UNIVERSITY OF PIRAEUS

DEPARTMENT OF STATISTICS AND INSURANCE SCIENCE

POSTGRADUATE PROGRAM IN APPLIED STATISTICS

Health Care Expenditures and Income

By
Christos A. Antoniadis

MSc Dissertation

submitted to the Department of Statistics and Insurance Science of the University of Piraeus in partial fulfillment of the requirements for the degree of Master of Science in Applied Statistics

Piraeus, Greece
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ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

ΤΜΗΜΑ ΣΤΑΤΙΣΤΙΚΗΣ
ΚΑΙ ΑΣΦΑΛΙΣΤΙΚΗΣ ΕΠΙΣΤΗΜΗΣ

ΜΕΤΑΠΤΥΧΙΑΚΟ ΠΡΟΓΡΑΜΜΑ ΣΠΟΥΔΩΝ
ΣΤΗΝ ΕΦΑΡΜΟΣΜΕΝΗ ΣΤΑΤΙΣΤΙΚΗ

Δαπάνες Υγείας και Ανάπτυξη

Χρήστος Α. Αντωνιάδης

Διπλωματική Εργασία

που υποβλήθηκε στο Τμήμα Στατιστικής και Ασφαλιστικής Επιστήμης του Πανεπιστημίου Πειραιώς ως μέρος των απαιτήσεων για την απόκτηση του Μεταπτυχιακού Διπλώματος ειδίκευσης στην Εφαρμοσμένη Στατιστική

Πειραιάς
Ιούνιος 2009

Η παρούσα Διπλωματική Εργασία εγκρίθηκε ομόφωνα από την Τριμελή Εξεταστική Επιτροπή που ορίσθηκε από τη ΓΣΕΣ του Τμήματος Στατιστικής και Ασφαλιστικής Επιστήμης του Πανεπιστημίου Πειραιώς στην υπ' αριθμ. …….. συνεδρίασή του σύμφωνα με τον Εσωτερικό Κανονισμό Λειτουργίας του Προγράμματος Μεταπτυχιακών Σπουδών στην Εφαρμοσμένη Στατιστική

Τα μέλη της Επιτροπής ήταν:

- ……………………………… (Επιβλέπων)
- ………………………………..
- ………………………………..

Η έγκριση της Διπλωματική Εργασίας από το Τμήμα Στατιστικής και Ασφαλιστικής Επιστήμης του Πανεπιστημίου Πειραιώς δεν υποδηλώνει αποδοχή των γνωμών του συγγραφέα.

To my parents,

Andreas and Mary

Abstract

Over recent decades, the relationship between (real) per capita health care expenditure (HCE) and (real) per capita income (GDP) has become an issue of particular interest in the health economics literature. Over 90% of the observed variation in HCE can be explained by the variation in GDP and more importantly, the income elasticity of demand for health care is found to be greater than one, suggesting that health care is a luxury good rather than a normal one.

In this study, we focus on the estimation of the income elasticity of the demand for health care for a sample of 19 OECD countries using data for the period 1970–2006. This paper contributes to the related literature by firstly extending the sample so as to cover the recent period and secondly, in contrast to previous research by employing not only Monte Carlo simulations but also a wide variety of asymptotically efficient cointegration estimators in order to reach more solid conclusions.

Based on the single equation estimators, we would subscribe to health being a luxury good in the majority of countries, while the system-based JOH estimator points to health being a necessity. The dividing line is the FMLS estimator which suggests that health spending moves one-to-one with income.

Περίληψη

Τα τελευταία χρόνια, η σχέση μεταξύ των πραγματικών κατά κεφαλήν δαπανών υγείας και του πραγματικού κατά κεφαλήν εθνικού εισοδήματος αποτελεί ένα ζήτημα ιδιαίτερου ενδιαφέροντος στη βιβλιογραφία που σχετίζεται με τα οικονομικά της υγείας. Πάνω από το 90% της παρατηρούμενης μεταβλητότητας των δαπανών για την υγεία μπορεί να εξηγηθεί από τη μεταβλητότητα του κατά κεφαλήν εθνικού εισοδήματος, και ειδικότερα, η εισοδηματική ελαστικότητα για τη ζήτηση της υγείας φαίνεται να ξεπερνά τη μονάδα, γεγονός που καθιστά την υγεία αγαθό πολυτελείας.

Στην παρούσα μελέτη, εστιάζουμε στην εισοδηματική ελαστικότητα της ζήτησης της υγείας για ένα δείγμα 19 χωρών του ΟΟΣΑ χρησιμοποιώντας δεδομένα που καλύπτουν το χρονικό διάστημα 1970-2006. Η εργασία αυτή συμβάλλει στη σχετική βιβλιογραφία αρχικά επεκτείνοντας το δείγμα έτσι ώστε να καλυφθεί και η πρόσφατη χρονική περίοδος και ακόμη σε αντίθεση με προηγούμενες μελέτες εφαρμόζοντας όχι μόνο προσομοιώσεις τύπου Monte Carlo αλλά επίσης μια μεγάλη ποικιλία ασυμπτωτικά επαρκών εκτιμητών συνολοκλήρωσης με στόχο να φτάσουμε σε πιο ικανοποιητικά και όσο το δυνατόν βέβαια συμπεράσματα.

Βασιζόμενοι σε εκτιμητές απλής εξίσωσης, θα καταλήγαμε στο συμπέρασμα ότι η υγεία αποτελεί ένα αγαθό πολυτελείας για τις περισσότερες από τις εξεταζόμενες χώρες που συμμετείχαν στην έρευνα, ενώ με βάση τον εκτιμητή Johansen θα μπορούσαμε να θεωρήσουμε την υγεία ως αναγκαίο αγαθό στις περισσότερες περιπτώσεις. Τέλος, προτείνοντας ότι οι δαπάνες υγείας εμφανίζουν μια ένα-προς-ένα σχέση με το εισόδημα, τα αποτελέσματα του εκτιμητή FMLS φέρεται με τη σειρά τους να βρίσκονται κάπου ενδιάμεσα σε σύγκριση με τα προηγούμενα.

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List of Abbreviations

AADL	Augmented Autoregressive Distributed Lag
ADF	Augmented Dickey-Fuller
ADL	Autoregressive Distributed Lag
AR	Autoregression
DF	Dickey-Fuller
DGLS	Dynamic Generalized Least Squares Estimator
DGP	Data Generating Process
DOLS	Dynamic Ordinary Least Squares Estimator
EC	European Community
FMLS	Fully Modified Least Squares Estimator
GDP	Gross Domestic Product
HCE	Health Care Expenditure
HE	Health Expenditure
IV	Instrumental Variables
JOH	Johansen's Maximum Likelihood Estimator
KPSS	Kwiatkowski, Phillips, Schmidt and Shin
LM	Lagrange Multiplier
MC	Monte Carlo
OECD	Organization of Economic Co-Operation and Development
OLS	Ordinary Least Squares Estimator
PPPs	Power Purchasing Parities

UK	United Kingdom
US	United States
VAR	Vector Autoregression
VEC	Vector Error Correction
VECM	Vector Error Correction Model
ΟΟΣΑ	Οργανισμός για την Οικονομική Συνεργασία και Ανάπτυξη

CHAPTER 1

Introduction

1.1 The issue of Health Care Expenditure

The growth of health expenditure and of its share in Gross Domestic Product (GDP) has always been an issue of special/general interest, raising various comments and discussions among academics, administrators and politicians in many countries.

One approach to this subject has been the international comparisons of HE as there are differences even when the relatively homogeneous industrialized market economies are being compared.

Since Newhouse (1977) first sought to identify the factors that determine the quantity of health care services in different countries, concluding that average income explains almost all –about 92% of – the variance in absolute health care quantity between countries, and that the income elasticity of health care is greater than unity, several regression analyses based on cross-sectional data have been used to explain the observed differences in per capita health care expenditure across countries. More specifically, researchers through an extended analysis of the time series properties of health expenditure and income respectively, question both about the existence of a long-run relationship between them and the characterization of health as a luxury good or a necessity for each country.

In general, most of the studies do meet / fall in with Newhouse's conclusions, arguing that aggregate income appears to be the most important factor explaining HE variation among countries and that the size of the estimate of the income elasticity is around or even higher than one. Health care expenditure seems to increase proportionally more than aggregate per capita income. In other words, empirical studies suggest that countries having higher levels of development and standards of living tend to spend more on health care.

Except Newhouse, various studies like Cullis and West (1979), Leu (1986), Parkin et al. (1987), Culyer (1990), Gerdtham and Jonssön (1991a), Hitiris and Posnett (1992) and later Hansen and King (1996), Blomqvist and Carter (1997) and Gerdtham and Löthgren (2000) establish a strong and positive correlation between national income and national health care expenditure through a demand function approach. Working at an individual level, i.e. country – by – country methods, they inferred in general terms that health care is a luxury commodity, at least for developed countries, as most estimates of the income elasticity of health care expenditure exceeded unity. To this end, using suitable tests, individual variables are found to be non-stationary and in a few cases these time series gave rise to a cointegration relationship. As a consequence, the presence of a long-run relationship is verified.

More specifically, the large amount of studies related to international health expenditure has, to some extent, been based on standard demand theory and could be distinguished in two main categories, the first and the second generation studies.

The former category of studies uses international cross-section data for single or selected years to analyze the cross country differences in health care expenditure. One particular methodological issue of these studies is the choice between different conversion factors such as exchange rates or purchasing power parities and whether this choice affects the empirical results. The latter uses both time series and panels of countries, each with a relatively long time series of annual data, which enables one to test a more extensive range of hypotheses, because of the larger sample size as well as to control for country and time-invariant variables whose omission might otherwise result in inconsistent estimates of the regression coefficients. Relationships involving non-stationary variables, cointegrating and dynamic relationships and heterogeneous relationships across countries form important parts of methodological issues in the second-generation studies.

The next chapter presents some of the studies that went a long way towards the two aforementioned generation studies with the passage of time. The rest of the paper is organized as follows. Section 3 provides some theoretical background. It presents the relevant methodology and the test strategy. Section 4 contains the data and the empirical results as well, while the final section presents conclusions and interpretations arising from the analysis.

CHAPTER 2

Literature Review

2.1 First-generation studies

2.1.1 Cross-section bivariate regressions

In this case studies have been based on standard demand theory. Researchers link per capita health care expenditure (HCE) to per capita gross domestic product (GDP) and focus on the estimated income elasticity in order to draw conclusions.

- *Newhouse (1977)*

With his article in 1977, Newhouse first attempted to identify factors determining the quantity of health care services in 13 developed countries using 1971 data. By regressing HCE on GDP and working in US dollars ($) at annual average exchange rates he obtained the following results:

$$HCE_i = -60 + 0.079GDP_i\,, \quad R^2 = 0.92\,, t - value = 11.47$$

The two principal results were that aggregate income explains almost all (about 92%) of the variance of the level of HCE between countries and that the income elasticity of health care exceeds unity. According to these results, Newhouse concluded that factors other than income such as the price paid by the consumer and the method of reimbursing the physician are of marginal significance as well as that health care is a luxury good, arising from the fact that the demand for health care may relate more to "caring" than to "curing".

