139.257***	243.491***
dlPGDP	-10.792***	-7.940***	-5.581***	199.449***	198.817***
dlPhy	-16.913***	-16.020***	-4.845***	220.972***	451.285***
dlPOP65	-10.146***	-7.858***	-4.238***	121.577***	184.193***
dlLE65	-27.339***	-26.326***	-9.576***	281.225***	817.221***
dlWage	-11.504***	-8.952***	-5.971***	174.793***	264.941***
dlProd	-13.613***	-11.381***	-8.237***	247.881***	285.757***

Notes: All the results in the table are given when adding an intercept and a linear trend. LLC, IPS and Breitung represent the panel unit root tests of Levin *et al.* (2002), Im *et al.* (2003) and Breitung (2001) respectively. ***,** and * indicate the statistical significance level at 1% , 5% and 10%, respectively. When carrying out the test, PHE, PGDP, Phy, POP65, LE65, Wage and Prod are formed in natural logarithm.

Notes: Each panel represents the relation in a particular country. From the first row to the last row, the names of countries are as follows: Sweden, Switzerland, United Kingdom, United States, Poland, Portugal, Slovenia, Mexico, Luxembourg, Spain, Netherlands, Norway, Ireland, Italy, Japan, Korea, France, Germany, Greece, Hungary, Czech Republic, Denmark, Estonia, Finland, Australia, Austria, Belgium and Canada.

Figure 1: Per capita health expenditure (in natural logarithm), 1990-2012

Notes: Each panel represents the relation in a particular country, and the dashed line represents the line of zero. From the first row to the last row, the names of countries are as follows: Sweden, Switzerland, United Kingdom, United States, Poland, Portugal, Slovenia, Spain, Luxembourg, Mexico, Netherlands, Norway, Ireland, Italy, Japan, Korea, France, Germany, Greece, Hungary, Czech Republic, Denmark, Estonia, Finland, Australia, Austria, Belgium and Canada.

Figure 2: The log difference of per capita health expenditure.

Table IV: Estimates of the quantile (model (2)) and linear panel data model (model (4))

	Model (2)							Model (4)
	$\tau=0.05$	$\tau=0.10$	$\tau=0.25$	$\tau=0.50$	$\tau=0.75$	$\tau=0.90$	$\tau=0.95$	
dlPHE _{t-1}	0.314*** (0.075)	0.273*** (0.071)	0.226*** (0.055)	0.242*** (0.046)	0.156*** (0.052)	0.099 (0.064)	0.108 (0.067)	0.158*** (0.041)
dlPGDP	0.116 (0.157)	0.169 (0.135)	0.196** (0.089)	0.363*** (0.065)	0.438*** (0.065)	0.561*** (0.082)	0.638*** (0.120)	0.421*** (0.053)
dlPhy	-0.178** (0.091)	-0.147** (0.069)	-0.094** (0.042)	-0.056** (0.027)	0.020 (0.037)	0.078 (0.059)	0.133 (0.101)	-0.032 (0.041)
dlPOP65	-1.938*** (0.372)	-1.376*** (0.306)	-0.584*** (0.198)	-0.148 (0.151)	0.240 (0.182)	0.904*** (0.221)	1.418*** (0.327)	-0.172 (0.170)
dlLE65	-0.664*** (0.239)	-0.586*** (0.218)	-0.236 (0.159)	-0.011 (0.103)	0.372*** (0.126)	0.779*** (0.164)	1.197*** (0.208)	-0.037 (0.125)
Bau	0.247** (0.104)	0.227** (0.093)	0.345*** (0.078)	0.424*** (0.071)	0.497*** (0.099)	0.649*** (0.117)	0.772*** (0.165)	0.464*** (0.062)

Notes: standard errors are reported in parentheses. *** ,** and * denote statistical significance at 1% , 5% and 10%, respectively.

Notes: The grey area is the 95% confidence interval for model (2). The horizontal solid lines represent the results obtained from model (4), and its 95% confidence band is shown with the long dashed line.

Figure 3: Response to specific determinants at various quantiles and mean by per capita health care expenditure growth when we use “Baumol variable” as one of the determinants of health care spending.

