

Financing Health Care Expenditure in the OECD Countries: Evidence from a Heterogeneous, Cross-Sectionally Dependent Panel *

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Abstract

This paper analyses the relationship between health expenditure and the way it is financed using a panel of 30 OECD countries observed since the 1990s. In particular, the non-stationarity and cointegration properties between health care spending and its sources of funding, income and non-income variables are studied. This is performed in a panel data context controlling for both cross-section dependence and unobserved heterogeneity. The findings suggest that when health care expenditure is mainly financed by government it becomes highly inelastic, with an income elasticity much smaller than expected, controlling for dependency rates for old and young age structure and technological progress.

JEL Classification: C33; H51; I10;

Keywords: Health Expenditure; Drivers of Health Expenditure; Panel Unit Root Tests; Panel Cointegration; Cross Section Dependence model.

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*We are grateful to the participants at the 17th International Conference on Panel Data, Symposium on Recent Advances in Methods for the Analysis of Panel Data, 4th CSDA International Conference on Computational and Financial Econometrics (CFE 10), 3rd International Conference of the ERCIM (European Research Consortium for Informatics and Mathematics) Working Group on Computing & Statistics (ERCIM 10) for useful comments and suggestions. We are also thankful to Mohammad Hashem Pesaran, Takashi Yamagata and Josep Carrion-i-Silvestre for the Gauss Codes and Peter Pedroni for the Rats Codes. Financial support from FCT, under UNIDE and under grant PTDC/EGE-ECO/104157/2008 is also gratefully acknowledged.

1 Introduction

Despite years of concern and attempts at cost containment, health spending per person increased by 4.2% a year on average between 2000 and 2010, according to the latest data from the OECD. In almost all countries, public expenditure accounts for the majority of health-care spending. It has increased from an average of 12% of total government spending in 1990 to a record of 16% in 2010. OECD has been pointing technological change, population expectations and ageing populations as the main drivers of the rise of health care expenditure.

This paper studies the long-run economic relationship between health care expenditure and different sources of health expenditure funding computed over total health care expenditure: public, private and expenditures in medicaments, income and other non-income determinants of health care spending in the OECD countries. Using a panel of 30 OECD countries over the period 1990-2009, we investigate the non-stationarity and cointegration properties between health care spending and a set of regressors including the shares of health care expenditure financed by the government, privately and medicaments, income per capita, the dependency rates for old and young age structure. We also attempt to study the relationship between technological progress and health care expenditure using infant mortality as a proxy for changes in medical care technology. The dynamics of health expenditure and this set of regressors as well as their relationship are investigated by estimating a heterogenous panel model with cross sectionally correlated errors. A factor structure is included in the econometric specification with the intent to synthesize the effects of shocks that may hit health spending such as advances in medical care technology, policy shifts, new diseases, and shifts in preferences and expectations by users of health services. The factor structure can capture any contemporaneous correlation that arises from the common response of countries to such unanticipated events.

Empirical Research on the causes for the increase of health care expenditures found that income is one of the most important drivers of health expenditures. Newhouse (1977) was one of the pioneers in analyzing the relation between income and health care expenditures, having found an income elasticity larger than one. Since then, several studies have been developed including in the analysis variables recognized by the literature to play an important role, such as government expenditure on health, the age structure of the population as well as technology.

The size of the estimated income elasticity has raised discussions over health being a luxury versus a necessity good. Newhouse (1977), Roberts (1999), Okunade and Murthy (2002), Gerdtham and Löthgren (2002) and Freeman (2003) have found an income elasticity larger than one, indicating that health care is a luxury good, while Blomqvist and Carter (1997) and Baltagi and Moscone (2010) have estimated an income elasticity inferior to one, interpreting health care as a necessity. The discussion over health being a luxury versus a necessity good has important policy implications, namely if health is a necessity, it should be the object of public intervention and public funding (Culyer, 1988, Di-Matteo, 2003). This debate receives additional attention with the pressure for the reduction of government budget and for guaranteeing debt sustainability (van Elk, Mot and Franses, 2009).

The large values obtained for the income elasticity in the macro studies do not find support in the micro evidence. At a micro level, the income elasticity seems to be smaller than one (Gerdtham and Jönsson, 1992, Moscone and Tosetti, 2010). As stated by Getzen (2000), health care is an individual necessity and a national luxury. At the individual level, the existence of health insurance makes the demand for health care, to a large extent, independent of an individual's income, which means that demand is highly inelastic. At the aggregate level, the situation is different since health care spending depends mainly on the level and composition of government expenditure, which evolves with income (Dybczak and Przywara, 2010).

More recently, several empirical studies pointed to the possible non-stationarity properties of

health care spending and income data, which in turn cast doubt on prior inference on income elasticity obtained from spurious regressions (Hansen and King, 1996). Carrion-i-Silvestre (2005) and Jewell, Lee, Tieslau and Strazicich (2003) find smaller values for the income elasticity after the introduction of a time trend. Recent literature has focused on studying the time series properties of health expenditure and income, and on assessing whether there exists a long-run relationship between them. A large number of studies investigate the non-stationarity in health expenditure and income and their long-run relationship in a panel data framework (Roberts, 1999, Gerdtham and Löthgren, 2002, Freeman, 2003, Jewell et al., 2003, Okunade, Karakus and Okeke, 2004a, Carrion-i-Silvestre, 2005, Dreger and Reimers, 2005, Moscone and Tosetti, 2010, Baltagi and Moscone, 2010).

