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HEALTH EXPENDITURE AND INCOME IN THE UNITED STATES

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Abstract

This paper investigates the long-run economic relationship between health care expenditure and income in the US at a State level. Using a panel of 49 US States followed over the period 1980-2004, we study the non-stationarity and cointegration between health spending and income, ultimately measuring income elasticity of health care. The tests we adopt allow us to explicitly control for cross-section dependence and unobserved heterogeneity. Specifically, in our regression equations we assume that the error is the sum of a multifactor structure and a spatial autoregressive process, which capture global shocks and local spill overs in health expenditure. Our results suggest that health care is a necessity rather than a luxury, with an elasticity much smaller than that estimated in other US studies. Further, we observe a significant spatial spill over, though with a smaller intensity than that detected in other studies on spatial concentration of US health spending. Our broad perspective of cross section dependence as well as the methods used to capture it give new insights on the debate over the relationship between health spending and income.

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1 Introduction

Despite years of concern and attempts at cost containment, aggregate health care expenditure in the US, and other western countries, has increased substantially. This has heated the discussion on the underlying reasons for the rise in health expenditure, as well as the alternative policy solutions to control such spending growth. Since the seminal papers by Kleiman (1974) and Newhouse (1977), much emphasis has been given to the role of income in determining health care expenditure. The debate is still open on whether health care is a luxury or a necessity good, namely, if income elasticity of expenditure is above or below unity (Parkin *et al.*, 1987; Gerdtham *et al.*, 1992; Hitris and Posnett, 1992; Hansen and King, 1996; Blomqvist and Carter, 1997; Di Matteo and Di Matteo, 1998, Freeman, 2003). The controversy over the nature of health care has been exacerbated by the policy implications of the empirical results. If one recognizes that health care is a necessity will often support the idea of greater public involvement in health care. Conversely, advocates of health care being a luxury, would argue it is a commodity much like any other and best left to market forces alone (Culyer, 1988). Empirical evidence varies according to the statistical units considered in the investigation (Manning *et al.*, 1987; Blomqvist and Carter, 1997; Getzen, 2000). As the focus shifts from fine disaggregations of the population (e.g.: individuals, provinces, regions) to larger groups of actors (e.g., States, Countries), we observe a higher estimated income elasticity of health care. Put differently, associations observed between macro-factors do not seem to reflect associations that exist at the individual level. As pointed out by Getzen (2000), one reason might be that individual budget constraints in health spending are largely removed through insurance financing, while at aggregate level the resources allocated on health care are constrained by the budget rather than being influenced by health status. Another explanation is that cross-country data are characterised by strong heterogeneity that, if not properly incorporated in econometric models, could lead to the estimation of income elasticities greater than one (Hansen and King, 1996). Limiting the analysis to one country with multiple jurisdictions might reduce this problem.

When looking at the link between spending and income, one important issue is whether the stationarity assumption holds for both time series variables. It is well known that the violation of this assumption leads to spurious statistical results under the OLS (Engle and Granger, 1987). Indeed, if the two series are both integrated, the absolute value of their correlation coefficient will be nonzero, whether or not an economic relationship between them exists. Nonstationarity in the two series introduces the issue of determining whether there is a long-run equilibrium between health expenditure and income. If both time series variables are integrated and there exists a linear combination of these variables that is itself stationary, we can conclude that the two variables are cointegrated. In this case, the stationary linear combination represents the cointegrating or long-run relationship, which can be specified in levels with short-run dynamics modelled via an error correction process. It follows that integration and cointegration between spending and income represent fundamental properties when specifying and interpreting a model for health expenditure.

A large number of studies investigate the non-stationarity in health expenditure and income and their long-run relationship in a panel data framework (McCoskey and Selden, 1998; Roberts, 1999; Gerdtham and Lothgren, 2000; Okunade and Karakus, 2001; Jewell *et al.*, 2003; Carrion-i-Silvestre, 2005; Dreger and Reimers, 2005; Freeman, 2003; Wang and Rettenmaier, 2006, Chou, 2007). Most empirical work has been focusing on OECD countries, while less attention has been paid to the US case, at a State level. Cross country analysis on the OECD area provide empirical evidence that is often contradictory. For example, Gerdtham and Lothgren (2000), using country-by-country and panel unit root tests, reach the conclusion that in OECD countries health care expenditure and GDP are non-stationary and cointegrated. Similar results, employing more advanced econometric techniques, are reported in Dreger and Meiers (2005). On the contrary, McCoskey and Selden (1998) reject the null of non-stationarity for health care expenditures and GDP, though they observe that results change when a time trend is included in the augmented Dickey-Fuller equation. Jewell *et al.* (2003) and Carrion-i-Silvestre (2005) conclude that health expenditure and GDP are stationary around one or two breaks. In general, major concern is expressed by several authors on how to deal with heterogeneity and cross section dependence, characteristics that are very likely to be present in health panel data, when testing for unit roots and cointegration (McCoskey and Selden, 1998; Roberts, 1999).