As we have already mentioned, Newhouse's article has a seminal form. Most empirical research later has confirmed these empirical results concerning the income elasticity and the high explanatory power of the relationship, irrespective of whether it is calculated at the mean from linear regressions or estimated directly as a constant in log-linear regressions. This holds both for rather heterogeneous samples and for homogeneous samples such as in the OECD countries.

It is surely remarkable that the studies of Parkin et al. (1987) and Gbesemete and Gerdtham (1992) criticized Newhouse's results and are considered as exceptions from the regular finding of an income elasticity of health spending higher than unity in cross-sectional data. They focus on the sensitivity of the estimated elasticity to the different methods of transformation and on the fact that the prices take place only as deflators rather than explanatory variables without constraints.

- *Parkin et al. (1987) – Gbesemete and Gerdtham (1992)*

In 1987, Parkin et al. replicated Newhouse (1977) with their research which was based on 18 OECD countries and 1980 data using different functional forms (linear, semi-log, double-log, exponential) and using different conversion factors (exchange rates and PPPs). Their results indicated that certain functional forms imply specific magnitudes of Engel income elasticities of medical care and that income elasticities are around unity in cross-sections when PPP conversion factors, rather than exchange rates, are used.

Gbesemete and Gerdtham (1992) investigated health expenditure in 30 African countries including additional explanatory variables and reported an income elasticity not significantly higher than one.

However studies are not restricted to the univariate case. Various problems in analysis, such as possible omitted variable bias in the income coefficient or other estimation problems led to multivariate regressions.

2.1.2 Cross-section multivariate regressions

In order to reach more solid conclusions, researchers wondered whether other variables have any significant independent impact on national HE.

- *Leu (1986)*

Leu (1986), following a public-choice approach, used national data of 19 OECD countries for 1974 and included as regressors a set of relevant exogenous variables[1], a variable to reflect the extent of public sector provision of health services[2] and finally dummies for the National Health Service[3].

Leu confirmed the predominant effect of the income variable. He also found that a number of additional variables were significant even though they had a lower participation in the model. His conclusions have remained controversial, particularly as regards the institutional variables. Various studies dealt with such a subject but Leu's results for the additional variables have not been verified yet.

- *Culyer (1988, 1989)*

Culyer (1988, 1989) dealt mostly with the difference between the public sector and the private one and criticized Leu's suggestions. He

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[1] These included the fraction of people under 15 and over 65 as these groups tend to use more health than others and urbanization because not only the risk of contagion is higher (see Kleiman, 1974) but also time and travel costs are lower in cities.
[2] Leu argued that an increase in the size of the public share would increase total spending. He also suggested that HCE should increase with an increased fraction of public finance, assuming implicitly that this fraction reduces the price to the consumer.
[3] In this case the centralized budgetary control might not only has a restraining effect but also a direct democracy on the grounds that controlling the HCE would be easier if voters had greater direct control over government and tax levels.

claimed that costs in the private sector may be larger due to advertizing and market pressures and as a result the conditions become inconsistent with the professional ethics and regulation. Using also a number of additional explanatory variables the author noted that countries with more closed health care financing systems are anticipated to have lower expenditure.

- *Gerdtham et al. (1992a, 1992b)*

Using cross-sectional and pooled cross-sectional (over three selected years) data sets Gerdtham et al. (1992a, 1992b) attempted to measure the effect of health expenditure on national finance. For both data sets, they specified the following log-linear model:

$$\begin{aligned} HCE_i = b_0 + b_1 GDP_i + b_2 RP_i + b_3 DOCT_i + b_4 TEXMC_i + b_5 PF_i \\ + b_6 FEE_i + b_7 GLOBAL_i + b_8 FP_i + b_9 AGE_i \\ + b_{10} URB_i + e_i \end{aligned}$$

where $i = 1,2,\dots,19$ (for 19 OECD countries respectively), $T = 1987$ for the first study and $T = 1974, 1980, 1987$ for the second one, and

- RP: relative prices (PPPs for health relative to PPPs for GDP)

- $DOCT$: number of doctors

- $TEXMC$: ratio of in-patient to total spending

- PF: ratio of government to total HCE

- FEE: dummy variable for the fee-for-service payment of doctors

- $GLOBAL$: dummy variable for global budgeting caps

- FP: female participation ratio

- AGE: ratio between population 65 years of age and over the population aged 15 to 64

- URB: urbanization

Carrying out strict cross-sectional methods and emphasizing on the variables' statistical significance the authors showed that GDP remained the most significant explanatory factor of Health Care Expenditure obtaining a value of elasticity equal to 1.33 and statistically different from unity.

2.1 Second-generation studies

2.2.1 Time-series approach

A time-series data set consists of observations of a variable or several variables over time. As past events can influence future events and lags in behavior are prevalent in the social sciences, time is an important dimension in a time-series data set. Unlike the arrangement of cross-sectional data, the chronological ordering of observations in a time series conveys potentially important information.

A key feature of time-series data that makes them more difficult to analyze than cross-sectional data is the fact that economic observations can rarely, if ever, be assumed to be independent across time. Most economic and other time-series are related, often strongly related, to their recent histories. For example, knowing something about the GDP from last quarter tells us quite a bit about the likely range of the GDP during this quarter, because GDP tends to remain fairly stable from one quarter to the next. Although most econometric procedures can be used with both cross-sectional and time-series data, more needs to be done in specifying econometric models for time-series data before standard econometric methods can be justified. In addition, modifications and embellishments to standard econometric techniques have been developed to account for and to exploit the dependent nature of economic time-series and to address other issues, such as the fact that some economic variables tend to display clear tends over time. Another feature of time-series data that can require special attention is the data frequency at which the data are collected.

Four of the most important recent articles have focused on time series non-stationarity and cointegration of HCE and GDP, reaching partly different conclusions and led to various subsequent studies.

- *Hansen and King (1996)*

Hansen and King (1996) used data for 20 OECD countries for the period 1960-1987 and presented individual country-by-country Augmented Dickey-Fuller (ADF) unit root and Engle-Granger cointegration tests. The unit root hypothesis could generally not be rejected for either HCE or GDP. Nor could the hypothesis of no-cointegrating relationship among HCE, GDP and a range of other variables generally be rejected. They consequently suggest that panel data estimations of the GDP/HCE relationship may be spurious.

- *Blomqvist and Carter (1997)*

Using data for 18 OECD countries for the period 1960-1991, Blomqvist and Carter reported various unit root and cointegration test results of an HCE model including GDP, an intercept and a time trend. Based on the Phillips and Perron (1988) test and in accordance to Hansen and King, the country-by-country results of Blomqvist and Carter reject the unit root hypothesis in only one case (Finland) for GDP and in no case for HCE. Consequently they proceeded by country residual-based cointegration tests based on static as well as dynamic models. The results differ from Hansen and King in that the null hypothesis of no-cointegration is rejected for all countries by the Phillips and Perron test and the null of cointegration by the Shin (1994) test cannot be rejected for any country.

- *Roberts (1998b)*

Roberts (1998b) used data for 10 EC countries for the time period 1960-1993 and reported individual country-by-country and panel data unit root tests and individual country-by-country cointegration tests. In the ADF regression, she included an intercept and time trend and found that the null hypothesis of a unit root cannot be rejected for HCE and GDP among a number of other variables. She reported contradictory results based on various country-by-country cointegration tests; Engle-Granger and Pesaran et al. (1996) tests failed to reject the null of no-cointegration but the Johansen (1991) test provided evidence for the existence of at least one cointegrating vector for most of the countries studied.

- *McCoskey and Selden (1998)*

McCoskey and Selden (1998) used the same data set as Hansen and King and applied the heterogeneous panel unit root test by Im et al. (1997). In contrast to the three previous mentioned studies, they rejected the null hypothesis of unit roots for both HCE and GDP and suggested that "researchers studying national health care expenditure need not be as concerned as previously thought about the presence of unit roots in the data".

The omission of the time trend in McCoskey and Selden and not so much any probable differences in the power of the employed tests is the reason for the disagreement between them and the other authors. Hansen and King argued that such an omission creates doubts about the validity of the results as both of the variables present trends.

In addition, arguments between the researchers also appeared with respect to the cointegration results. The most likely explanation for the contradicting results is the fact that different methods for the estimation of the cointegration relationships are used.

To conclude with, both HCE and GDP proved to be non-stationary as the three studies which include a time trend don't reject the hypothesis of a unit root. However, the existence of a long-run relationship between them remains in doubt.

As we mentioned above, these studies concern a basis of the subject of stationarity and cointegration of HCE and GDP. According to these, various researchers dealt with health expenditures' issues and advanced the substantial findings. Some of the most important recent studies are the following:

- *Gerdtham and Löthgren (2000)*

Gerdtham and Löthgren (2000) used a data of 21 OECD countries covering the time period from 1960 to 1997. Applying the ADF and Kwiatkowski et al. (1992) for stationarity, they indicated that both HCE and GDP are non-stationary variables. Such a result gave rise to a possible long-run relationship between them. As a consequence, they applied suitable cointegration tests, such as the Shin (1994) test, and concluded that there is a strict evidence of the existence of a long-run relationship between HCE and GDP respectively.

- *Jewell et al. (2003)*

Jewel et al. (2003) used a data set of 20 OECD countries for the period 1960-1975. They claimed that HCE and GDP are stationary variables with one or two structural changes/breaks which are present in recession periods. Their results are in contrast to Hansen and King (1996), Blomqvist and Carter (1997) and Gerdtham and Löthgren (2000) who didn't take into account any structural change/break and meet those of McCoskey and Selden (1998) even if the latter didn't consider any time trends or structural changes/breaks.

- *Clemente et al. (2004)*

In contrast to previous studies, these authors test the hypothesis of non-cointegration provided that the long-run relationship presents a structural break. They showed that such breaks don't affect the relationship between HCE and GDP with a homogeneous mode. More specifically, they indicated that public and private HCE follow different models because they present different values for the estimated parameters and different periods of breaks.

They estimated the long-run relationship between HCE and GDP including the existence of the pre mentioned breaks for the definition of the model. They indicated that when including such structural breaks there is no enfeeblement of the previous results and they develop an economic model in order to give an economic illustration about the finance, the politics and the health system.

Clemente at al. claimed that health concerns a luxury good as well as that the decrease of the public health care expenditures doesn't mean a reduction of the total one as private expenditures can be increasing more. They also admitted that politics can create undesirable results such as an ineffective system of health.

We ought to mention that in this research, a time-series approach is used for our analysis.

2.2.2 Panel Data Methods

Panel data analyses are additional methods of analysis which have gradually grown recently. According to Greene (1993), panel data enable one to test for country and time-invariant effects and carry out appropriate estimation procedures in their presence.

- *Gerdtham (1992)*

Gerdtham (1992) used data for 22 OECD countries for the period 1972-1987, exploring different panel data models and issues of lags and dynamic adjustment of HCE to movements in exogenous variables. Through suitable methods he managed to specify a reduced number of explanatory variables such as GDP, inflation, fraction of public financing as well as the fraction of the aged in the population.

Based on both static and restricted error-correction models and on appropriate tests which were carried out using five different panel data models Gerdtham concluded that country or time-specific effects and whether these were treated as fixed or random variables had important implications for the results.