This paper contributes to the literature on the determinants of health care expenditure in several ways. First, we extend the sample to cover the recent period. Second, we account for the way health care expenditure is financed, i.e. by the government, privately and expenditures in medicaments. We also account for the fact that health care expenditures are not only driven by income but also by technological progress and by dependency rates of the population. Finally, the empirical methods applied are more comprehensive and recent developments in the field of panel cointegration are taken into account.

The remainder of this paper is organized as follows. Section 2 reviews related literatures. In Section 3, an empirical model specification is presented and the time series properties of the data analyzed through several panel data unit root tests. Section 4 provides the empirical results for panel cointegration tests. Section 5 discusses the long run relationship and Section 6 concludes.

2 Related Literature

Besides income variables, a number of non-income determinants of health care spending have been identified in the literature as important factors in explaining variations of health care expenditure across countries. For example, government expenditure on health, the age structure of the population and technological progress have traditionally been taken into account when trying to explain what drives health care expenditure. Evidence indicates that when all relevant explanatory variables are included, the income elasticity is found to be smaller than one (van Elk et al., 2009).

Technological progress has been proxied by several variables such as time trend, life expectancy, infant mortality, the surgical procedures (Weil, 1995), the number of specific medical equipment (Baker and Wheeler, 2000), or the number of tomographic scanners (Christiansen, Bech, Lauridsen and Nielsen, 2006). Newhouse (1992) is again innovator in the introduction of this variable in the explanation of health care levels, claiming that technology accounts for as much as 75% of the increase in health care expenditure. Generally, when including a trend or some other proxy for technological progress, the income elasticities are found to be lower than one. However, Roberts (1999) even including a time trend in the estimation, found an income elasticity higher than one. Okunade and Murthy (2002) when studying USA, included health R&D or total R&D as a proxy for technological progress and found high income elasticity. A common result in these studies is that the trend is usually found to be positive (Ariste and Carr, 2003, Freeman, 2003, O’Connell, 1996), an outcome that is seen as an indicator of the cost-increasing effect of technology (van Elk et al., 2009). Gerdtham, Sögaard, MacFarlan and Oxley (1998) included the number of renal dialyses per million of the population as a proxy for technology and found a positive and significant effect for this variable. Okunade and Murthy (2002) estimated a coefficient for total expenditure in R&D more than twice as large then the coefficient of technology specific to the health sector, both being significant and positive. Dreger

and Reimers (2005) found income elasticity smaller than one, provided that medical progress materializes through a decrease of infant mortality. Their results indicate that medical progress is expected to increase real health expenditures and this result is robust for alternative proxies of medical progress.

The age structure of the population is another crucial driver in health care expenditure. The share of the young population (usually, population under 15 years old, or even under 5) and the share of the old (above 65) or very old population (above 75) have been used to characterize the dependency rates of the populations. The indicator that has been receiving attention is ageing, but the estimated coefficient has been weak (Grossman, 1972, Leu, 1986, Culyer, 1988, 1990, Gerdtham, Sogaard, Jönsson and Andersson, 1992, Hitiris and Posnett, 1992, Di-Matteo and Di-Matteo, 1998, Zweifel, Felder and Meiers, 1999, Richardson and Roberston, 1986, Gerdtham and Jönsson, 2000, Moise and Jacobzone, 1986, Jönsson and Eckerlund, 2003). However, more recent studies have found a significant and positive effect of ageing on health care expenditures and there is the belief that it will increase in the future (Christiansen et al., 2006, Dreger and Reimers, 2005, Okunade, Karakus and Okeke, 2004*b*, O'Connell, 1996, Murthy and Ukpolo, 1994). This conclusion is based on the combined effect of the estimated increase in the share of older people and the tendency for health expenditures per capita to increase with age (Oliveira Martins and de la Maisonneuve, 2006). Gerdtham et al. (1998) found a positive effect on health care expenditures for the share of ages 0-4, but a slight negative effect for the share of population over 75.

Institutional factors are also pointed as drivers of health expenditure (Gerdtham et al., 1992, 1998, Roberts, 1999, Murthy and Ukpolo, 1994, O'Connell, 1996, Okunade et al., 2004*b*)¹. Institutional factors are sometimes proxied by the share of public financing in health care (van Elk et al., 2009). This variable, jointly with the extent to which health care expenditure is privately financed or even is due to pharmaceutical expenditures has been considered in estimations of health care expenditures (Clemente, Marcuello and Montañés, 2008). Note that the extent to which health care expenditure is financed by the government leads political factors to play an important role in explaining health care expenditures (Potrafke, 2010). There is not a consensus in the literature on the effect of public health financing on health-care expenditure. Leu (1986), Culyer (1988) and Hitiris and Posnett (1992) claim that it has a positive effect on health care spending, while Okunade et al. (2004*b*) and Moscone and Tosetti (2010) find a negative effect on health expenditure.