The empirical evidence on US is scant. Freeman (2003) finds that health care expenditure and income at State level in the US in the period 1966-1998 are non-stationary and cointegrated, ultimately observing that health care is a necessity good. More recently, Wang and Rettenmaier (2006), allowing for structural breaks in unit root tests, support the evidence that spending and income in US States are non-stationary, though not cointegrated. Further, they find an income elasticity below 1 for 16 States, and above 1 for the remaining 32 States.

In this paper we aim at giving new insights on the debate over the long-run economic relationship between health care expenditure and income, focusing on the US case. Using a panel of 49 US States followed over the period 1980-2004, we study the non-stationarity and cointegration properties of health spending and income. Our ultimate goal is to provide an estimate of income elasticity of health care which is more accurate than that offered by the current literature. To this end, we apply newly developed econometric techniques for panel data that explicitly control for cross-section dependence as well as unobserved heterogeneity. Following recent contributions to the literature on panel unit roots, cross section dependence is incorporated in econometric models through an approximate multifactor structure (Pesaran, 2006; Bai and Ng, 2004). Specifically, in our regression equations we assume that the error term is a linear combination of few common time-specific effects with heterogeneous loadings plus a spatial process. Hence, we examine the extent to which spending is driven by income, unobservable common shocks and spatial spill overs, determining the speed of adjustment of health expenditure to deviations from the long-run equilibrium relation.

Though the issue of cross section dependence in this strand of health economics has been tackled by other authors, our broader perspective of cross section dependence as well as the methods used to capture it give new insights on the debate on the long-run relationship between health spending and income.

In the following, we first discuss the issue of contemporaneous correlation in health expenditure and its econometric representation. We then turn to a preliminary descriptive analysis of cross section dependence for health and income. Hence, we compute a set of panel unit root tests to investigate the possible non-stationarity of temporal patterns of these variables. We perform a cointegration analysis, focusing on the long-run relationship between health spending and income, assessing whether expenditure on health care is a necessity or a luxury good. Finally, we measure the amount of spatial correlation in the data due the possible presence of spill over effects.

The plan of the paper is as follows. In Section 2 we discuss the issue of cross section dependence in health expenditure. In Section 3 we introduce the econometric methods used in the empirical study. Section 4 describes the data and provides a preliminary exploratory analysis. Section 5 goes through the empirical econometric evidences, giving economic content to the findings. Finally, Section 6 ends with some concluding remarks.

2 Cross section dependence in health expenditure

An important characteristic of health expenditure is the presence of cross section dependence in the data. The assumption of zero correlation on the shocks affecting individual population units[1] in a given cross section is very strong and is not likely to hold in empirical studies of health expenditure. We can recognize two sources of interdependence among statistical units. The first arises when agents react in a similar manner to external forces and unanticipated events such as technological advances, health shocks, the implementation of new health policies and sociological structural changes (Andrews, 2003). Correlation arises because the responses to such common external forces or perturbations is similar − though not identical − across individuals. For example, innovations in diagnostic tools and therapies such as a new vaccine might render treatable health conditions for which past options consisted only of minimal treatments. Epidemics or diseases whose incidence suddenly raises regionally or worldwide might generate a risk adverse behaviour that translates in the accumulation of drugs and increase of pharmaceutical expenditure. The sexual behaviour of a generation may also exacerbate the spread of certain epidemics, thus, impacting on health services use. The implementation of new health policies, such

[1] Population units can be individuals, households, hospitals, cities, states, countries etc.

as campaigns through the media on highway regulations may reduce avoidable accidents, ultimately impacting on costs of the health system. These shocks are often unobservable to the econometrician and perturb the health system as a whole, simultaneously affecting the behaviour of agents (e.g., recipients, providers, etc.), ultimately impacting on health costs. An important feature of these shocks is that they induce a correlation between pairs of statistical units that does not depend on how close they are in the geographical space. Accordingly, we will refer to this type of correlation as long-range or *global* interdependence. We finally note that some of the unexpected events that affect health spending directly might also impact indirectly by hitting the fundamentals of health expenditure, such as disposable income.

An alternative source of interdependence, namely spatial correlation, is related to location and distance among units, with respect to the geographical, economic or social space in which they are embedded (Anselin, 2001). Neighbouring US States may share common general population characteristics or underlying socio-economic features that have an effect on the consumption of health care resources. For example, environmental stressors such as air pollution could be linked to regional rather than simply local trends, influencing prevalence and need across a wide area, eventually affecting health spending (Moscone *et al.*, 2007). States from the Southwest region, such as Arizona and Texas, are likely to face high rates of illegal immigration, which may directly or indirectly influence their health costs. Spatial correlation might also be generated by cross State borders movements of health services beneficiaries (Centers for Medicare & Medicaid Services, 2007). Indeed, it is plausible that individuals move to regions whose revenues and expenditure pattern best match their preferences (Tiebout, 1956; Baicker, 2005). Other reasons of why we should expect spatial dependence in health spending have been suggested by a recent strand of literature in public economics and health economics, which focuses on strategic interaction among jurisdictions in deciding resources allocation (Brueckner, 2000; Revelli, 2006, Moscone *et al.*, 2007a, 2007b; Moscone and Knapp, 2005; Costa-i-Font and Moscone, 2007).