- *Hitiris and Posnett (1992)*

Hitiris and Posnett (1992) re-analyzed the models of Newhouse (1977) and Leu (1986) using panel data for 20 OECD countries for the period 1960-1987. Their results re-confirmed the importance of GDP as a major determinant of HCE, with an elasticity of about one. The importance of some non-income variables was also confirmed, although the direct effect of such factors appeared to be small. However, the presence of non-stationary variables in the econometric model creates doubts for the credibility of the results.

- *Barros (1998)*

Barros dealt with the same issue in a different way. He concentrated on differences in growth rates (averaged across decades) rather than on levels of health care expenditure. He used data for 24 OECD countries from the period 1960-1990. The explanatory variables were as follows:

- Initial health care expenditure, i.e. health expenditure per capita (in levels) in the first year of the period
- Square of initial health care expenditure
- Gatekeeper dummy
- Public reimbursement and integrated system dummies
- GDP growth rate
- % of population aged over 65 years
- Two-time decade dummies (1970-1980 and 1980-1990)

Barros indicated that the health system dummies as well as the two-time decade ones were clearly insignificant and the only significant variables were the first three mentioned above. His results showed not only a negative effect of initial health expenditure implying that higher initial health expenditure would lead to lower growth rate in the next decade[4] but also a positive effect of the square of initial health expenditure indicating that the absolute effect is stronger for

[4] Such a situation indicates convergence among countries.

heavier spenders but at a decreasing rate. He also concluded that the income elasticity was lower than but close to one.

- *Roberts (1998a)*

Roberts (1998a) considered three issues in HCE modeling; heterogeneous relationships across countries, dynamic relationships, and relationships including non-stationary variables. The author used new methods to estimate the average effects of explanatory variables in heterogeneous dynamic and non-stationary relationships. It is quite remarkable that four alternative estimation methods were considered, namely the homogeneous fixed-effects estimator with common slopes, the mean group (country) estimator in which separate time series regressions are estimated for each group and the coefficients are averaged across groups, the time-series regressions with the data averaged across countries and finally the cross-section regressions with the data averaged over time. Roberts used data from 20 OECD countries over the period 1960-1993 and estimated static and dynamic models employing estimation methods. The exogenous variables included in the HCE models were:

- GDP
- Proportion of public finance of HCE

- Proportion of population above 65 years

- Relative price of HCE

Her results showed that the estimated mean group dynamic long-run income elasticity was significantly higher than unity and higher compared with Gerdtham's fixed-effects estimates. Similarly to Leu (1986) but differently from Gerdtham (1992) and Barros (1998) respectively Roberts also indicated a positive and significant long-run elasticity of public financing[5]. In accordance with Gerdtham (1992) and Barros (1998), the effects of aging of the population were not significant. The relative price of health care was also not significant.

Based on all the aforementioned studies, numerous studies followed in order for the literature to become more clear and explicit and to advance on econometric issues. Over recent years, most of the studies deal with panel data approaches to draw more solid conclusions.

The next chapter presents the econometric methodology we employ in this study to deal with the aforementioned issues.

[5] Roberts suggested that a 10% increase in the fraction of public financing increases health expenditure by 7%.

CHAPTER 3

Methodology

The analysis of international health spending is based on standard demand theory. The income elasticity of health expenditure is estimated by a function that links per capita health care expenditure to per capita GDP. Suitable methods and tests take place in order for us to achieve robust results through a time-series approach.

3.1 Stationarity-Unit root tests

The first step in determining the validity of our model is to determine the order of integration of each variable included. Building upon previous research, we initially test whether HCE and GDP are stationary series by employing suitable stationarity and unit root tests. This is important since empirical tests that ignore this issue can lead to spurious regressions and meaningless results even if the variables are generated independently (see Phillips (1986), Engle and Granger (1987)). As non-stationarity in the data can arise from deterministic trends or stochastic ones, a careful discrimination between these trends has also to be taken into account to avoid misleading inferences.

As a result, the test for stationarity of each variable is an important issue and to this end, in this section, we use the following stationarity-unit root tests:

The Augmented Dickey Fuller test (ADF), which is a modified version of Dickey and Fuller (1979, 1981) test (DF), and the Kwiatkowski, Phillips, Schmidt and Shin test (KPSS, 1992) as well.

To understand the function of the first mentioned test, we initially present the standard Dickey – Fuller (DF) test.

We consider an AR (1) model:

$$y_t = \rho y_{t-1} + x_t' \delta + e_t \, , \; e_t \sim Niid \qquad (1)$$

where x_t are optional exogenous regressors which may consist of a constant, or a constant and trend, ρ and δ are parameters to be estimated and the e_t are assumed to be white noise.

- If $-1 < \rho < 1$, then y_t is a stationary series.

- If $|\rho| = 1$, y_t is a non-stationary series and the variance of y_t increases with time and approaches infinity.

As a consequence, the hypothesis of stationarity can be evaluated by testing whether the absolute value of ρ is strictly less than one.

More in detail, in the analysis of economic series, we test the null hypothesis of unit root $H_0: \rho = 1$ against the one-sided alternative of no unit root $H_0: |\rho| < 1$.

According to the standard DF test, we estimate equation (1) after subtracting y_{t-1} from both sides.

$$\Delta y_t = \alpha y_{t-1} + x_t^{'}\delta + e_t \, , e_t \sim Niid$$

where $\alpha = \rho - 1$. . In this respect, the null hypothesis of unit root in series y is $H_0: \alpha = 0$ while the alternative one of no unit root is $H_1: \alpha < 0$ and is evaluated using the conventional t-ratio for : $t_a = \hat{a}/(se(\hat{a}))$ where $\hat{a}$ is the estimate of α and $se(\hat{a})$ is the coefficient standard error.

Dickey and Fuller (1979) show that under the null hypothesis of a unit root, this statistic does not follow the conventional Student's t-distribution, and they derive asymptotic results and simulate critical values for various test and sample sizes. More recently, MacKinnon (1991, 1996) implements a much larger set of simulations than those tabulated by Dickey and Fuller. In addition, MacKinnon estimates response surfaces for the simulation results, permitting the calculation of Dickey-Fuller critical values and p-values for arbitrary sample sizes.

The DF test considered above is valid only in the case that the series is an AR(1) model. If the series is correlated at higher order lags, the assumption of white noise disturbances e_t is violated.
The ADF test constructs a parametric correction for higher-order correlation by assuming that the series y_t series follows an AR(p) process and adding p lagged difference terms of the dependent variable y_t to the right-hand-side of the test regression:

$$\Delta y_t = a y_{t-1} + x_t'\delta + \beta_1 \Delta y_{t-1} + \beta_2 \Delta y_{t-2} + \beta_3 \Delta y_{t-3} + \ldots + \beta_p \Delta y_{t-p} + u_t,$$

$e_t \sim Niid$

This augmented specification is used to test the null hypothesis $H_0: a = 0$ against the alternative one $H_1: a < 0$. Dickey and Fuller showed that the asymptotic distribution of the t-ratio for a, which is used for this test, is independent of the number of lagged first differences included in the ADF regression.
Quite often the ADF approach faces low power for near unit root generating processes. Mainly in cases of trending series, such a low power is usually due to the strong multicollinearity in the ADF regression between the deterministic trend and the lagged variable. An alternative way to handle this potential multicollinearity is to switch the null and alternative hypothesis and consider the stationarity test by KPSS (see also Gerdtham-Löthgren (2000)).

Kwiatkowski, Phillips, Schmidt and Shin proposed a LM test to test for unit root. The KPSS test differs from the previous mentioned tests in that the series y_t is assumed to be (trend-) stationary under the null. It is a stationarity test which is based on the residuals from the OLS regression of y_t on the exogenous variables x_t :

$$y_t = x_t'\beta + u_t \qquad (2)$$

The LM statistic is being defined as:

$$LM = \sum_t S(t)^2/(T^2 f_0)$$

where f_0 is an estimator of the residual spectrum at frequency zero and where $S\,(t\,)$ is a cumulative residual function:

$$S(t) = \sum_{r=1}^{t} \widehat{u_r}$$

based on the residuals $\widehat{u_r} = \; y_t - x_t'\widehat{\beta(0)}$.
As we see, the LM-statistic is always positive. We do not reject the null hypothesis of stationarity if the LM-statistic is lower than the critical value for a standard level of significance.

3.2 Cointegration

A large part of studies in empirical macroeconomics involve nonstationary and trending variables such as income, consumption, price level and trade flows. Accumulated wisdom suggests that the appropriate way to manipulate such series is the usage of differencing and other transformations to reduce them to stationarity and then to analyze the resulting series as VARs or with the methods of Box and Jenkins (1976). Nevertheless, a growing literature has shown that there are also more interesting and suitable methods to analyze trending variables.

Arriving at the conclusion of cointegration, we can distinguish between a long-run relationship between y_t and x_t, that represents the way in which the two variables drift upward together, and the short-run dynamics, that is, the relationship between deviations of y_t and of x_t from their long run trend. In such a case, differencing of the data would be counterproductive, since it would obscure the long-run relationship between y_t and x_t.

The Engle-Granger (1987) & Johansen (1987, 1991) tests are two of the most famous techniques in econometric bibliography to test for cointegration.

<u>*Engle and Granger*</u> employ a two-step methodology for such a purpose. Their test amounts to testing for a unit root in the residuals of a first stage regression. In essence, it is based on the performance of

the residuals arising from the OLS method. If these residuals are a stationary series, then our variables are cointegrated.

Practically, we run a regression in which the logarithm of health expenditure reflects the dependent variable and the logarithm of gross domestic product expresses the independent one.

Let the residuals of this regression have the form of an AR(1) model:

$$\widehat{u_t} = \rho\widehat{u_{t-1}} + e_t$$

If $\rho = 1$ then $\hat{u}_t$ is not a stationary series. On the contrary, if $|\rho| < 1$ the series is stationary. According to the Engle-Granger method, in this paper, the previously mentioned tests, namely ADF and KPSS, are used in order for us to test for cointegration. It is noticeable that since these residuals are estimates of the disturbance term, the asymptotic distribution of the test statistic differs from the one for ordinary series. The correct critical values for a subset of the tests may be found in Davidson and MacKinnon (1993).

The *Johansen Test* is an alternative way to test for cointegration. This method is usually applicable to the multivariate case.

Quite often, in the analysis of economic data, more than one variables are involved and as a result of this, the vector of cointegration is now transformed into a space with a known dimension.

The Johansen Test is a VAR-based cointegration test. Consider a Vector Autoregressive Model (VAR) of order p:

$$Y_t = \delta + \Theta_1 Y_{t-1} + \cdots + \Theta_p Y_{t-p} + \varepsilon_t$$

or $$\Theta(L) Y_t = \delta + \varepsilon_t$$

We may rewrite this VAR as:

$$\Delta Y_t = \delta + \Gamma_1 \Delta Y_{t-1} + \cdots + \Gamma_{p-1} \Delta Y_{t-p+1} + \Pi Y_{t-1} + \varepsilon_t \qquad (3)$$

where the long-run matrix $\Pi \equiv -\Theta(1) = -(I_k - \Theta_1 - \cdots - \Theta_P)$ shows the long-run dynamic properties of Y_t. This equation is a generalized form of the regressions which are used in the ADF test.