Private health care financing has been analyzed through health insurance variables. Cameron, Trivedi, Milne and Piggott (1988) found a strong and positive impact of different health insurance cover on the demand for health services. The level of spending on private health care is related to the ability to pay, not to the need for health care. Many forms of private expenditure on longevity are determined positively and negatively by public expenditure decisions (Scherer and Devaux, 2010), and as a consequence, it is necessary to analyze private and public components of expenditure separately. A particular form of health expenditures is pharmaceutical expenditures, which has been identified as an important determinant of health care outcomes (Guindon and Contoyannis, 2008, Crémieux, Meilleur, Ouellette, Petit, Zelder and Potvin, 2005*a,b*).

From microeconomic theory, the relative price of health has been identified as another driver of health care expenditure. According to Baumol (1967) the health sector has lower productivity than the other sectors, which will keep relative prices of health higher. van Elk et al. (2009), Pomp and Vujic (2008) and Hartwig (2008) report a positive effect for the so-called Baumol effect, i.e. an increase in price decreases volume and increases real health care expenditure in the long run. However, Gerdtham et al. (1992) find a not significant effect for the relative price

¹Barros (1998) finds no significant results between Institutional factors and health expenditure.

of health.

Reactions to external events as well as spatial spillovers are expected to induce a structure of correlation in health expenditure data. When data contain cross-section dependence, conventional estimators such as ordinary least squares (OLS) are inefficient and the estimated standard errors are biased (Andrews, 2005). Jewell et al. (2003) introduce time-specific effects in the econometric specification to control for contemporaneous correlation. Nevertheless, the inclusion of time-specific effects implies that the common shocks have identical influences on each unit, an assumption that might be quite restrictive in empirical analysis. Other studies build the empirical distribution of unit root test statistics by bootstrap techniques (Freeman, 2003, Carrion-i-Silvestre, 2005). Though, the bootstrap procedure is subject to size distortions in finite samples, particularly in cases where N is small relative to T , as in the study of health expenditure in the OECD countries (Maddala and Wu, 1999, Smith, Leybourne, Kim and Newbold, 2007). Few works on health expenditure explicitly account for cross-section dependence when studying its long-run economic relationships (Moscone and Tosetti, 2010, Baltagi and Moscone, 2010).

In this paper we consider that health expenditures per capita are explained by different sources of health expenditure funding: public, private and expenditures in medicaments, income per capita, the dependency rates of the population and technological progress. We also consider the effects of shocks that may hit health spending, such as advances in medical care technology, policy shifts, new diseases, and shifts in preferences and expectations by users of health services. With that intent we follow closely Pesaran (2004) and Pesaran (2006) including a factor structure in the econometric specification. The factor structure can capture any contemporaneous correlation that arises from the common response of countries to such unanticipated events. Recent literature has recognized that cross section dependence is an important characteristic of health data, and has tried to incorporate it (Jewell et al., 2003, Freeman, 2003, Carrion-i-Silvestre, 2005, Moscone and Tosetti, 2010, Baltagi and Moscone, 2010). According to Moscone and Tosetti (2010) when the existence of global and local forms of cross-section dependence in health spending and income is not taken into account in the study of health expenditure, it is likely to provide policy makers with misleading results.

3 Model Specification and Time Series Analysis

The empirical model that motivates our research of the determinants of health expenditures is the following linear heterogeneous panel framework:

$$H_{it} = \beta_i' X_{it} + u_{it} \quad (1)$$

where $\begin{cases} i = 1, 2, \dots, 30, \text{ denotes countries;} \\ t = 1, \dots, 20, \text{ denotes periods (years).} \end{cases}$

In Equation (1), H_{it} , real per-capita health care expenditure in the i th country at time t , health care expenditure is estimated against the way it is financed, i.e. by government (H^{PU}), privately (H^{PR}) and expenditures in medicaments (H^{PH}). These expenditures were computed over total health care expenditure. The set of regressors also includes income per capita (Y), the dependency rates for old (DR^{65}) and young (DR^{15}) age structure. We also attempt to study the relationship between technological progress and health care expenditure using infant mortality (IM) as a proxy for changes in medical care technology. All variables are expressed in natural logarithm and description of all data and data sources is provided in appendix A.

The three-way error component term of Equation (1) is given by:

$$u_{it} = \lambda_t + \eta_i + \gamma_i' C_t + \varepsilon_{it} \quad (2)$$

where λ_t accounts for time-specific effects and η_i accounts for unobservable country-specific effects. The term ε_{it} is the random disturbance in the regression, varying across time and country cells. We may also have a third error component, C_t that accounts for unobserved common effects. From Equation (2), correlation arises because the responses to common external forces or perturbations is similar, though not identical, across countries. Notice that common factors induce a correlation between pairs of statistical units that does not depend on how close they are in the geographical space. In model (1), we allow X_{it} to be correlated with the unobserved effects C_t . Therefore, common factors can impact health expenditure not only directly via the factor structure (2), but also indirectly by affecting the regressors.