From the above discussion it emerges that reactions to external events as well as spatial spill overs are likely to induce a structure of correlation in health expenditure data. The distinction between global interdependence and local correlation arising from spatial spill overs is that the latter concerns only finite subsets of statistical units that do not spread widely as sample size increases.

When data contain cross section dependence, conventional estimators such as ordinary least squares are inefficient, and the estimated standard errors are biased (Andrews, 2003). Phillips and Sul (2003) proved that when cross section dependence occurs but is not incorporated in the panel regression, the pooled ordinary least squares (OLS) estimator provides little gain in precision compared with single OLS equation. Further, least squares may be biased if regressors are correlated with the source of interdependence. Ignoring contemporaneous correlation has also serious drawbacks on commonly used panel unit root tests.

Indeed, stationary tests that assume independence might have substantial size distortions when this assumption does not hold (Phillips and Sul, 2003; Maddala and Wu, 1999).

Few works on health expenditure explicitly account for cross section dependence when studying its long-run economic relationships. Jewell *et al.* (2003) control for contemporaneous correlation by introducing time-specific effects in the econometric specification. However, the inclusion of time-varying effects implies that the common shocks have identical influences on each unit, an assumption that might be quite restrictive in empirical analysis. In fact, it is reasonable to expect the effect of global shocks to vary considerably across individuals, also depending on the characteristics of the population units. To allow for more general error cross section dependence, other studies build the empirical distribution of unit root test statistics by bootstrap techniques (Freeman, 2003; Carrion-i-Silvestre, 2005; Wang and Rettenmaier, 2006; Chou, 2007). However, 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). Also, a recent Monte Carlo study in Smith *et al.* (2004) indicates that the bootstrap statistic tends to be undersized when N and T are the same order of magnitude.

In the following we review a number of methods that allow us to study the long-run relationship of health care expenditure in the US, taking into account possible cross section correlation arising from unobservable common shocks and local interdependence.

3 Methods

3.1 The econometric model

The econometric framework of our analysis is the following simple linear heterogeneous panel

$$h_{it} = \alpha_i + \beta_i y_{it} + u_{it}, \qquad i = 1, ...N; t = 1, ...T, \tag{1}$$

where h_{it} and y_{it} indicate, respectively, the logarithm of real per-capita health expenditure and the logarithm of real per-capita disposable income in the i^{th} State at time t, α_i is a State-specific intercept, and u_{it} is the error term. In this paper we suggest to incorporate in equation (1) cross section dependence arising from global shocks by assuming that the errors have the following multifactor structure

$$u_{it} = \boldsymbol{\gamma}_i' \mathbf{f}_t + \upsilon_{it}, \tag{2}$$

in which $\mathbf{f}_t$ is the $m \times 1$ vector of unobserved common effects and υ_{it} is a State-specific error. The coefficients γ_{ij}, for $i = 1, ..., N$ and $j = 1, ..., m$, are called factor loadings, and represent the sensitivities of statistical units, here the US States, to movements in the factors $\mathbf{f}_t$. Hence, according to this specification, each State can respond, with a different intensity, to unanticipated events, or perturbations, such as new medical technologies and health shocks.

We incorporate cross section dependence arising from spatial spill overs by assuming that υ_{it} follows a spatial autoregressive process (Cliff and Ord, 1981)

$$\upsilon_{it} = \rho\overline{\upsilon}_{it} + \varepsilon_{it}, \tag{3}$$

where ρ is a scalar parameter, and

$$\overline{\upsilon}_{it} = \sum_{j=1}^{N} w_{ij}\upsilon_{jt},$$

is the so-called spatial lag of υ_{it} (Anselin, 1988). w_{ij} is the generic (i, j)th element of a $N \times N$ nonnegative matrix, $\mathbf{W}$, known as spatial weights matrix, which provides information on the neighborhood linkages among States. In our empirical study we define neighbourliness via a contiguity criterion, and assign $w_{ij} = 1$ when States i and j share a common border or vertex, and $w_{ij} = 0$ otherwise. Hence, in model (3) the error term, υ_{it}, associated to the i^{th} State at a point in time t depends on the average of errors in its adjacent States at time t.

In model (1), we allow y_{it} to be correlated with the unobserved effects $\mathbf{f}_t$, and assume that

$$y_{it} = c_i + \boldsymbol{\lambda}_i'\mathbf{f}_t + \mathrm{v}_{it}.\ i = 1, ...N; t = 1, ...T, \tag{4}$$

where $\boldsymbol{\lambda}_i$ is a $m \times 1$ vector of factor loadings, and v_{it} is an error term assumed to be distributed independently of the common factors $\mathbf{f}_t$ and of ε_{it}. Therefore, common factors can impact on health expenditure not only directly via the factor structure (2), but also indirectly by hitting income via equation (4).