On the assumption that ΔY_t and ε_t are stationary series, it follows from (3) that ΠY_t is stationary as well.

All these can lead to three different situations about Π considering not only the form of Y_t but also the trace/rank of Π.

Especially, if Π has reduced rank then it can be written as the product of $k \times r$ matrix α by a $r \times k$ matrix β' of order r.

So,

$$\Delta Y_t = \delta + \Gamma_1 \Delta Y_{t-1} + \cdots + \Gamma_{p-1} \Delta Y_{t-p+1} + \alpha\beta' Y_{t-1} + \varepsilon_t$$

(VECM)

The linear relations $\beta' Y_{t-1}$ presents the r cointegrating relations (the cointegrating rank) and α the adjustment parameters in VEC model respectively (how the elements in ΔY_t are adjusted in r residuals).

The Johansen's method involves estimating the matrix Π from an unrestricted VAR and to test whether we can reject the restrictions implied by the reduced rank of Π. This estimation is done via maximum likelihood.
In our case, the Johansen's Test is being applied to a two-dimension model in order for us to establish a possible long-run relationship between Health Care Expenditures and GDP (existence of cointegration).

The methodology is applied as follows:

Let the following VAR(k) model for $z_t = \{x_{1t}, x_{2t}\}$ where x_{1t} and x_{2t} represents Health Care Expenditures and GDP respectively:

$$z_t = c + A_1 z_{t-1} + \cdots + A_k z_{t-k} + u_t, u_t \sim Niid \qquad (4)$$

where u_t is now a vector. Model (4) can be written in the following error-correction form:

$$\Delta z_t = c + \Gamma_1 \Delta z_{t-1} + \cdots + \Gamma_{k-1} \Delta z_{t-k+1} + \Pi z_{t-1} + u_t, u_t \sim Niid \quad (5)$$

where $\Gamma_i = -(A_{i-1} - \cdots A_k), i = 1, \ldots, k-1$ and $\Pi = -(I - A_1 - \cdots - A_k)$.

The rank of matrix Π determines the existence of cointegration between HCE and GDP. The following are being distinguished:

• If $rank\ (\Pi) = 2$, then x_{it}, i=1,2 are stationary series

• If $rank\ (\Pi) = 0$, then model (5) is a VAR(k-1) model for the first differences of the variables and there is no long-run relationship between the previous mentioned variables. In this case, Π is the zero matrix and all x_{it} are I(1) processes but they are not cointegrated.

• If $rank\ (\Pi) = 1$, then our variables are cointegrated and the matrix Π can be written as the product of two $(2x1)$ matrices A and B, i.e. $\Pi = AB''$. Matrix B contains the coefficients of the cointegrated relationship and the elements of matrix A determine the magnitude of each variable's influence caused from divergences from the equilibrium relationship of the examined variables. In other words, B contains the cointegration vectors and A the adjustments coefficients. Generally, according to Johansen's maximum likelihood approach for the determination of $rank(\Pi)$ we test in succession for ρ = 0 and 1 (till we cannot reject H_0 for first time) the following hypothesis:

$$H_0{:}\,rank(\Pi) = p \quad vs.\ H_1{:}\,rank(\Pi) = p + 1$$

Alternatively, to this end, Johansen has also proposed a trace method. According to this, we test in succession for ρ = 0 and 1 (till we cannot reject H_0 for first time) the following hypothesis:

$$H_0{:}\,rank(\Pi) = p \quad vs.\ H_1{:}\,rank(\Pi) = k$$

3.3 Estimation

In this study, the form of the included variables (HCE & GDP are I(1) series) prohibits us to use the OLS estimator in order to estimate cointegrating relations. In spite of its super consistency (converges with a sample size rate, irrespective of the correlation structure between the cointegrating error and the independent variable, see Stock 1987) the OLS estimator is not an ideal choice for statistical induction because there are second – order effects. These effects are nuisance parameters in the asymptotic distribution of the OLS estimator that stem from possible long-run endogeneity and serial correlation. (see Phillips, 1988, Phillips & Hansen, 1990).

There are various parametric and non- parametric methods for the treatment of such problems. Particularly, the usage of asymptotically efficient cointegration estimators corrects parametrically the asymptotic distribution of the OLS estimator.

The cointegrating estimators employed in this section are the following ones:

Simple OLS: This is the ordinary least square estimator of $\beta\theta$, applied to equation (2) for t = 1,2,…,T.

DOLS(p,t) (Dynamic OLS): Saikonnen (1991), Phillips & Loretan (1991), and Stock & Watson (1993) proposed the Dynamic Ordinary Least Squared estimator. Stock and Watson who first used the term "DOLS" in 1993, generalized it into systems with higher orders of integration. It is based on the static equation (2), augmented with lags and leads of the first difference of the independent variable (regressor), i.e.:

$$y_t = \beta x_t + \sum_{i=1}^{p-1} \gamma_i \Delta x_{t-i} + \sum_{j=1}^{t-1} d_j \Delta x_{t+j} + u_t \qquad (6)$$

Having such a form, this model can offer us a direct way to estimate the cointegrating relationship and asymptotically lead to valid test statistics as well. The estimator DOLS(1,1) arises from the equation $y_t = \beta x_t + \gamma_1 \Delta x_t + d_1 \Delta x_{t+j} + u_t$.

It is noticeable that any serial correlation of u_t does not raise any serious problems in the estimation of β and can be dealt with by consistently estimating the long-run variance of u_t as proposed by Newey and West (1987).

DGLS (Dynamic Generalized Least Squares): This estimator (see Stock and Watson, 1993) is the feasible GLS estimator applied to equation (6), in which the regression error is usually modeled parametrically as an AR(1) process.

ADL (q,r) (Autoregressive Distributed Lag): It is an estimator that is based on the following ADL(q,r) model:

$$y_t = \sum_{i=0}^{q} a_i x_{i-1} + \sum_{j=1}^{r} b_j y_{t-j} + v_t$$

The parameter of interest is equal to the long-run multiplier of y_t with respect to x_t. The transformation of the ADL model into the Bewley form gives an appropriate way to directly estimate the parameter of β along with its standard error (see Bewley 1979, Wickens and Breusch 1988, and Banerjee et. al. 1993):

$$y_t = \beta x_t + \sum_{i=1}^{q-1} a_i \Delta x_{t-i} + \sum_{j=1}^{r-1} b_j \Delta y_{t-j} + e_t$$

Using the Instrumental Variables (IV) estimator we can estimate the coefficients and their standard errors, with the original matrix of regressors being the instrumental variables (see Wickens and Breusch 1988). This means that the ADL estimator of β is very easy to be applied since it involves just only IV estimation techniques.

AADL(q,r,s) (Augmented Autoregressive Distributed Lag): Where there is Granger causality running from the cointegration error to the error that drives the independent variable, augmentation of an ADL model by the leads of the regressor restores super-exogeneity and removes the second order asymptotic biases. The specification is as follows:

$$y_t = \beta x_t + \sum_{i=1}^{q-1} a_i \Delta x_{t-i} + \sum_{j=1}^{r-1} b_j \Delta y_{t-j} + \sum_{k=1}^{s-1} c_k \Delta x_{t+k} + e_t$$

Using the Instrumental Variables (IV) estimator becomes easy for us to estimate the coefficients and their standard errors, with the original matrix of regressor being the instrumental variables (see Wickens and Breusch 1988).

FMLS (Fully Modified Least Squares estimator): Phillips and Hansen (1990) employ semi-parametric corrections for the long run correlation and endogeneity effects, which fully modify the OLS estimator and its attendant standard error, thus obtaining the so called Fully- Modified Least Squares (FMLS) estimation method.

We will briefly discuss this procedure which gives rise to the Fully Modified Least Squares (FMLS) estimator. Phillips and Hansen decompose the limiting distribution of the OLS estimator where $B(r,\Sigma)$ a Brownian motion with covariance matrix Σ, which we partition with the error process u_t, i.e. $B(r) = (B_1(r), B_2'(r))$, and σ_{21} and λ_{21} the endogeneity and autocorrelation effect respectively.

$$T(\hat{\theta}-\theta) \xrightarrow{D} \left(\sigma_{21}+\lambda_{21}+\int_0^1 B_2 dB_1\right)\left(\int_0^1 B_2 B_2' dr\right)$$

as follows:

$$T(\hat{\theta}-\theta) \xrightarrow{D} \left(\int_0^1 B_2 dB_{1.2} + \sigma_{21} + \lambda_{21} + \int_0^1 B_2 dB_2' \omega_{22}^{-1}\omega_{21}\right)\left(\int_0^1 B_2\, B_2'\right)^{-1} \quad (7)$$

where $B_{1.2} = B_1 - \omega_{21}'\omega_{22}^{-1}B_2$, $\Omega^* = \begin{bmatrix} \omega_{11.2} & 0 \\ 0 & \omega_{22} \end{bmatrix}$

where $\omega_{11.2} = \omega_{11} - \omega_{21}'\omega_{22}^{-1}\omega_{21}$ and $dB_1 = dB_{1.2} + dB_2'\omega_{22}^{-1}\omega_{21}$.

The first of the four terms in (7) has a mixed Gaussian distribution. What have to be done are the necessary corrections to eliminate the extra terms directly. The FMLS estimator of θ takes the following form:

$$\widehat{\theta^+} = (X'X)^{-1}(X'Y^+ - T\widehat{\delta^+})$$

where $X_{(T\times1)}$ is the observation matrix of x_t, $Y^+_{(T\times1)}$ is the observation vector for $y_t^+ = y_t - \widehat{\omega_{21}}'\widehat{\omega_{22}}'\Delta x_t$, $\hat{\delta}^+ = \hat{\Delta}\begin{bmatrix} 1 \\ -\widehat{\omega_{22}}^{-1}\widehat{\omega_{21}} \end{bmatrix}$ is a bias correction term with $\hat{\Delta}$ a consistent estimate of $\Delta = \sum_{k=0}^{\infty} E(u_{20}u_k')$ and $\widehat{\omega_{21}}', \widehat{\omega_{22}}$, are also consistent estimates of the corresponding elements of the long-run covariance matrix Ω. It is easy to show that

$$T(\hat{\theta}-\theta)\xrightarrow{D}\left(\int_0^1 B_2 dB_{1.2}\right)\left(\int_0^1 B_2 B_2' dr\right)^{-1}$$

which is found to be $N(0,\omega_{11.2}G)$ conditional on $G=\left(\int_0^1 B_2 B_2' dr\right)^{-1}$ and thus standard asymptotic inference procedures apply, just as for OLS in the strongly exogenous case.