We estimate the parameters β_i in model (1) applying Common Correlated Effects (CCE) method developed by Pesaran (2006):

$$h_{it} = \lambda_t + \eta_i + \beta_i' x_{it} + \pi_i' \bar{w}_t + \nu_{it} \quad (3)$$

where $\bar{w}_t = (\bar{h}_t, \bar{X}_t')'$, with \bar{h}_t being the cross section average of the dependent variable and \bar{X}_t' being the cross section average of the regressors. Here, heterogeneity is captured by the individual specific fixed effects, η_i , the time dummies, λ_t , and the loadings, π_i . In our analysis we will compute CCE-Pesaran Pooled Estimator (CCE-PPE) for the average of the coefficients (Pesaran, 2006). Pesaran and Tosetti (2009) performing Monte Carlo experiments have shown that this estimator has good small sample properties when the errors follow either a pure factor structure, a pure spatial process, or a linear combination of them.

3.1 Time Series Properties of the Data

Since the appropriateness of the methodology to be applied to the econometric estimation depends on the time series properties of the data, such properties must be ascertained before any estimation is carried out. There are several statistics that may be used to test for a unit root in panel data, but since we have a not so long panel data set, we implement the Im, Pesaran and Shin (2003) test (IPS). In contrast to the Levin, Lin and Chu (2002) test, the IPS's t-bar statistic is based on the mean augmented Dickey-Fuller (ADF) test statistics and is calculated independently for each cross-section of the panel. Based on Monte Carlo experiment results, IPS demonstrate that their test has more favorable finite sample properties than the LL test.

(Insert table 1 here)

Table 1² reports the test results based on the inclusion of an intercept and trend. In every case the null that every variable contains a unit root for the series in logs is not rejected³.

The panel unit root tests applied previously do not account for cross-sectional dependence of the contemporaneous error terms. It has been shown in the literature that failing to consider cross-sectional dependence may cause substantial size distortions, see, for example, Banerjee (1999) and Pesaran (2007). To avoid this mis-performance of the unit root tests we proceed our panel unit root analysis relaxing the assumption of cross sectional independence, the test proposed by Pesaran (2007). The Cross-sectionally Augmented IPS Panel Unit Root Test (CIPS) proposed by Pesaran (2007) is a panel fixed effects test allowing for parameter heterogeneity and serial correlation between the cross-sections, correcting their dependency.

²This estimation was performed using the Rats code that is available upon request to Peter Pedroni.

³To test for the possibility that the variables which were found to be non-stationary are integrated of second order, $I(2)$, unit root tests on the first differences of the variables were run. Although not shown here, these tests suggest that all variables are stationary in first differences.

Consider the p^{th} order augmented Dickey Fuller regression (4) given by:

$$q_{it} = a_i + b_it + c_i q_{i,t-1} + \sum_{j=1}^p d_{ij} \Delta q_{i,t-j} + e_{it} \quad (4)$$

where q_{it} is either the logarithm of real per-capita health spending, the logarithm of the j^{th} regressor X_{it} , or regression residuals from equation (1). e_{it} are errors that we assume to have a single factor structure, where the idiosyncratic component follows a spatial autoregressive process as in (3). When testing for unit roots, the null hypothesis is

$$H_0 : c_i = 0; i = 1 \dots N; \quad (5)$$

against the alternative that

$$H_1 : c_i < 0; i = 1 \dots N_1, c_i = 0; i = N_1 + 1 \dots N; \quad (6)$$

where N_1 is such that $N_1 = N$ is nonzero and tends to a fixed constant as N goes to infinity. Pesaran (2007) proposes to test (5) against (6) by computing the simple average of the t-ratios of the OLS estimates of c_i in equation (8), namely,

$$CISP = \frac{\sum_{i=1}^N \tilde{t}_i}{N} \quad (7)$$

where \tilde{t}_i is the OLS t-ratio of b_i in the following Dickey Fuller (CADF) regression augmented with the cross section averages \bar{q}_t and $\Delta \bar{q}_t$

$$q_{it} = a_i + b_it + c_i q_{i,t-1} + \sum_{j=1}^p d_{ij} \Delta q_{i,t-j} + f'_i \bar{Z}_t + v_{it} \quad (8)$$

where $\bar{Z}_t = (\bar{q}_{t-1}, \Delta \bar{q}_t, \Delta \bar{q}_{t-1}, \dots, \Delta \bar{q}_{t-p})$.

The CIPS test⁴ has been designed for testing the unit root hypothesis when the variable under study has a factor structure.

(Insert table 2 here)

In Table 2⁵ we report the results for the Pesaran cross-sectionally augmented IPS test. The model used to test the unit root hypothesis is the one with intercept and trend. Because our data is annual we test until 3 lag lengths. The unit root test hypothesis is not rejected at the conventional level of significance for the three variables considering a lag length of 2 or 3. These results indicate that variables under analysis are integrated of order 1.

4 Cointegration Analysis

In this section we report our cointegration analysis results based on Pedroni (1999, 2001, 2004) cointegration test. Two classes of statistics are considered in the context of the Pedroni test. The first type is based on pooling the residuals of the regression along the within-dimension of the panel, whereas the second type is based on pooling the residuals of the regression along the between-dimension of the panel. For the first type, the test statistics are the panel v-statistic,

⁴The critical values for the CIPS tests are given in Tables 2 in Pesaran (2007).