To sum up, model (1)-(4) represents the relationship between health spending and income, taking into account the sources of cross section dependence described in Section 2, namely global shocks and spatial spill overs.

Our estimation and testing strategy is based on the Common Correlated Effects (CCE) approach advanced by Pesaran (2006). According to this method, the unobservable effects $\mathbf{f}_t$ can be well approximated by the cross section averages of the dependent and explanatory variables. As a way of illustrating this result, rewrite equations (1)-(4) more compactly as

$$\mathbf{z}_{it} = \begin{pmatrix} h_{it} \\ y_{it} \end{pmatrix} = \mathbf{b}_i + \mathbf{C}_i'\mathbf{f}_t + \boldsymbol{\xi}_{it}, \tag{5}$$

where

$$\mathbf{b}_i = \begin{pmatrix} \alpha_i \\ c_i \end{pmatrix}, \mathbf{C}_i = \begin{pmatrix} \boldsymbol{\gamma}_i & \boldsymbol{\lambda}_i \end{pmatrix} \begin{pmatrix} 1 & 0 \\ \beta_i & 1 \end{pmatrix}, \text{ and } \boldsymbol{\xi}_{it} = \begin{pmatrix} \upsilon_{it} + \beta_i \mathrm{v}_{it} \\ \mathrm{v}_{it} \end{pmatrix}.$$

and consider the simple cross section average of (5)

$$\overline{\mathbf{z}}_t = \overline{\mathbf{b}} + \overline{\mathbf{C}}'\mathbf{f}_t + \overline{\boldsymbol{\xi}}_t, \tag{6}$$

with

$$\bar{\mathbf{z}}_t = \frac{1}{N}\sum_{i=1}^{N}\mathbf{z}_{it},\ \bar{\boldsymbol{\xi}}_t = \frac{1}{N}\sum_{i=1}^{N}\boldsymbol{\xi}_{it},\ \bar{\mathbf{b}} = \frac{1}{N}\sum_{i=1}^{N}\mathbf{b}_i, \quad \text{and } \bar{\mathbf{C}} = \frac{1}{N}\sum_{i=1}^{N}\mathbf{C}_i.$$

Assume that $Rank\left(\bar{\mathbf{C}}\right) = m$, we can rewrite (6) as

$$\mathbf{f}_t = \left(\bar{\mathbf{C}}\bar{\mathbf{C}}'\right)^{-1}\bar{\mathbf{C}}\left(\bar{\mathbf{z}}_t - \bar{\mathbf{b}} - \bar{\boldsymbol{\xi}}_t\right) \tag{7}$$

Under the condition that the spatial weights matrix, $\mathbf{W}$, has bounded absolute row and column sums, it is possible to show that (Pesaran and Tosetti, 2007)

$$\bar{\boldsymbol{\xi}}_t \overset{q.m.}{\to} 0, \quad \text{as } N \to \infty.$$

It follows that the cross section averages, $\bar{\mathbf{z}}_t$, can be used to approximate the common factors. Hence, the slope parameters β_i can be consistently estimated applying standard panel techniques to the following equation

$$h_{it} = \alpha_i + \beta_i y_{it} + \mathbf{g}_i'\bar{\mathbf{z}}_t + e_{it}, \tag{8}$$

where $\bar{\mathbf{z}}_t = \left(\bar{h}_t, \bar{y}_t\right)'$. Once the slope parameters have been estimated, since $\bar{\mathbf{z}}_t$ is consistent for $\mathbf{f}_t$, the spatial coefficient ρ in (3) can be obtained by applying the maximum likelihood method (Anselin, 1988) to residuals $\hat{e}_{it}$ from equation (8). Estimation of income elasticity (average, and State by State) is provided in Section 5.2, while the estimation of the spatial parameter is considered in Section 5.5.

Pesaran (2006) suggests the following CCE estimator for the i^{th} slope coefficient

$$\hat{\beta}_{CCE,i} = \left(\mathbf{y}_i'\bar{\mathbf{M}}\mathbf{y}_i\right)^{-1}\mathbf{y}_i'\bar{\mathbf{M}}\mathbf{h}_i, \tag{9}$$

with $\mathbf{M} = \mathbf{I}_T - \bar{\mathbf{H}}\left(\bar{\mathbf{H}}'\bar{\mathbf{H}}\right)^{-1}\bar{\mathbf{H}}'$, and $\bar{\mathbf{H}} = \left(\boldsymbol{\tau}, \bar{\mathbf{Z}}\right)$ with $\boldsymbol{\tau} = (1, ..., 1)'$ and $\bar{\mathbf{Z}}$ being the $T \times 2$ matrix of observations on $\bar{\mathbf{z}}_t$, $t = 1, ..., T$. Further, he proposes the following two estimators for the mean of the slope coefficients

$$\hat{\beta}_{MG} = \frac{1}{N}\sum_{i=1}^{N}\hat{\beta}_{CCE,i}. \tag{10}$$

$$\hat{\beta}_P = \left(\sum_{i=1}^{N}\mathbf{y}_i'\bar{\mathbf{M}}\mathbf{y}_i\right)^{-1}\sum_{i=1}^{N}\mathbf{y}_i'\bar{\mathbf{M}}\mathbf{h}_i. \tag{11}$$