The FMLS estimator is based on consistent estimation of the matrices Ω and Δ, which in turn requires the selection of a kernel and the determination of the bandwidth. We employ the Quadratic Spectral Kernel, since it is the best with respect to an asymptotic truncated mean square error criterion in the class of kernels that necessarily generate positive semi-definite estimators of the long-run variance covariance matrix in finite samples. The bandwidth parameter, S_T , has been selected by applying the Andrews (1991) data-dependent procedure. Specifically, the optimal bandwidth parameter S_T^+ for the Quadratic Spectral kernel is $S_t^+ = 1.3221[a(2)T]^{1/5}$ where $a(2)$ is a function of the unknown spectral density matrix of u_t at frequency zero, its second generalized derivative and a 4x4 weighting matrix of known constants. This means that $a(2)$ and hence S_T^+ are also unknown in practice. Estimates of $a(2)$ may be obtained by estimating simple parametric models, as suggested by Andrews (1991). Moreover, the "prewhitened" version of FMLS which filters the error vector $\hat{u}_t$ prior to estimating Ω and Δ is also employed (see Andrews and Monahan, 1990 and Christou and Pittis 2002, for a discussion on the performance of the various versions of the FMLS estimator).

JOH (Johansen's Maximum Likelihood Estimator): Apart from single-equation estimators as these discussed above, we also consider the system-based maximum likelihood estimator of θ, suggested by Johansen (1988, 1991). The order of the JOH estimator corresponds to the lag-order of the Vector Autoregressive Model on which the estimator is based. This estimator differs from all the above mentioned estimators in an important respect: It has been developed and proved to be asymptotically optimal in the context of a Gaussian Vector Autoregression which accommodates a rather narrow class of DGPs. In this study we use a VAR(1) model.

3.4 Monte Carlo Simulation

The Monte Carlo method is an econometric approach which has grown in popularity as a consequence of the great advances in computing technology, programming and calculating machines. The object of interest is usually an estimator or a test statistic that has unknown finite sample properties and its function in practice. Very often the issue is whether the unknown asymptotic properties of an estimator provide a useful guide for the estimator's unknown finite sample properties.

Even if there may be more analytical ways to study the finite sample distribution of estimators, it is often easier to apply Monte Carlo experiments. To be more precise, a Monte Carlo experiment is performed when the computational resources of a researcher are more abundant than the researcher's "mental" resources.

In general terms, the ideal steps for such an experiment as Jack Johnston and John DiNardo proposed in "Econometric Methods" proceeds as follows:

- Specification of a "true" model. As an example, if the true model is the standard linear model, this means specifying the distribution of the error term, the explanatory variables, the coefficients, and the sample size.

- Generation of a data set using this true model.

- Calculation of the test statistic or estimator that is being evaluated with this artificially generated sample and storage of the results.

- Repetition of steps 2 and 3 for a large number of times. Each generation of a new data set is called a replication.

- Evaluation of how well each estimator performs, or of how frequently the test statistic rejects or not the "true" model in the set of replications.

In other words, in the case that we are not exactly sure about the properties of a specific estimator or test in practice, we perform an experiment.

In this study we employ Monte Carlo methods in order to reach more confident conclusions about the estimate of the income elasticity. Such an application is necessary for robust inference as standard distributions are based on asymptotic approximations and the small sample of our dataset affects the performance of the estimators. Generally, through these methods, we subject a number of estimators to a variety of different conditions (different simulated samples) and evaluate their performance. As a consequence the results of our regression analysis are being summarized in a simple form.

The Data Generating Process (DGP) is assumed to be the following triangular system:

$$lhe_t = b * lgdp_t + u_{1t}$$

$$\Delta lgdp_t = u_{2t}, t = 1,2,\dots,T$$

where $u_t = (u_{1t}, u_{2t})'$ follows a VAR(1) process:

$$u_t = Au_{t-1} + e_t,\ \ e_t \sim Niid(0, \Sigma)$$

Estimates of the *2x2 A* matrix, and of the variance-covariance matrix of the DGP (needed for each country) are used for the Monte Carlo simulations and the exact distribution of each estimator is obtained. Through such a distribution, we can perform valid tests of the null hypothesis that the coefficient b is equal to one or not.

CHAPTER 4

Data and Empirical Results

4.1 Growth in HCE in OECD countries – Data Set

The Organization of Economic Co-Operation and Development (OECD) offers a rich data base suitable for studies related to Health Economics.

The OECD Health Data set is the most comprehensive source of comparable statistics on health and health systems across the 30 OECD countries. It can be used for comparative analyses of:

- Health status
- Non-medical determinants of health (including smoking and obesity)
- Health care resources and utilization

- Long-term care resources and utilization
- Expenditure and financing of health care
- Social protection (including public and private health insurance coverage)
- Pharmaceutical consumption.

According to the references of the pre-mentioned Organization in 2008, a combination of slower growth in spending on healthcare and expanding economies has led to a stabilization of health spending as a proportion of GDP in many OECD countries.

Based on OECD Health Data, in 2006, the latest year for which comparable data are available, health spending on average across OECD countries grew in real terms by just over 3%, the lowest rate since 1997. Looking at the trend during this decade, health expenditure grew rapidly in many countries between 2000 and 2003, with an annual average growth rate of 6.2% over that period. Since 2003, the rise in health expenditure has slowed, however, to an average of 3.6% per year.

The health expenditure share of GDP on average across OECD countries remained unchanged in 2006 compared with 2005, at 8.9%. In several countries, the percentage of GDP devoted to health actually fell slightly between 2005 and 2006, while in others it stabilized. Overall, this marked a pause in a long-term rising trend that has seen health spending rise from 6.6% of GDP on average in OECD countries in 1980.

In many countries, slower growth in health spending in recent years has been aided by a slowing in the growth of pharmaceutical spending. In 2006, pharmaceutical spending on average across OECD countries increased by only 2% in real terms, compared with growth rates of 6% to 7% per year between 2000 and 2003 and 3% to 3.5% per year over 2004 and 2005.

Public spending on prescription drugs in the United States increased by 30% in 2006, because of the introduction of the new Medicare drug programme for the elderly and the disabled. This increase in public spending was partly offset by a reduction of 4% in private spending for prescribed drugs. The public share of pharmaceutical spending increased from 24% in 2005 to 30% in 2006, but it is still the second lowest share among OECD countries. Overall, in the United States, drug spending rose by 4.5% in real terms in 2006 after a 2.2% increase in 2005.

The United States led in terms of total drug expenditure per capita, including both prescribed and non-prescribed drugs at US$843 per person in 2006, followed by Canada, Belgium and France. At the other end of the scale, Mexico, Poland, Denmark and New Zealand spent the least, with spending ranging from US$182 per person in Mexico to US$303 in New Zealand. Variations in drug spending across countries reflect differences in prices and consumption as well as how fast and widely new and often more expensive drugs are put on the market.

The data set that has been used in this dissertation comes from the OECD Health Data 2008 Source. It consists of 19 OECD countries covering the time period from 1970 to 2006. Both HCE (Health Care Expenditure) and GDP (Gross Domestic Product), which are annual series, are measured in real per capita National Currency Units, at constant 2000 GDP price level. The following nations are included: Australia, Austria, Belgium, Canada, Denmark, Finland, Germany, Iceland, Ireland, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, United States. Eleven of the original 30 OECD countries, i.e. Czech Republic, France, Greece, Hungary, Italy, Korea, Luxemburg, Mexico, Poland, Slovak Republic and Turkey, are excluded due to data limitations. All variables have been transformed in natural logarithms for the analysis.

4.2 Results

As in most of the earlier literature, we postulate a model which represents a simple relationship between the logarithms of real per capita health care spending and those of real per capita income.

Initially, Table A-I (see Appendix A) presents the Descriptive Statistics of the countries included in the analysis. For each of the countries the Mean, the Minimum and the Maximum values are presented as well as the Standard Deviations respectively for both HCE and GDP. This table provides a first idea about the variables under examination for each nation. Having such a table makes it easier to interpret the coefficient estimates in the next section, and it emphasizes the units of measurement of the variables. Suitable country-by-country graphs of the logarithms of HCE and GDP respectively (see Appendices B) contribute to a visual examination of the variables and help us to determine the methods needed for our analysis as well.

***Table A - I** – Descriptive Statistics*

It is remarkable that countries like Denmark, Iceland, Japan, Norway, and Sweden have the higher per capita means of health spending and Gross Domestic Product respectively, quite different from the others. As we see, the results indicate the greatest standard deviation for the series in these countries too. Portugal, Spain and United Kingdom seem to spend the least for health in accordance to the lowest levels of GDP in means.

Table A-II (see Appendix A) summarizes the nonstationarity test results for the levels of the national per capita Health Care Expenditure and GDP respectively. It presents the test statistics on a country-by-country basis based on the augmented Dickey-Fuller (ADF) and Kwiatkowski et al. (KPSS) test as well, as discussed above.

Our results suggest that both Health expenditure and GDP are nonstationary series. The existence of a unit root for each country is a conclusion that is reached both by tests. It is noticeable that the ADF tests do not reject the existence of a unit root in levels at almost all levels of significance when the alternative test rejects the stationarity at the 0.1 level at most cases. As the ADF tests fail to reject the null hypothesis and the KPSS tests reject, we obtain more confident results about the nonstationarity of the series.

Table A - II – Results of Stationarity tests-Unit root tests for levels

Table A-III (see Appendix A), indicates the stationarity test results for the first differences of the examined variables. It becomes clear that both the HCE and GDP are I(1) variables as they are stationary in the first differences.

Table A - III – Results of Stationarity tests-Unit root tests for the 1st differences

Our results about the nonstationarity of the individual series are similar to the findings of Hansen and King (1996), Blomqvist and Carter (1997) and Gerdtham and Löthgren (2000). Next, we test whether a cointegrated relationship exists between the series.

Table A-IV (see Appendix A) displays the results of the Cointegration tests that were employed in this research. Through ADF and KPSS tests, the Engle-Granger (1987) method was used to test for the stationarity of the deviations from the cointegrating relationship. Indeed, according to this test, we fail to reject the stationarity. Both KPSS tests (at all levels of significance) and ADF tests indicate a cointegrating relationship in all cases.

The Johansen's tests reach the same conclusion offering us more substantial evidence. Both the Trace and the Maximum Eigen-value methods agree to the presence of cointegration mainly at a 5% level of significance.

Table A - IV – Results of Cointegration tests

In line with the previous literature, the country-by-country cointegration test results clearly indicate that there is a cointegration relationship between Health expenditure and GDP in our sample. Establishing that HCE and GDP are cointegrated, we can afterwards estimate the long-run relationship for each of the 19 countries.

In Table A-V (see Appendix A) we report the income elasticity estimates for HCE. We present the cointegrating estimators and for each one of them the t-statistics too. These t-statistics are not those of the regression but they are the test statistics for the null hypothesis, b=1, i.e. $(t = (\hat{b} - 1)/\widehat{se}(\hat{b}))$. In detail, the arising t-stats are employed to test if b exceeds statistically unity or not and as a consequence if health is a luxury good or not for each country. We should note that through such a method the resultant prices are conventional and they offer us just a first picture of what is really in effect. In general, we prefer t-stats prices to range from -1.96 to 1.96. After a brief look at this Table, we notice considerable heterogeneity in the income responses of health spending across the countries.

Table A - V- Cointegration Estimators-Estimates

The range of the estimated slopes is:

- 1.031 - 2.945 for the OLS
- 1.055 - 2.979 for the DOLS(1,1)
- 0.414 - 2.744 for the ADL(1,2)
- 0.095 - 2.719 for the AADL(1,2,1)

- -0.397 - 1.954 for the DGLS(1)
- 1.083 - 3.200 for the FMLS and
- -0.016 - 13.459 for the JOH(1)

In general, estimated slopes do not always lie close to the hypothesized value of one.