⁵CISP-estimation was performed using the GAUSS code available on line at <http://www.econ.cam.ac.uk/faculty/pesaran/>

the panel ρ -statistic, the panel PP-statistic, and the panel ADF-statistic. These statistics are constructed by taking the ratio of the sum of the numerators and the sum of the denominators of the analogous conventional time-series statistics across the individual members of the panel. The tests for the second type include the group ρ -statistic, the group PP-statistic, and the group ADF-statistic. They are simply the group mean statistics of the conventional individual time-series statistics. All statistics have been standardized by the means and variances so that they are asymptotically distributed $N(0,1)$ under the null of no cointegration. As one-sided tests, large positive values of the panel v-statistic reject the null hypothesis of no cointegration. For the remaining statistics (the panel ρ , the panel PP, the panel ADF, the group ρ , the group PP, and the group ADF tests), large negative values reject this null. See Pedroni (2004) for a detailed discussion.

(Insert table 3 here)

The panel cointegration test proposed by Pedroni (2004) is reported in Table 3⁶. Pedroni (1999) showed that the panel-ADF and group-ADF statistics have better small sample properties than the other statistics, and hence, they are more reliable. Table 3 shows that the panel-ADF and group-ADF statistics significantly reject the null of no cointegration as given by equation (1).

The cointegration test applied previously do not account for cross-sectional dependence of the contemporaneous error terms. Now, the cross-section augmented regression is given by equation (3) and to estimate β parameters Holly, Pesaran and Yamagata (2010), use the pooled CCE estimator in Pesaran (2006), which is given by:

$$\hat{\beta}_{CCE} = \left(\sum_{i=1}^N X_i' \bar{M} X_i \right)^{-1} \left(\sum_{i=1}^N X_i' \bar{M} H_i \right) \quad (9)$$

where $M = I - \bar{A}(\bar{A}'\bar{A})^{-1}\bar{A}'$ and $\bar{A} = [\eta\lambda\bar{w}]$. After proofing the consistency of the pooled CCE estimator under the null hypothesis of spurious regression, Banerjee and Carrion-i-Silvestre (2011), use the CCE estimated parameters $\hat{\beta}_{CCE}$, in the second stage to define the variable:

$$\tilde{H}_{it} = H_{it} - X_{it}' \hat{\beta}_{CCE} \quad (10)$$

for which the following model is estimated using the OLS estimation procedure:

$$\tilde{H}_{it} = \lambda_t + \eta_i + f_{it} \quad (11)$$

and the OLS residuals are then computed as $\hat{f}_{it} = \tilde{H}_{it} - \hat{\lambda}_t - \hat{\eta}_i$. The null hypothesis of no cointegration is tested analyzing the order of integration of \hat{f}_{it} through the application of the cross-section augmented ADF cointegration (CADFC) statistic:

$$CADFC = \frac{\sum_{i=1}^N t_{\hat{\alpha}_i}}{N} \quad (12)$$

where $t_{\hat{\alpha}_i}$ denotes the pseudo t-ratio of the estimated α_i parameter in the regression:

$$\Delta \hat{f}_{it} = \alpha_i \hat{f}_{it-1} + \sum_{j=1}^p \alpha_{ij} \Delta \hat{f}_{it-j} + \xi_i \bar{f}_{it-1} + \sum_{j=0}^p \delta_{ij} \Delta \bar{f}_{it-j} + g_{it} \quad (13)$$

⁶This estimation was performed using the Rats code that was available upon request to the author.

We have computed the CCE test statistics proposed by Banerjee and Carrion-i-Silvestre (2011) using up to three lags for the autoregressive correction in (13). The computation of the CADFC statistic gives $CADFC = -2.56$ when $p = 0$, $CADFC = -2.98$ when $p = 1$, $CADFC = -2.93$ when $p = 2$ and $CADFC = -3.29$ when $p = 3$, p being the order of the autoregressive correction that is used. When we compare the values of the CADFC statistic with the critical values given in Table 4 of Banerjee and Carrion-i-Silvestre (2011) for $N = 30$ and $T = 20$, we conclude that except for $p = 0$ and $p = 2$, the null hypothesis of no cointegration is rejected at the 5% level of significance. We also conclude that except for $p = 0$ the null hypothesis is rejected at the 10% level of significance.

5 Estimation of the Long-Run Equilibrium

Our final step is the estimation of the long-run relationships between real per capita health expenditure and health expenses financed by government, privately and spent on medicaments, income, age structure of the population and technology. In this Section, we begin performing the general diagnostic tests for cross section dependence in panels suggested by Pesaran (2004). The hypothesis that there is not cross-sectional dependence is rejected. Therefore, we proceed to estimate our panel data model subject to cross section dependence as suggested by Pesaran (2006).