The first, known as CCE Mean Group estimator, is a simple average of the individual CCE estimators in (9). The second is the CCE Pooled estimator, which gains efficiency from pooling observations. Their variances is provided in Pesaran (2006).

Monte Carlo studies in Pesaran (2006) and in Pesaran and Tosetti (2007) have shown that these estimators perform well in small samples as small as

N=20 and T=10. We stress that one important advantage of this approach is that it does not require to know the number of factors m. Further, it allows common factors and the idiosyncratic component, v_{it}, to be serially correlated, and it yields consistent estimators regardless of the factors being stationary or non-stationary, as long as v_{it} is stationary and m is a finite fixed number (Kapetanios at al., 2006).

Before concluding, we note that model (1)-(4) is able to capture some discontinuities in the relationship between spending and income by the means of the factor structure. However, we remark that it does not allow for the presence of structural breaks in the slope coefficients, β_i. In principle, we do recognize the potential role of structural breaks in the relation between health expenditure and income. However, we believe that this would be marginal in our empirical application given the relatively short time span considered (see Section 4).

In the following section, we explain how the CCE approach can be adopted when testing for unit roots, controlling for cross section dependence. Again, the idea is to use cross section averages of health expenditure and disposable income as proxies for the unobserved common factors, in the context of a Dickey Fuller regression.

3.2 Testing for unit roots

Consider the p^{th} order augmented Dickey Fuller regression

$$\Delta q_{it} = a_i + b_i q_{i,t-1} + c_i t + \sum_{j=1}^{p} d_{ij} \Delta q_{i,t-j} + u_{it}, \tag{12}$$

where q_{it} is either the logarithm of real per-capita health spending, the logarithm of real disposable income, or regression residuals from equation (1). u_{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

$$H_0 : b_i = 0, i = 1, ..., N, \tag{13}$$

against the alternative that (Breitung and Pesaran, 2007)

$$H_1 : b_i < 0, i = 1, ..., N_1; b_i = 0, i = N_1 + 1, ..., N, \tag{14}$$

where N_1 is such that N_1/N is nonzero and tends to a fixed constant as N goes to infinity. Following the same rational as in Section 3.1, we consider the following Dickey Fuller (CADF) regression augmented with the cross section averages $\bar{q}_{t-1}$ and $\Delta\bar{q}_{t-j}$, for $j = 0, ..., p$

$$\Delta q_{it} = a_i + b_i q_{i,t-1} + c_i t + \sum_{j=1}^{p} d_{ij} \Delta q_{i,t-j} + \mathbf{g}_i' \bar{\mathbf{z}}_t + e_{it}. \tag{15}$$

where $\bar{\mathbf{z}}_t = (\bar{q}_{t-1}, \Delta\bar{q}_t, \Delta\bar{q}_{t-1}, ..., \Delta\bar{q}_{t-p})'$. Pesaran (2007) proposes to test (13) against (14) by computing the simple average of the t-ratios of the OLS estimates of b_i in equation (15), namely,

$$CIPS = \frac{1}{N}\sum_{i=1}^{N}\tilde{t}_i, \tag{16}$$

where $\tilde{t}_i$ is the OLS t-ratio of b_i. The critical values for the $CIPS$ tests are given in Tables 2(a)-2(c) in Pesaran (2007).

We remark that the CIPS unit roots test requires that the errors u_{it} in (12) have a single factor structure. However, controlling for only one global shock might not be enough to capture the whole, long-range, contemporaneous correlation present in the data. In our empirical investigation we provide some statistics of cross section dependence after having controlled for such common factor to see whether significant correlation is left in the residuals.

3.3 Cross section dependence tests

We now briefly review some statistics of cross section dependence that we use in our empirical work. A statistic which captures the overall amount of cross section dependence in the data, at a descriptive level, is the following average pairwise correlation coefficient

$$\overline{\rho} = \frac{2}{N(N-1)}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\rho_{ij}, \tag{17}$$

where ρ_{ij} is given by

$$\rho_{ij} = \frac{\sum_{t=1}^{T} q_{it}q_{jt}}{\left(\sum_{t=1}^{T} q_{it}^2\right)^{1/2}\left(\sum_{t=1}^{T} q_{jt}^2\right)^{1/2}},$$

and q_{it} is either the logarithm of real per-capita health spending or the logarithm of real disposable income, expressed in first differences, or regression residuals from equations (1), and (12).