Initially, it is noticeable that both OLS and Dynamic OLS estimators have similar behavior. In almost all countries, based on asymptotic critical values (i.e. the confidence interval would be -1.96 to 1.96 for a 5% significance level), the income elasticity exceeds unity and we can reject the null of a unit coefficient with the exception of Denmark and Ireland which appear to converge to unity. Austria, Iceland, Norway, Spain, United Kingdom and States offer the largest t-stats away from the conventional levels.

With no so serious differences from the two above mentioned estimators the estimates of b, on the basis of ADL(1,2) and AADL(1,2,1) obtain a bit more suitable t-stats leading to more confident conclusions. Although the t-stats for them are not the ideal, Germany and Japan now indicate an income elasticity under the unity. More specifically, the related t-stats point to a rejection of the null for all the countries but Denmark, Germany, Japan and Sweden.

It is remarkable that the estimated income elasticities proposed by the DGLS(1) estimator reveal some heterogeneity. The estimated values of b seem to exceed unity in only seven countries, namely Australia, Austria, Iceland, Netherlands, Norway, Portugal.

Next, the results of the Fully Modified OLS are presented. Quite interestingly, the semi-parametric corrections of the FMLS estimator seem to work well as they offer support in favor of a unit elasticity in the majority of the countries; the exception being Canada, Denmark, Iceland, Japan, Norway, the UK and the US. More importantly, in the case of Canada, Denmark, Japan, the UK and the US, the associated t-stats suggest a coefficient below unity pointing to health being a necessity rather than a luxury good. Arising from semi-parametric corrections and having a function quite different from the others, FMLS estimator seems to offer us confident results about the income elasticity for each country.

Finally, the Johansen's estimator is the only estimator that provides us with consistent coefficient estimates below unity in the majority of cases considered and as such health expenditure can be considered as a necessity.

In summary, except for JOH(1) and to a lesser extent DGLS(1), all the aforementioned estimators support the conclusion that income elasticity exceeds unity in most cases and as a result health care spending could be considered as a luxury commodity. Even though our results are not consistent and confident enough, due to the small sample employed, we can form a first idea on the performance of the national income elasticity for each country.

We also conducted a Monte Carlo study to obtain the 2.5% and 97.5% points of the empirical distribution of the t-statistic for each estimator in each of the 19 countries. This is necessary for us to conduct valid statistical inference, as standard distributions do not apply in this case. Our ultimate goal of this Monte Carlo study is to compare the sample properties of the estimators under scrutiny. Although our Monte Carlo experiment revealed various properties of the empirical distribution of the cointegration estimators, we only report (see Table A – VI) the $t_{0.025}$ and $t_{0.975}$ empirical critical values necessary for hypothesis testing in the current context.

Table A - VI – Results of Monte Carlo Simulation

On the whole, it is clear that there is a shift in the empirical distributions compared to the Standard Normal. Using the critical values from the latter as a benchmark for rejection of the null hypothesis that b = 1 would have resulted in a higher percentages of rejections. The distributions of the estimators provided by our Monte Carlo simulations are less leptokurtic than the Standard Normal, leading to an augmented area of no rejection. Our Monte Carlo results may be summarized as follows:

- The OLS and DOLS estimators point to a non rejection of the null only in three countries, namely Denmark, Ireland and Sweden when empirical critical values are employed. For the remaining countries our results point to a rejection of the null in favor of an income elasticity greater than one.

- Similar conclusions are reached when the ADL and AADL estimators are considered. The set of countries for which the cointegrating coefficient is equal to one includes Austria, Denmark, Germany, Ireland, Japan and Sweden.

- The results arising from DGLS(1) estimator indicate an income elasticity greater than unity with the exception of Belgium, Ireland and Sweden.

- On the basis of FMLS our results suggest a more homogenous picture for the OECD countries. Specifically, we cannot reject the null of a unit income elasticity in all countries but Iceland and Norway for which health care is a luxury good.

- When the JOH estimator and empirical critical values are employed, the countries at hand fall in three categories. We cannot reject the null for Canada, New Zealand, Spain, Sweden and the US, while for Australia, Netherlands and the

UK we reject the null in favor of the alternative of a greater than one unit coefficient. For the remaining 11 countries, our results point to health being a necessity.

Overall, it is noticeable that the majority of the estimators come to similar results. Most of the estimators included in the analysis suggest that for these nations health could be considered as a luxury commodity. We can note that JOH(1) estimator fails to differentiate countries that their income elasticity exceeds unity from the others. Another result that we could refer to is the fact that the range of t-ratios obtained from the Monte Carlo simulation was highly noncentral and mainly sifted to the left when employing the single equation estimators, namely OLS, DOLS, ADL, AADL and DGLS. We get substantial evidence in favor of health being a luxury good, while the system based JOH estimator points to health being a necessity. The semi-parametric FMLS estimator suggests that health spending and income move one-to-one.

CHAPTER 5

Conclusions

A number of studies have focused on the association between health spending and income and more importantly revealed an income elasticity of the demand for health care greater than one suggesting that health is a luxury good rather than a necessity. This study has re-examined this relationship in a sample of 19 OECD countries adopting a time-series approach. Unlike earlier contributions, a variety of estimators which correct for both serial correlation and long-run endogeneity has been employed to estimate the income elasticity of demand for health. Second, we have tested the hypothesis of a unit coefficient using the critical values obtained from Monte Carlo simulations, which replicated the processes followed by the health spending and income series.

On the whole, we found mixed evidence with respect to the wide consensus that health care is a luxury good. There appears to be considerable heterogeneity across countries and across estimators in terms of the health spending-income association. The single equation estimators, suggest that health is a luxury good in the majority of countries, while the system-based JOH estimator points to health being a necessity. The dividing line is the FMLS estimator which suggests that health spending moves one-to-one with income.

A promising route for further research is the investigation of the health spending-income association in a panel data setting. The employment of panel cointegration estimators would increase the power of our tests and lead to more robust results for the panel of the OECD countries as a whole.

APPENDIX A - Tables

Table A - I –Descriptive Statistics

Country	Health Care Expenditure				Gross Domestic Product			
	Mean	Min.	Max.	Std. Dev.	Mean	Min.	Max.	Std. Dev.
AUSTRALIA	2076	1075	3521	745	28941	21531	40697	5958
AUSTRIA	1680	635	2849	718	20224	12286	28201	4583
BELGIUM	1484	484	2773	643	19416	12401	26555	4091
CANADA	2399	1328	3841	740	28211	19308	38448	5357
DENMARK	16443	10626	25044	3797	191652	132522	263340	39207
FINLAND	1436	673	2436	475	19867	12190	29886	4774
GERMANY	1976	914	2796	528	21422	15218	26502	3198
ICELAND	153893	50297	268848	64881	1958570	1063290	2892936	453278
IRELAND	1166	402	2706	610	16677	7936	34136	8212
JAPAN	210518	85162	342785	75603	3172074	1863638	4300512	768794
NETH/NDS	1605	947	2596	496	20145	13849	27975	4312
N. ZEALAND	1820	1126	3198	535	26568	21567	34274	3483
NORWAY	18920	5762	33978	8636	243531	130957	361547	70253
PORTUGAL	599	122	1243	345	8632	4843	12227	2444
SPAIN	765	259	1459	343	11852	7403	17444	2950
SWEDEN	17352	10301	26864	4267	206671	152074	292596	38570
SWITZ/ND	4517	2338	7012	1396	52130	43623	61999	5369
UK	826	389	1539	324	12736	8628	18379	2933
US	3145	1274	5759	1388	27113	18151	37626	5827

Table A - II – Results of Stationarity tests-Unit root tests for levels

Country	Unit root tests for lhe		Unit root tests for lgdp	
	ADF (t-stats)	KPSS	ADF (t-stats)	KPSS
AUSTRALIA	-3.176	0.311	-2.203	0.188*
AUSTRIA	-1.727	0.445	-1.045	0.163*
BELGIUM	-2.804	0.139*	-2.422	0.126*
CANADA	-2.410	0.123*	-3.315**	0.348
DENMARK	-1.294	0.730*	-3.436**	0.204*
FINLAND	-2.662	0.146*	-1.887	0.602*
GERMANY	-2.841**	0.173*	-2.667	0.163*
ICELAND	-1.662	0.160*	-1.808	0.142*
IRELAND	-1.523	0.127*	-1.410	0.175*
JAPAN	-2.294	0.181*	-1.565	0.168*
NETH/NDS	-2.322	0.201*	-2.199	0.133*
N.ZEALAND	-0.951	0.159*	-2.185	0.144*
NORWAY	-2.551	0.168*	-2.377	0.154*
PORTUGAL	-3.958***	0.125*	-3.125	0.143*
SPAIN	-2.710	0.172*	-3.254	0.336
SWEDEN	-3.487**	0.181	-2.207	0.304
SWITZ/ND	-3.235**	0.148*	-3.593*	0.315
UK	-1.960	0.109*	-1.646	0.124*
US	-2.903	0.119*	-2.983	0.120*

*Note: *, ** and *** identify significance at the 0.1, 0.05 and 0.01 levels respectively*

Table A - III – Results of Stationarity tests-Unit root tests for the 1st differences

Country	Unit root tests for d(lhe)		Unit root tests for d(lgdp)	
	ADF (t-stats)	KPSS	ADF (t-stats)	KPSS
AUSTRALIA	-3.595	0.061	-5.238	0.290
AUSTRIA	-4.519	0.152	0.163	0.396
BELGIUM	-3.031	0.349	-5.916	0.291
CANADA	-3.757	0.095	-4.171	0.091
DENMARK	-6.740	0.203	-5.219	0.052
FINLAND	-4.104	0.253	-5.545	0.148
GERMANY	-3.195	0.435	-6.385	0.265
ICELAND	-5.774	0.337	-5.552	0.263
IRELAND	-3.340	0.168	-3.510	0.302
JAPAN	-4.084	0.423	-3.752	0.426
NETH/NDS	-4.451	0.083	-3.362	0.072
N.ZEALAND	-4.114	0.166	-3.897	0.129
NORWAY	-4.260	0.138	-3.788	0.390
PORTUGAL	-4.254	0.386	-4.048	0.138
SPAIN	-4.309	0.187	-2.795**	0.070
SWEDEN	-3.753	0.148	-3.473	0.252
SWITZ/ND	-6.365	0.385	-4.836	0.084
UK	-5.496	0.110	-4.710	0.089
US	-2.842	0.291	-4.698	0.260

Note: **, ** and *** identify significance at the 0.1, 0.05 and 0.01 levels respectively*