Table V: Chi-square test for the slope equality across quantiles (model (2))

	$\tau=0.05$	$\tau=0.10$	$\tau=0.25$	$\tau=0.50$	$\tau=0.75$	$\tau=0.90$
dlPHE _{t-1}						
$\tau=0.10$	1.418					
$\tau=0.25$	1.330	0.687				
$\tau=0.50$	1.269	0.545	0.243			
$\tau=0.75$	4.557**	3.423*	1.832	3.040		
$\tau=0.90$	5.465**	4.603**	4.067**	4.968**	1.488	
$\tau=0.95$	3.448*	3.280*	3.303*	3.383*	1.282	0.251
dlPGDP						
$\tau=0.10$	0.736					
$\tau=0.25$	1.455	0.712				
$\tau=0.50$	4.336**	4.174**	6.134**			
$\tau=0.75$	7.797***	8.636***	11.152***	5.756**		
$\tau=0.90$	10.065***	10.324***	12.365***	8.607***	3.208*	
$\tau=0.95$	9.915***	9.746***	9.963***	7.426***	4.153**	1.878
dlPhy						
$\tau=0.10$	1.451					
$\tau=0.25$	3.308*	1.919				
$\tau=0.50$	4.011**	3.645*	1.336			
$\tau=0.75$	5.981**	6.073**	3.792*	3.238*		
$\tau=0.90$	6.341**	6.307**	4.640**	4.403**	2.145	
$\tau=0.95$	6.842***	6.838***	5.458**	5.224**	3.427*	1.652
dlPOP65						
$\tau=0.10$	12.359***					
$\tau=0.25$	49.750***	18.935***				
$\tau=0.50$	74.542***	35.925***	35.763***			
$\tau=0.75$	94.013***	53.091***	57.934***	17.543***		
$\tau=0.90$	117.076***	76.769***	75.068***	41.864***	18.178***	
$\tau=0.95$	98.259***	64.277***	58.192***	41.320***	25.748***	8.039***
dlLE65						
$\tau=0.10$	2.085					
$\tau=0.25$	7.099***	5.788**				
$\tau=0.50$	11.929***	9.154***	4.668**			
$\tau=0.75$	20.382***	21.519***	18.010***	9.078***		
$\tau=0.90$	29.869***	31.465***	30.264***	23.223***	7.899***	
$\tau=0.95$	29.022***	35.738***	39.819***	32.103***	17.876***	8.866***
Bau						
$\tau=0.10$	0.070					
$\tau=0.25$	0.986	2.695				
$\tau=0.50$	3.131*	6.036**	1.902			
$\tau=0.75$	3.952**	5.739**	3.408*	1.601		
$\tau=0.90$	6.627**	8.782***	6.251**	3.999**	2.911*	
$\tau=0.95$	7.183***	8.742***	7.518***	5.128**	4.328**	2.020

Notes: *** , ** and * denote the statistical significance level at 1% , 5% and 10%, respectively.

Table VI: Estimates of model (2) and model (4): splitting “Baumol variable”

	Model (2)							Model (4)
	$\tau=0.05$	$\tau=0.10$	$\tau=0.25$	$\tau=0.50$	$\tau=0.75$	$\tau=0.90$	$\tau=0.95$	
dlPHE $_{t-1}$	0.239*** (0.078)	0.221*** (0.066)	0.199*** (0.055)	0.206*** (0.050)	0.186*** (0.058)	0.086 (0.074)	0.094 (0.065)	0.155*** (0.041)
dlPGDP	0.255* (0.135)	0.315** (0.133)	0.261*** (0.090)	0.281*** (0.064)	0.241*** (0.069)	0.174* (0.101)	0.123 (0.106)	0.372*** (0.068)
dlPhy	-0.179** (0.073)	-0.133*** (0.051)	-0.074* (0.043)	-0.034 (0.030)	0.056 (0.043)	0.103 (0.080)	0.156 (0.093)	-0.030 (0.041)
dlPOP65	-1.814*** (0.317)	-1.295*** (0.288)	-0.516*** (0.169)	-0.179 (0.137)	0.135 (0.150)	0.703*** (0.254)	1.394*** (0.401)	-0.178 (0.170)
dlLE65	-0.632*** (0.171)	-0.429** (0.189)	-0.174 (0.136)	-0.006 (0.105)	0.351*** (0.112)	0.699*** (0.186)	0.778*** (0.250)	-0.044 (0.125)
dlWage	0.170 (0.117)	0.193** (0.085)	0.278*** (0.075)	0.501*** (0.045)	0.735*** (0.086)	1.034*** (0.129)	1.170*** (0.194)	0.508*** (0.073)
dlProd	-0.511*** (0.176)	-0.458*** (0.158)	-0.352*** (0.126)	-0.278** (0.109)	-0.185 (0.165)	-0.060 (0.223)	0.193 (0.281)	-0.378*** (0.099)

Notes: standard errors are reported in parentheses. *** , ** and * denote the statistical significance level at 1% , 5% and 10%, respectively.