We also consider two diagnostic tests for cross section dependence, based on the above pairwise correlation coefficients. The CD_P test, recently advanced by Pesaran (2004), is

$$CD_P = \sqrt{\frac{2T}{N(N-1)}}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\rho_{ij}, \tag{18}$$

and the CD_{LM} test based on the Lagrange Multiplier statistic (Frees, 1995) is

$$CD_{LM} = \sqrt{\frac{1}{N(N-1)}}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\left(T\rho_{ij}^2 - 1\right). \tag{19}$$

Under the null hypothesis of no cross section dependence, the CD_P tends to a $N(0,1)$ for N and T going to infinity in any order, and the CD_{LM} tends to a $N(0,1)$ with $T \to \infty$ and then $N \to \infty$. We note that, while the CD_P is based on the pair-wise correlation coefficients, the CD_{LM} uses their squares. In practice, the CD_P test might give misleading results when the cross correlations cover negative as well as positive values. Though the CD_{LM} does not suffer from this problem, we note that it is likely to exhibit some size distortions for N large and T small (Frees, 1995).

These statistics measure the average amount of dependency between all pairs of units. They assign equal weights to all pairwise correlations regardless the geographical position of the US States. In other words, in these statistics the correlation between California and Maine has the same importance as the correlation between California and its adjacent States such as Oregon. Accordingly, the above CD statistics do not consider the distance decay effect that underlies spatial interaction theory, and should be interpreted as measures of long-range or *global* dependency.

In our empirical study we also test for spatial correlation, after having controlled for long-range dependence represented by the common factors structure. In particular, we compute the following Moran's I test statistic[2] (Kelejian and Prucha, 2001)

$$I = \frac{1}{T} \sum_{t=1}^{T} \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij} \hat{e}_{it} \hat{e}_{jt}}{s_t^2 \sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij}}, \tag{20}$$

where $s_t^2 = \frac{1}{N} \sum_{i=1}^{N} \left(\hat{e}_{it} - \bar{\hat{e}}_{.t} \right)^2$, and w_{ij}, $i, j = 1, ..., N$, are the spatial weights, and $\hat{e}_{it}$, for $i = 1, ..., N$, are the estimated regression residuals in (8) or in (15). The Moran's I is asymptotically normally distributed[3] as N goes to infinity, for fixed T. Spatial statistics such as the Moran's I differ from the CD statistics (17)-(19) since they exploit information on the spatial ordering of data, giving more importance to States that are close to each other. As such, the Moran's I should be interpreted as a measure of *local* cross section dependence. In the computation of (20), again we use contiguity as measure of distance among States, and assign a non-zero link only to pairs of States that share a common border or vertex.

4 Data description

Our investigation uses annual data on the US States plus the District of Columbia, from 1980 to 2004. Given their unusual socio-economic characteristics we excluded Alaska and Hawaii from our analysis, leaving us with 49 units.

We gathered data on personal health care expenditure at State level from the Centers of Medicaid and Medicare Services[4]. This aggregate, which represents the total amount spent to treat individuals, includes private funds, mainly

[2] Note that we compute an average of the Moran's I_t for each t.
[3] The mean and variance of I_t can be found in Kelejian and Prucha (2001).
[4] http://www.cms.hhs.gov/

private insurance and out-of-pockets payments, and public resources, for the majority composed by Medicare and public assistance (Medicaid)[5]. On aggregate, in the US, private funds represent the largest figure of total expenditure, though we observe that they have been decreasing over time, from 58 per cent in the 1980 to roughly 54 per cent as a proportion of total expenditure. We note that personal health care expenditure is measured by the States of the provider without distinguishing between local and cross-border beneficiaries of services.

We obtained data on disposable income and the State population from the Bureau of Economic Analysis[6]. Finally, as there is no US State level consumer price index (CPI), we constructed State level general price index, based on the CPI of the cities/areas[7], which are available from the Bureau of Labor Statistics[8]. We used this index to deflate health expenditure and income.

We begin our empirical investigation with a preliminary analysis on the spatial distribution and concentration of health expenditure and income across the 49 US States. In Table 2 we show the statistics (17)-(19) for the first differences of the logarithm of per-capita health expenditure and per-capita income. Results suggest the existence of cross section correlation among States of pervasive nature, which should be taken into consideration when studying income elasticity. At this stage we have not tested for spatial correlation in the data, something that we will do after controlling for long-range dependence arising from the common factor structure (see Section 5). However, in Table 3 we show the average correlation coefficients within and between the 8 Bureau of Economic Analysis (BEA) regions[9], which provides a subdivision of US states in larger units that are similar in terms of historical development, population characteristics, and economy. This should capture at descriptive level spatial concentrations of our variables across the territory. Looking at the values in the diagonal of Table 3, compared with the off-diagonal elements, we observe that for many regions the within region correlation is larger than the between region correlation. Such difference is more marked for income than for spending. For example, the States of the Mideast region are more correlated on average among themselves than with the States of South West, both for spending and income. The difference is more marked for income. This might suggest the presence of geographical concentration both in health expenditure and income, though with a more important role in the latter. We will explore these issues later in the paper.