Table A - IV – Results of Cointegration tests

Country	Cointegration tests			
	Engle-Granger (t-stats)		Johansen	
	ADF	KPSS	Max Eig H_0:r=0	Trace H_0:r=0
AUSTRALIA	-3.460*	0.094	17.707**	17.980**
AUSTRIA	-3.721	0.073	18.771**	24.154**
BELGIUM	-2.477*	0.122	22.330**	33.711**
CANADA	-3.274*	0.133	19.427**	28.204**
DENMARK	-1.737*	0.103	25.750**	30.790**
FINLAND	-3.401*	0.131	16.384**	19.975**
GERMANY	-3.741	0.147	15.424**	16.363**
ICELAND	-2.891*	0.205	10.199*	10.593*
IRELAND	-3.312*	0.113	24.059**	30.135**
JAPAN	-2.027	0.096	19.407**	23.002**
NETH/NDS	-3.029*	0.069	16.123**	23.996**
N.ZEALAND	-2.892*	0.100	15.332**	15.916**
NORWAY	-4.124	0.115	13.792**	16.134**
PORTUGAL	-3.483*	0.114	14.661**	15.318**
SPAIN	-2.167*	0.148	11.887**	15.513**
SWEDEN	-2.110*	0.110	15.332**	15.916**
SWITZ/ND	-3.725	0.143	16.717**	18.185**
UK	-3.710	0.074	15.975**	24.943**
US	-3.440*	0.117	27.033**	29.542**

*Note: *, ** and *** identify significance at the 0.1, 0.05 and 0.01 levels respectively*

Table A - V – Cointegration Estimators- Estimates

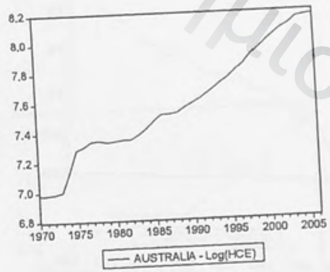
Country	OLS		DOLS(1,1)		ADL(1,2)		AADL(1,2,1)		DGLS(1)		FMLS		JOH(1)	
	b	t-stat	b	t-stat	b	t-stat	b	t-stat	b	t-stat	b	t-stat	b	t-stat
AUSTRALIA	1.745	7.952	1.727	7.719	1.664	4.128	1.678	4.707	1.470	2.447	1.711	0.862	13.459	3.407
AUSTRIA	1.922	12.793	1.959	9.915	1.718	2.217	1.906	2.944	1.788	2.809	2.121	0.949	0.84	-8.059
BELGIUM	2.158	9.661	2.068	10.168	1.829	7.036	1.861	7.116	-0.012	-1.598	1.967	-0.008	0.812	-11.45
CANADA	1.628	9.849	1.663	10.068	1.678	8.402	1.695	8.474	-0.258	-5.909	1.627	-4.076	0.873	-3.311
DENMARK	1.085	1.254	1.058	0.867	1.101	0.585	1.036	0.272	-0.202	-4.274	1.100	-2.050	-0.016	-7.343
FINLAND	1.408	6.488	1.403	6.906	1.383	7.805	1.385	7.156	0.501	-2.295	1.426	-0.046	0.799	-10.37
GERMANY	1.828	6.909	1.829	8.466	0.414	-0.494	0.095	-0.437	-0.046	-6.305	1.873	-0.061	0.786	-37.36
ICELAND	1.910	13.26	1.958	18.133	1.933	11.417	2.024	19.411	1.954	12.975	1.883	5.917	0.891	-5.273
IRELAND	1.031	0.485	1.055	1.256	1.066	1.435	1.118	2.212	0.977	-0.31	1.083	0.007	0.839	-5.134
JAPAN	1.522	5.501	1.485	4.419	0.843	-0.57	0.847	-0.522	-0.397	-6.155	1.490	-8.447	0.846	-41.61
NETH/NDS	1.425	7.369	1.424	8.508	1.462	9.425	1.448	8.899	1.372	3.421	1.446	1.672	1.954	2.825
N.ZEALAND	2.026	7.759	2.079	10.116	2.518	3.644	2.521	3.089	0.788	-0.492	2.339	0.003	0.239	-3.574
NORWAY	1.661	14.423	1.617	17.805	1.556	12.415	1.573	13.577	1.568	12.574	1.608	7.358	0.838	-12.15
PORTUGAL	2.157	8.449	2.087	11.568	1.929	11.183	1.952	12.437	1.813	4.625	2.089	1.857	0.765	-10.88
SPAIN	1.886	9.497	1.855	10.505	1.794	8.903	1.807	8.168	1.263	0.881	1.865	-0.066	0.819	-3.822
SWEDEN	1.288	2.7	1.274	2.192	1.169	0.618	1.127	0.453	0.766	-0.84	1.327	-0.013	0.512	-4.199
SWITZ/ND	2.945	7.613	2.979	8.555	2.744	6.35	2.719	4.892	-0.009	-6.105	3.200	-0.080	0.913	-4.11
UK	1.697	14.179	1.69	15.05	1.706	9.096	1.687	9.267	0.081	-3.586	1.725	-2.718	1.734	3.296
US	2.138	22.553	2.162	21.51	1.876	3.928	1.952	5.183	-0.06	-6.874	2.134	-4.034	0.957	-0.888

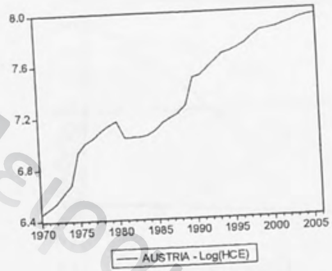
Table A - VI – Results of Monte Carlo Simulation

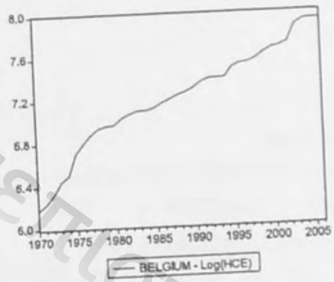
Country	OLS t		DOLS(1,1) t		ADL(1,2) t		AADL(1,2,1) t		DGLS(1) t		FMLS t		JOH(1) t	
	0.025	0.975	0.025	0.975	0.025	0.975	0.025	0.975	0.025	0.975	0.025	0.975	0.025	0.975
AUSTRALIA	-0.801	3.041	-4.359	3.662	-2.977	2.471	-2.928	2.576	-3.085	2.285	-2.005	4.140	-3.197	3.096
AUSTRIA	-4.575	5.471	-3.964	6.090	-3.467	3.540	-3.885	3.805	-1.842	3.829	-3.524	4.372	-3.800	4.083
BELGIUM	-5.619	2.472	-5.350	3.209	-3.930	3.397	-4.207	3.788	-4.557	1.722	-4.870	2.672	-4.550	3.961
CANADA	-8.286	0.351	-7.529	1.178	-5.592	1.335	-5.104	1.958	-5.691	-0.712	-5.797	1.946	-3.397	2.903
DENMARK	-6.577	2.271	-6.236	2.553	-5.825	1.524	-5.890	2.106	-4.639	0.236	-4.665	2.687	-3.581	3.242
FINLAND	-7.411	0.372	-7.820	0.933	-4.527	1.211	-4.318	1.707	-6.412	-0.548	-5.751	1.844	-3.391	2.463
GERMANY	-5.938	0.743	-5.134	1.885	-4.842	0.892	-3.884	1.581	-5.301	-0.060	-4.390	2.035	-2.955	2.657
ICELAND	-4.576	2.194	-4.444	2.576	-3.008	2.389	-3.105	2.510	-3.347	1.727	-3.825	2.527	-3.208	2.665
IRELAND	-5.185	3.854	-4.293	2.586	-1.944	2.942	-2.413	2.617	-2.884	2.171	-3.413	3.039	-2.805	2.514
JAPAN	-8.397	2.293	-7.843	2.561	-5.997	2.294	-5.880	2.542	-5.322	0.047	-9.435	1.327	-4.317	3.839
NETH/NDS	-7.547	0.844	-7.108	1.551	-4.587	1.866	-4.453	2.274	-5.423	-0.015	-5.644	2.090	-3.781	2.623
N. ZEALAND	-8.024	2.204	-7.116	2.572	-5.359	2.474	-5.597	2.872	-5.353	0.538	-6.202	2.721	-4.348	3.884
NORWAY	-3.668	2.269	-3.770	2.995	-2.953	2.077	-2.747	2.293	-3.026	2.040	-3.395	2.567	-3.333	2.629
PORTUGAL	-6.374	0.483	-6.039	1.479	-4.362	1.401	-3.863	1.841	-4.773	-0.014	-4.841	1.918	-3.323	2.484
SPAIN	-7.814	2.192	-8.225	2.147	-4.769	2.901	-5.165	3.005	-5.168	0.779	-6.114	2.806	-4.342	2.994
SWEDEN	-8.385	4.111	-7.540	3.734	-6.062	2.905	-5.851	2.918	-4.982	1.457	-5.760	3.624	-4.642	4.716
SWITZ/LAND	-7.128	-0.055	-6.735	1.069	-5.266	1.168	-4.909	1.675	-4.776	-0.389	-5.409	1.817	-2.998	2.531
UK	-7.822	0.095	-6.862	1.165	-5.318	0.927	-4.362	1.424	-6.375	-0.654	-5.048	1.827	-3.101	2.542
US	-7.285	0.372	-6.770	1.357	-5.506	1.077	-5.204	1.402	-5.601	-0.661	-5.134	1.927	-3.147	2.631

APPENDIX B - I - Graphs

HEALTH EXPENDITURE-GRAPHS:



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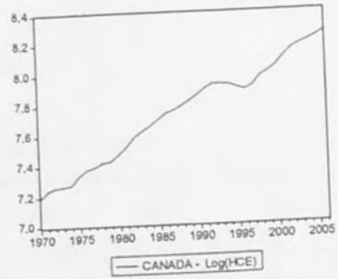
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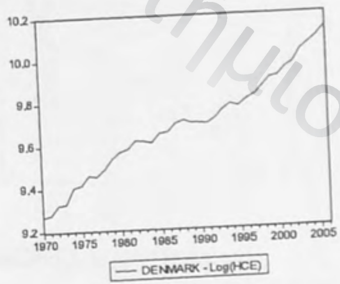
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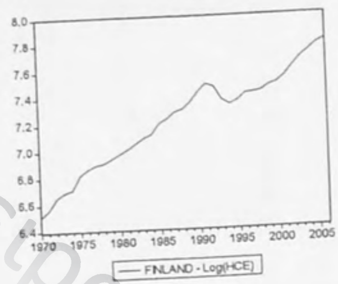
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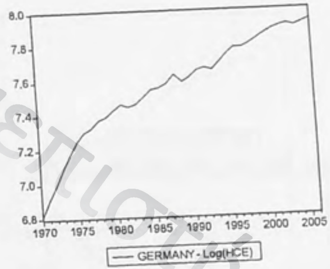
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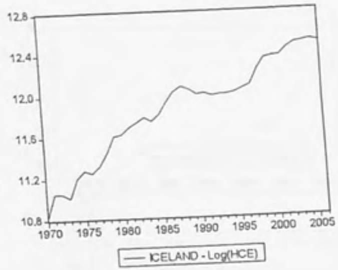
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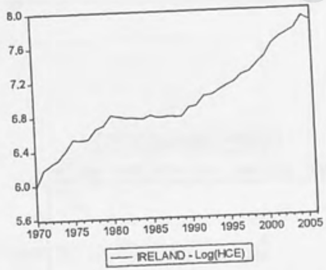
ICELAND - Log(HCE)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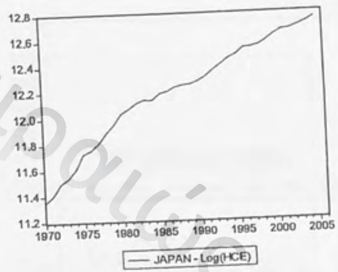
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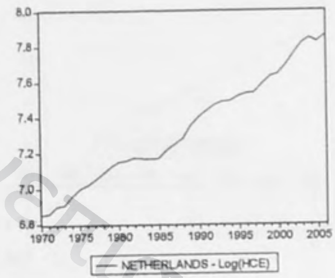
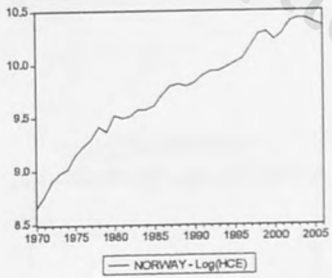
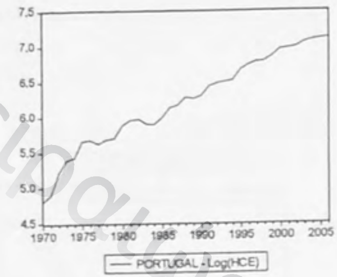
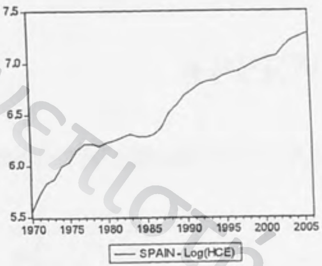
11.2
1970 1975 1980 1985 1990 1995 2000 2005
JAPAN - Log(HCE)