When the cointegration relation does not account for cross-sectional dependence of the contemporaneous error terms, it has been shown in the literature that failing to consider cross-sectional dependence may cause substantial size distortions, see, for example, O'Connell (1998) and Pesaran (2007). We performed the general diagnostic tests for cross section dependence in panels suggested by Pesaran (2004) as shown in Table 4⁷. The hypothesis that there is not cross-sectional dependence is rejected. Therefore, we proceed to estimate our panel data model subject to error cross section dependence as suggested by Pesaran (2006). The Pesaran (2006)'s Monte Carlo simulations show that common correlated effects-Pesaran (2006) pooled estimator (CCE-PPE) has satisfactory small sample⁸ properties.

(Insert table 4 here)

Table 4⁹ shows that when removing the cross dependency, real per-capita health care expenditure clearly increases with health care expenditure financed by government. Health care expenditure also increases with income per capita, with the elderly and young dependents on the society, with the advances in technology and with health care expenditure financed privately and with medicaments' expenses.

Health care expenditure financed by government explains around 65% of the increase in health expenses, the out of the pocket health care expenses explains 9% and the expenses on pharmaceutical goods explains 5.6% of the variations in the real per-capita health care expenditure. Here, we have to note that previous studies have focused in the relation between health care expenditure and income and other non-economic determinants. By introducing in our estimation the way health care expenditure is financed, we observe that the importance of the income variable fades away at the expense of the health care expenditure financed by the government, privately and expenditures in medicaments. Our results follow Moscone and Tosetti (2010) who in a comparable study developed for the United States, achieved a similar result

⁷These estimations were performed using the GAUSS code available upon request to the authors.

⁸Pesaran (2006)'s Monte Carlo simulations also showed that the mean group estimators (CCE-PMG) have satisfactory properties when N and T are relatively large.

⁹This estimation was performed using the Rats code available upon request to the author.

when controlling for other non-income determinants of health expenditure. They concluded that while the ability to pay is a determinant of health care spending, the existence of publicly financed programs weakens the link between income and the standard of care. The estimator for the GDP per capita elasticity is around 6.6% which means that demand for health care is highly inelastic. The existence of public intervention and public funding as well as health insurance make the demand for health care independent of an individual's income. The youth dependency rate's estimator coefficient is around 28%, whether the old-dependency rate is around 23%. The technology progress helps driving the health care expenses up in approximately 3%.

(Insert table 5 here)

In Table 5 we present the estimation results for each individual country. In some cases, less than 20% of the countries, health care appears as an inferior good, since the public funding as well as health insurance make demand for health care to be inversely related to individual's income. Regarding individual countries estimators, we also find that the estimation results for the determinants of health expenditure in the OECD varies substantially across countries what corroborates with the microeconomic methodology undertaken in this article.

6 Conclusion

This paper analyzes the long-run economic relationship between health care expenditure and a set of determinants of health expenditure in the OECD countries. Using a panel of 30 OECD countries over 20 years, we have studied the non-stationarity and cointegration properties of health care spending and its sources of funding, income and non-income variables. Our analysis indicates that health care expenditure, the different sources of health expenditure funding computed over total health care expenditure: public, private and expenditures in medicaments, as well as, income per capita, the dependency rates of the population and technological progress are non-stationary, and that they are linked in the long-run. We also detect a significant cross country dependence. Our results show that when health care expenditure is mainly financed by government it becomes highly inelastic, with an income elasticity much smaller than expected, controlling for dependency rates for old and young age structure and technological progress. The weight of the income therefore dilutes when controlling for the way health care expenses are financed, as well as, other non-income determinants of health expenditure. As for non-income determinants, technological progress, the percentage of young and elderly people reveal a positive impact on health care expenditures.

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Appendix

A DATA

Our empirical work uses annual data on 30 OECD countries from 1989 to 2009 ($T = 20$), gathered from the OECD Data Set. We collected information on per-capita total health care expenditure and per-capita income estimated in GDP purchasing power parity, and expressed in US Dollars. We also gathered data for the following variables that have been identified by the literature as having a role in determining health care expenditure taken from OECD Health Database: the dependency rates for old and young people, defined as the population aged over 65 years old and under 15 years old, respectively; the infant mortality rate and; the public expenditure on health care computed as government expenditure over total health care expenditure; private expenditure computed as out of pocket expenditure on health over total health care expenditure; and finally the pharmaceutical expenditure computed as expenses on medicaments over total health care expenditure.

Data Sources

From the OCDE Database, it was obtained for the period 1990-2009:

H : Total health expenditure per capita, US dollars, purchasing power parity (PPP).

Y : GDP per capita, US dollars, current prices and purchasing power parity (PPP).

DR^{65} : Dependency rate as the ratio of population aged 65 and over as percentage of total population.

DR^{15} : Dependency rate as the ratio of population aged less than 15 as a percentage of total population.

IM : Infant mortality: Deaths per 1 000 live births.

H^{PH} : Pharmaceutical expenditure computed as expenditure on medicaments over total health care expenditure.

H^{PR} : Private health expenditure computed as out-of-pocket expenditure over total health care expenditure.

H^{PU} : Public health expenditure computed as government expenditure over total health care expenditure.