[5] See Centers for Medicare & Medicaid Services, (2007) for a description of Medicare and Medicaid aggregates.

[6] http://bea.gov/

[7] In doing this, we followed the procedure outlined in Holly et al. (2007).

[8] http://www.bls.gov/

[9] See Table 1 for a list of the States belonging to BEA regions.

5 Empirical evidences

5.1 Non-stationarity of health expenditure and income

Table 4 reports the CIPS statistics for the logarithm of real per-capita health expenditure and real per-capita disposable income for the 49 US States over the years from 1980 to 2004 for the lag orders $p = 0, 1, 2, 3$. The inclusion of lags allow us to control for possible serial correlation in the data.

Health expenditure is non-stationary when including an intercept, as well as when adding an intercept and a linear trend in the CADF regression. The non-stationary nature of health care expenditure may be explained by the increase of disposable income, as well as changes in medical technology and treatment. As for income, the unit root hypothesis is rejected when an intercept only is included, while it cannot be rejected in the intercept and trend case, for any choice of p. Given the trended nature of our variables, these results lead us to conclude that health expenditure and disposable income are non-stationary. This empirical evidence is consistent with research on US data at a State level by Freeman (2003) and other works on national-level OECD data by Blomqvist and Carter (1997) and Gerdtham and Lothgren (2000).

In Table 5 we compute the cross section dependence statistics (17)-(19) on residuals from the CADF regressions, before and after having controlled for the common factor. Specifically, in panel (A) we base the CD statistics on residuals $\hat{u}_{it} = \Delta q_{it} - \hat{a}_i - \hat{b}_i q_{i,t-1} - \hat{c}_i t - \sum_{j=1}^{p} \hat{d}_{ij} \Delta q_{i,t-j}$, while in panel (B) we use residuals that have been defactored, namely $\hat{e}_{it} = \Delta q_{it} - \hat{a}_i - \hat{b}_i q_{i,t-1} - \hat{c}_i t - \sum_{j=1}^{p} \hat{d}_{ij} \Delta q_{i,t-j} - \hat{\mathbf{g}}_i' \bar{\mathbf{z}}_t$ where $\bar{\mathbf{z}}_t = (\bar{q}_{t-1}, \Delta\bar{q}_t, \Delta\bar{q}_{t-1}, ..., \Delta\bar{q}_{t-p})'$, (see equation (15)).

As we move from panel (A) to panel (B) all CD statistics report a sizeable reduction in the degree of cross section dependence, with the average pairwise correlation coefficient going from roughly 55 per cent for health spending (40 per cent for disposable income) to zero. It follows that the inclusion of cross section averages in the ADF regressions, as in (15), seems to capture well the cross section dependence present in the data. This may suggest that the CIPS panel unit root test can effectively deal with correlation across section. Panel (B) in Table 5 also reports the Moran's I test statistic on $\hat{e}_{it}$, to check whether there exists any residual spatial correlation after having controlled for the common factor. Results show a significant value for the Moran's I for disposable income and not for health care expenditure. This is in line with our preliminary exploratory statistics that suggested the presence of geographical concentration both in health expenditure and income, though more pronounced in the latter.

5.2 The income elasticity of health expenditure

We now turn our attention to the relationship between health expenditure and disposable income.

Table 6 reports the estimated income elasticity for each of the 49 States. It clearly emerges a wide variation in how health expenditure responds to income across territory. Though elasticity is above unity for six States, it is significantly larger than 1, indicating that health care is a luxury good, only for four States, namely Washington, Wisconsin, South Carolina and Florida. The majority of the States presents an income elasticity lower than one, confirming that health care is, overall, a necessity good. We note that three States, namely, Maine, North Dakota, and District of Columbia, display negative significant coefficients, while several other States show statistically insignificant coefficients. One reason behind these results might be that there exist unobserved cross border movements of recipients that alter the relationship between health spending and income at State level. This problem is more pronounced when estimating a State by State elasticity than when considering the average relation, since averaging is likely to cancel out the estimation error due to movements. Finally, we note that estimating coefficients States by States reduces the degrees of freedom, implying wider confidence intervals.

Our results differ from those in Wang and Rettenmeir (2006), who obtain an income elasticity between 0 and 1 in 16 States, and larger than 1 in 32 States. However, we note that when estimating elasticity, they do not allow for contemporaneous correlation[10], which might lead to erroneous conclusions. We further observe that they do not report the t-statistics and associated p-values for their estimates of income elasticity.