8.0
7.8
7.6
7.4
7.2
7.0
6.8
1970 1975 1980 1985 1990 1995 2000 2005
NETHERLANDS - Log(HCE)

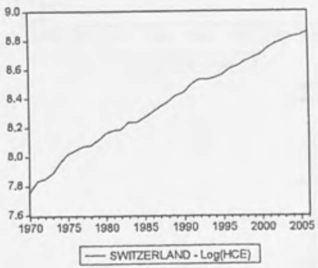

8.2
8.0
7.8
7.6
7.4
7.2
7.0
1970 1975 1980 1985 1990 1995 2000 2005
NEW ZEALAND - Log(HCE)

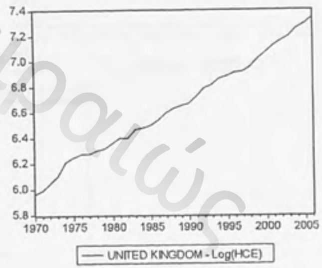

10.5
10.0
9.5
9.0
8.5
1970 1975 1980 1985 1990 1995 2000 2005
NORWAY - Log(HCE)

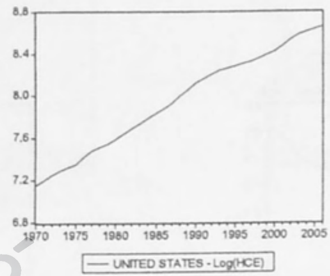

7.5
7.0
6.5
6.0
5.5
5.0
4.5
1970 1975 1980 1985 1990 1995 2000 2005
PORTUGAL - Log(HCE)


7.5
7.0
6.5
6.0
5.5
1970
1975
1980
1985
1990
1995
2000
2005
SPAIN - Log(HCE)


10.4
10.2
10.0
9.8
9.6
9.4
9.2
1970
1975
1980
1985
1990
1995
2000
2005
SWEDEN - Log(HCE)

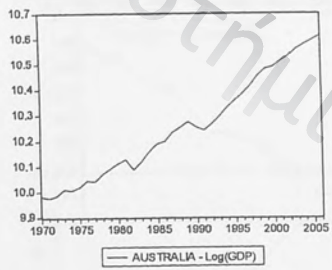

9.0
8.8
8.6
8.4
8.2
8.0
7.8
7.6
1970
1975
1980
1985
1990
1995
2000
2005
SWITZERLAND - Log(HCE)

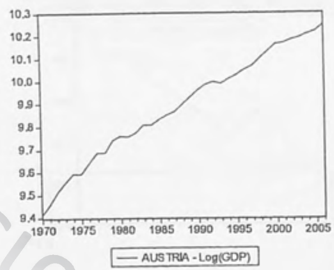

7.4
7.2
7.0
6.8
6.6
6.4
6.2
6.0
5.8
1970
1975
1980
1985
1990
1995
2000
2005
UNITED KINGDOM - Log(HCE)

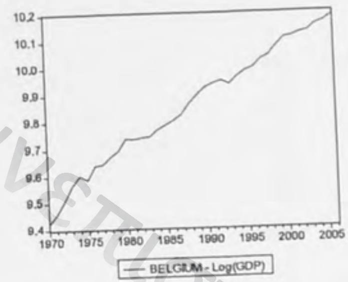

8.8
8.4
8.0
7.6
7.2
6.8
1970 1975 1980 1985 1990 1995 2000 2005
UNITED STATES - Log(HCE)

APPENDIX B - II - Graphs

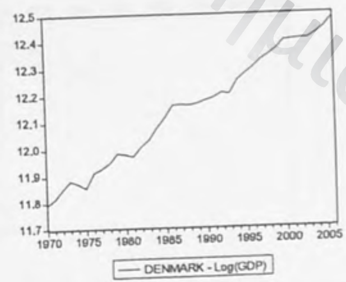
GROSS DOMESTIC PRODUCT-GRAPHS:

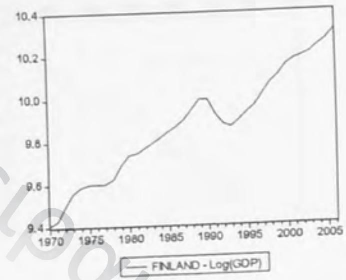


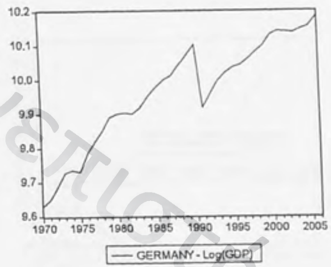


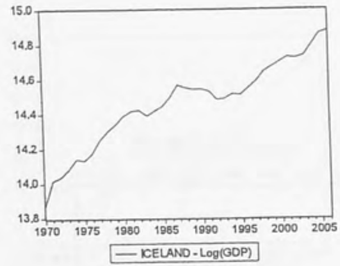

10.2
10.1
10.0
9.9
9.8
9.7
9.6
9.5
9.4
1970 1975 1980 1985 1990 1995 2000 2005
BELGIUM - Log(GDP)

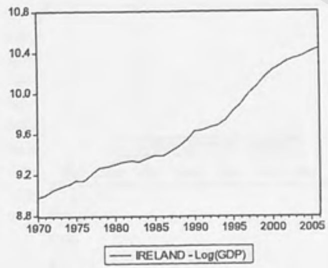

10.6
10.5
10.4
10.3
10.2
10.1
10.0
9.9
9.8
1970 1975 1980 1985 1990 1995 2000 2005
CANADA - Log(GDP)

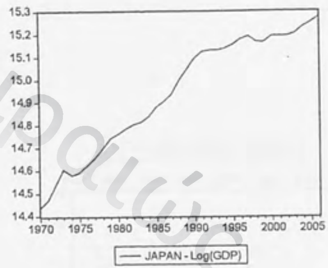

12.5
12.4
12.3
12.2
12.1
12.0
11.9
11.8
11.7
1970 1975 1980 1985 1990 1995 2000 2005
DENMARK - Log(GDP)

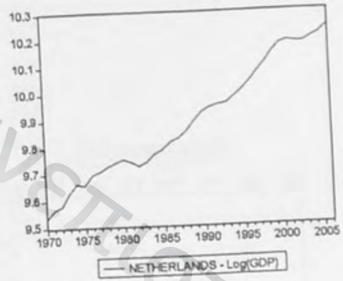

10.4
10.2
10.0
9.8
9.6
9.4
1970 1975 1980 1985 1990 1995 2000 2005
FINLAND - Log(GDP)


10.2
10.1
10.0
9.9
9.8
9.7
9.6
1970 1975 1980 1985 1990 1995 2000 2005
GERMANY - Log(GDP)

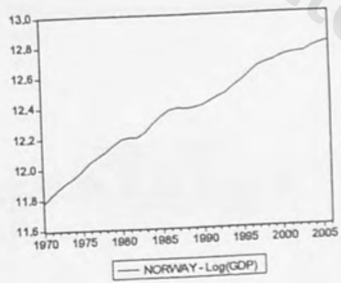

15.0
14.8
14.6
14.4
14.2
14.0
13.8
1970 1975 1980 1985 1990 1995 2000 2005
ICELAND - Log(GDP)

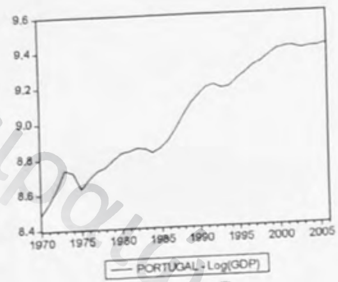

10.8
10.4
10.0
9.6
9.2
8.8
1970 1975 1980 1985 1990 1995 2000 2005
IRELAND - Log(GDP)

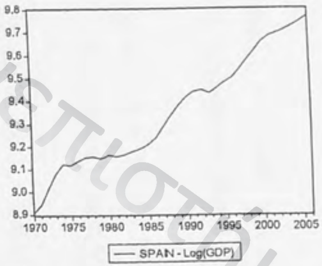

15.3
15.2
15.1
15.0
14.9
14.8
14.7
14.6
14.5
14.4
1970 1975 1980 1985 1990 1995 2000 2005
JAPAN - Log(GDP)

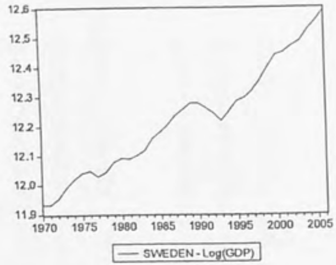

NETHERLANDS - Log(GDP)

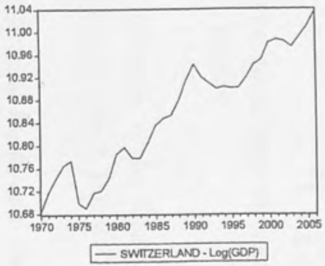

NEW ZEALAND - Log(GDP)

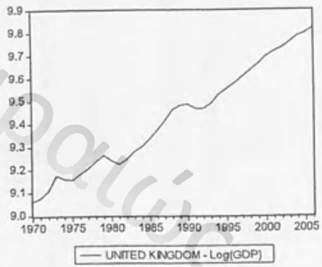

NORWAY - Log(GDP)


PORTUGAL - Log(GDP)


SPAIN - Log(GDP)


SWEDEN - Log(GDP)


SWITZERLAND - Log(GDP)


UNITED KINGDOM - Log(GDP)


10.6
10.5
10.4
10.3
10.2
10.1
10.0
9.9
9.8
1970
1975
1980
1985
1990
1995
2000
2005
UNITED STATES - Log(GDP)

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