Tables

Table 1: Panel Unit Root Tests

Series in Log-Levels	H	Y	DR^{65}	DR^{15}	IM	H^{PH}	H^{PR}	H^{PU}
IPS Test								
Im et al. (2003) Test	-2.22	-2.30	-1.06	-1.70	-1.96	-1.78	-2.27	-1.83

The null hypothesis is that the series is a unit root process. An intercept and trend are included in the test equation. The lag length was selected by using the Akaike Information Criteria. The critical values are taken from Im et al. (2003).

* Rejects the null at the 10% level ($CV \approx -2.39$).

** Rejects the null at the 5% level ($CV \approx -2.46$).

*** Rejects the null at the 1% level ($CV \approx -2.58$).

Table 2: Pesaran (2007) Cross-sectionally Augmented IPS (CIPS) Test

Series in Log-Levels	Lag	$p = 0$	$p = 1$	$p = 2$	$p = 3$
H		-2.237	-2.499	-2.468	-2.183
Y		-1.929	-2.197	-1.701	-1.920
DR^{65}		-1.678	-1.721	-1.501	-1.424
DR^{15}		-1.349	-1.260	-1.319	-1.314
IM		-2.722**	-1.905	-1.761	-1.578
H^{PH}		-2.258	-2.588	-2.130	-1.677
H^{PR}		-2.163	-2.127	-2.003	-2.010
H^{PU}		-2.155	-2.331	-1.962	-2.009

The null hypothesis is that the series is a unit root process. Critical values for the CIPS test with an intercept and trend are: $CV \approx -2.59$ (10%), $CV \approx -2.68$ (5%), and $CV \approx -2.84$ (1%), see Pesaran (2007).

* Rejects the null at the 10% level.

** Rejects the null at the 5% level.

*** Rejects the null at the 1% level.

Table 3: Pedroni (2004) Panel Cointegration Tests

Test the following relation: $H_{it} = \alpha_i + \beta_i' X_{it} + u_{it}$ ^a	
Test Statistics ^b	
Panel v-stat	1.127
panel ρ -stat	4.299
panel PP-stat	-7.539 ^{***}
panel ADF-stat	-7.678 ^{***}
group ρ -stat	5.469
group PP-stat	-11.265 ^{***}
group ADF-stat	-11.603 ^{***}

^a Where, X_{it} contains Y_{it} , DR_{it}^{65} , DR_{it}^{15} , IM_{it} , H_{it}^{PH} , H_{it}^{PR} and H_{it}^{PU} . We only report the intercept and the trend case.

^b The tests statistics are distributed as $N(0, 1)$ under the null of no cointegration. The statistics are constructed using small sample adjustment factors from Pedroni (1999, 2004).

* Rejects the null at the 10% level.

** Rejects the null at the 5% level.

*** Rejects the null at the 1% level.

Table 4: Panel Estimates of the Cointegration Relationship: CCE-PPE

	Y_{it}	DR_{it}^{15}	DR_{it}^{65}	IM_{it}	H_{it}^{PH}	H_{it}^{PR}	H_{it}^{PU}
Fixed Effects Estimates	0.057	0.174	0.082	0.005	0.044	0.095***	0.668***
t-stat in brackets	(0.963)	(1.488)	(0.586)	(0.219)	(1.746)	(4.506)	(13.604)
CD Test Statistic^a	5.408						
Pesaran's (2006) CCE Pooled Estimates^b	0.066	0.284***	0.227	0.029	0.056***	0.090***	0.651***
t-stat in brackets	(1.148)	(2.426)	(1.596)	(1.003)	(2.532)	(3.948)	(12.833)

^a) Pesaran's (2004) General Diagnostic Tests for Cross Section Dependence (residuals).

^b) CCE Pooled Estimator is defined by eq(65) and t-stat is the associated t-ratio of the standard error based on Newey-West type variance estimator of eq(74) in Pesaran (2006).