Notes: The grey area is the 95% confidence interval for model (2). The horizontal solid lines represent the results obtained from model (4), and its 95% confidence band is shown with the long dashed line.

Figure 4: Response to specific determinants at various quantiles and mean by per capita health care expenditure growth when we split “Baumol variable” into two variables, namely wage growth and labor productivity growth.

Table VII: Chi-square test for the slope equality: splitting “Baumol variable”

	$\tau=0.05$	$\tau=0.10$	$\tau=0.25$	$\tau=0.50$	$\tau=0.75$	$\tau=0.90$
dlPHE _{t-1}						
$\tau=0.10$	0.799					
$\tau=0.25$	1.287	0.365				
$\tau=0.50$	0.841	0.104	0.083			
$\tau=0.75$	1.537	0.334	0.077	0.318		
$\tau=0.90$	3.097*	2.844*	2.924*	3.438*	3.435*	
$\tau=0.95$	2.894*	2.784*	2.803*	3.273*	3.071*	0.024
dlPGDP						
$\tau=0.10$	1.051					
$\tau=0.25$	0.003	0.653				
$\tau=0.50$	0.061	0.135	0.112			
$\tau=0.75$	0.018	0.547	0.061	0.506		
$\tau=0.90$	0.383	1.299	0.687	1.435	1.028	
$\tau=0.95$	0.600	1.431	0.997	1.573	1.162	0.380
dlPhy						
$\tau=0.10$	0.891					
$\tau=0.25$	2.508	1.782				
$\tau=0.50$	5.279**	4.297**	1.940			
$\tau=0.75$	9.188***	8.385***	5.940**	5.009**		
$\tau=0.90$	9.518***	7.667***	6.461**	4.642**	1.773	
$\tau=0.95$	9.221***	7.465***	5.895**	4.587***	2.437	1.060
dlPOP65						
$\tau=0.10$	10.129***					
$\tau=0.25$	41.412***	22.822***				
$\tau=0.50$	55.826***	33.895***	11.970***			
$\tau=0.75$	61.126***	39.373***	23.143***	12.986***		
$\tau=0.90$	74.621***	51.924***	36.806***	24.352***	11.633***	
$\tau=0.95$	64.794***	53.043***	40.121***	30.768***	20.401***	10.111***
dlLE65						
$\tau=0.10$	2.251					
$\tau=0.25$	6.207**	3.595**				
$\tau=0.50$	9.063***	5.645**	2.556			
$\tau=0.75$	16.837***	16.104***	14.737***	11.017***		
$\tau=0.90$	22.387***	22.566***	20.610***	15.900***	4.843**	
$\tau=0.95$	13.141***	12.419***	10.159***	10.139***	4.976**	1.467
dlWage						
$\tau=0.10$	0.905					
$\tau=0.25$	3.548*	2.320				
$\tau=0.50$	8.046***	6.685***	6.942***			
$\tau=0.75$	16.378***	15.479***	8.982***	8.252***		
$\tau=0.90$	19.162***	20.431***	12.201***	11.718***	4.256**	
$\tau=0.95$	18.592***	16.924***	12.525***	10.883***	6.216**	2.676
dlProd						
$\tau=0.10$	0.055					
$\tau=0.25$	0.655	0.645				
$\tau=0.50$	1.966	1.784	1.205			
$\tau=0.75$	3.709*	3.429*	2.749*	1.728		
$\tau=0.90$	4.448**	4.514**	3.618*	2.717*	1.061	
$\tau=0.95$	6.558**	5.788**	5.003**	4.628*	0.912	0.182

Notes: ***, ** and * denote the statistical significance level at 1% , 5% and 10%, respectively.