*** Rejects the null at the 1% level.

Table 5: Individual Estimates of the Cointegration Relationship: CCE-PPE

CCE Estimator for each country ^a							
	Y_{it}	DR_{it}^{15}	DR_{it}^{65}	IM_{it}	H_{it}^{PH}	H_{it}^{PR}	H_{it}^{PU}
Australia	0.29 (2.64)	0.136 (0.54)	-0.008 (-0.07)	0.019 (1.06)	0.109 (4.54)	0.079 (2.93)	0.189 (2.91)
Austria	0.103 (1.07)	0.687 (5.59)	0.114 (0.86)	0.047 (3.92)	-0.006 (-0.19)	0.098 (2.18)	0.676 (10.73)
Belgium	0.154 (0.41)	-1.755 (-2.19)	2.634 (3.81)	0.081 (1.25)	-0.111 (-0.75)	0.435 (3.57)	-0.100 (-1.30)
Canada	-0.125 (-3.68)	-0.007 (-0.06)	-0.426 (-2.58)	-0.062 (-3.10)	-0.015 (-0.23)	0.19 (7.31)	0.806 (20.15)
Czech Republic	0.27 (4.36)	-1.342 (-3.48)	-0.69 (-1.73)	0.091 (2.76)	-0.094 (-1.65)	0.076 (3.62)	0.941 (22.95)
Denmark	0.061 (0.60)	-0.397 (-2.32)	-0.81 (-3.05)	-0.01 (-0.44)	-0.093 (-3.72)	0.231 (6.24)	1.052 (5.13)
Finland	0.033 (1.22)	0.607 (1.75)	-0.332 (-1.71)	-0.025 (-1.32)	-0.048 (-0.65)	0.198 (2.79)	0.819 (16.71)
France	0.000 (0.00)	0.412 (4.63)	-0.08 (-1.04)	0.026 (2.00)	0.04 (1.82)	0.047 (3.62)	0.811 (45.06)
Germany	0.115 (0.73)	-0.969 (-1.25)	-0.556 (-0.69)	0.021 (0.15)	-0.092 (-1.17)	-0.072 (-0.73)	0.385 (2.29)
Greece	0.046 (0.56)	0.151 (1.58)	-1.584 (-6.47)	-0.009 (-0.69)	0.14 (6.67)	0.26 (23.64)	0.603 (15.87)
Hungary	-0.105 (-0.81)	5.103 (7.48)	5.094 (3.70)	-0.18 (-3.67)	0.118 (4.72)	0.368 (10.51)	1.029 (14.49)
Iceland	0.043 (1.54)	-0.015 (-0.13)	0.061 (0.73)	0.015 (2.50)	0.041 (4.10)	0.157 (39.25)	0.777 (40.89)
Ireland	-0.36 (-3.50)	-0.466 (-1.69)	0.063 (0.24)	-0.042 (-1.27)	0.143 (2.01)	-0.046 (-1.15)	0.866 (7.53)
Italy	0.106 (1.26)	0.129 (0.92)	-0.099 (-0.51)	-0.013 (-0.43)	0.009 (0.22)	0.208 (3.92)	0.732 (13.56)
Japan	0.397 (3.48)	-0.848 (-1.70)	0.603 (1.21)	-0.146 (-2.09)	-0.006 (-0.13)	-0.033 (-0.61)	0.295 (2.73)
Korea	0.071 (1.01)	-0.065 (-0.18)	-0.143 (-0.42)	-0.137 (-1.85)	-0.174 (-1.18)	0.747 (5.49)	0.463 (8.74)
Luxembourg	-1.321 (-2.15)	4.313 (2.92)	2.993 (0.80)	-0.076 (-0.62)	-0.194 (-0.63)	-0.108 (-1.05)	1.103 (3.09)
Mexico	0.028 (3.50)	0.027 (0.63)	0.054 (2.57)	0.023 (3.83)	-0.007 (-3.50)	0.547 (54.70)	0.435 (87.00)
Netherlands	-0.561 (-2.41)	-2.181 (-2.96)	-0.785 (-0.87)	-0.079 (-0.75)	0.053 (0.22)	0.097 (3.35)	0.145 (0.87)
New Zealand	-0.022 (-0.39)	0.066 (0.61)	-0.073 (-0.66)	-0.039 (-1.86)	0.173 (5.41)	0.09 (1.96)	0.669 (13.12)
Norway	-0.055 (-5.00)	-0.866 (-4.35)	-1.281 (-5.14)	0.04 (1.91)	0.01 (0.53)	0.165 (5.89)	0.892 (15.93)
Poland	0.608 (4.90)	-2.426 (-3.33)	1.316 (2.31)	-0.093 (-1.12)	0.178 (0.98)	0.213 (11.21)	0.93 (5.78)
Portugal	-0.004 (-0.02)	0.531 (1.12)	0.593 (0.98)	-0.066 (-0.47)	0.621 (5.05)	0.002 (0.14)	0.357 (3.16)
Slovak Republic	0.238 (2.74)	1.722 (2.90)	0.716 (4.12)	-0.079 (-2.08)	0.058 (86.45)	0.215 (13.44)	0.814 (14.03)
Spain	-0.166 (-2.34)	-0.452 (-6.46)	-0.325 (-2.52)	0.122 (1.42)	0.102 (1.89)	-0.002 (-0.50)	0.732 (8.61)
Sweden	0.007 (0.06)	1.677 (2.34)	0.045 (0.12)	-0.003 (-0.12)	-0.034 (-0.35)	-0.558 (-1.83)	0.941 (6.23)
Switzerland	0.153 (3.12)	-0.452 (-1.97)	-1.349 (-2.47)	-0.003 (-0.16)	0.118 (1.67)	0.24 (3.75)	0.713 (19.81)
Turkey	-0.267 (-1.32)	5.698 (2.80)	-0.061 (-0.11)	-0.206 (-3.49)	0.29 (5.58)	0.364 (4.18)	1.182 (18.76)
United Kingdom	0.358 (3.85)	0.401 (2.57)	0.272 (1.28)	0.01 (0.25)	-0.11 (-3.44)	0.106 (2.65)	0.922 (12.46)
United States	0.096 (3.84)	-0.091 (-0.25)	0.093 (0.35)	-0.074 (-0.90)	0.134 (3.35)	0.408 (8.00)	0.764 (12.32)

^a) CCE Estimator for a Country is defined by eq(26) and the corresponding t-stat associated to the standard error based on Newey-West type variance estimator of eq(50) in Pesaran (2006). t-stat in brackets.