Table 7 reports results from the fixed effects (FE) estimation (column I), the CCE Mean Group (column II), and the CCE Pooled estimator (column III). From column I the coefficient on income is roughly 0.90. However, such estimator, ignoring the sizeable amount of cross section dependence in spending, is likely to be seriously biased. Our FE coefficient, though close to 1, is smaller than that obtained by Freeman (2003), which is roughly 1.30. We note that Freeman's study differs from ours in a number of characteristics that might explain (in part) the differences in the FE estimation. First, Freeman's analysis covers the time period from 1966 to 1998, which is different from ours. Further, in his study health care spending is missing in some years, and has been estimated via geometric interpolation, thus adding uncertainty on his results. Finally, while we use the State level CPI index as deflator of expenditure and income, Freeman adopts the national CPI.

When controlling for cross section dependence, the coefficient on income is significantly lower, 0.45 in the CCE Mean Group and 0.36 for the CCE Pooled estimator. Overall, our results show that growth in income boosts health expenditure. However, health expenditure rises less than proportionally, thus, supporting the hypothesis that health care is a necessity good. This is in line with Freeman (2003), who, by using a dynamic OLS approach, obtains an elasticity of 0.82. The relatively low income elasticity we obtain supports the idea that, while the ability to pay is a determinant of health care spending, the exis-

[10] They allow for cross section dependence only when testing for non-stationarity.

tence of publicly financed programmes such as Medicare and Medicaid weakens the link between disposable income and the standard of care.

Table 7 also reports the cross section dependence statistics (17)-(19) on residuals from the CCE regression, before and after having controlled for common factors. We observe the sizeable reduction of contemporaneous correlation when passing from panel (A) to panel (B). In panel (B), the average pairwise correlation coefficient and the CD_P test statistic indicate that there is no significant long-range cross section dependence left in the residuals, once controlled for common factors. On the contrary, the CD_{LM} points to the existence of significant cross section dependence in the residuals. One reason behind such difference might be that CD_{LM} is detecting some spatial correlation present in the data, an hypothesis that is supported by the significant value obtained for the Moran's I test. This issue will be explored in Section 5.5.

We conclude this section by checking how robust our estimated income elasticity is when controlling for other non-income determinants of health expenditure that have been identified by the literature (Karatzas, 2000; Hansen and King, 1996; Hitiris and Posnett, 1992). We have estimated by CCE Mean Group and by fixed effects four different specifications that include the following variables: percentage of people over 65 years old, numer of phisicians per 100,000 population, numer of beds per 100,000 population[11], and the share of public financed total health spending[12]. Table 8 shows that the CCE Mean Group estimation of income elasticity is robust to the introduction of other regressors, falling in the range 0.36-0.43. The FE estimator still remains close to one. We also report a not significant effect of people over 65 on health spending, and a negative relationship between proportion of public spending and total health expenditure. This latter result might indicate the importance of fostering public expenditure in reducing total health expenditure.

5.3 Cointegration analysis

The possibility of cointegration between health expenditure and disposable income is explored using a two-stages procedure, along the lines suggested by Pesaran *et al.* (2006), Chang (2005), and Bai and Kao (2006). In a first step we estimate the CCE Mean Group (CCE Pooled) estimator $\hat{\beta}$ and compute the residuals $\hat{u}_{it} = h_{it} - \hat{\beta} y_{it} - \hat{\alpha}_i$; while in the second stage we run the CIPS panel unit root tests to assess whether $\hat{u}_{it}$ is stationary. If results lead to a rejection of a unit root in $\hat{u}_{it}$, we can conclude that health spending and income are cointegrated. One advantage of this procedure is that we take into account contemporaneous correlation in both steps, rather than only in one step as in

[11] These data have been gathered from the Statistical Abstract of the United States.

[12] This variable has been computed as the ratio of Medicare and Medicaid spending over total health expenditure. Note that Medicare and Medicaid expenditures account for roughly 90% of public health spending.

Wang and Rettenmeir (2006). As a comparator, we also implement this two-stages procedure using the fixed effects estimator in the first step, which ignores cross section dependence.

As shown in Table 9, when using the FE estimator, we reject the unit root hypothesis in the residuals, for $p = 0, 1$. The use of the CCE Mean Group or Pooled estimators in the first step shows that residuals are stationary for $p = 0, 1, 2$, leading to a strongest evidence in favour of the existence of a long-run relationship between health spending and income. On the basis of these results we can conclude that health spending and income are cointegrated, hence, that the rise in health expenditure is sustained by movements in disposable income.

This conclusion conforms well to the of work of Freeman (2003), who, by using first generation panel unit root tests on OLS residuals, finds evidence of cointegration between expenditure and income. We note however that his procedure neglects the possibility that observations are correlated. Finally, our conclusions diverge from those in Wang and Rettenmeir (2006), who report weak evidence on the existence of cointegration in a State by State analysis. Their analysis is based on Maddala and Wu (1999) test applied to the residuals from an OLS regression where one structural break is permitted. To allow for dependent observations they compute the empirical distribution of their unit root tests via the bootstrap method. However, the approach used to compute the residuals does not allow for cross section dependence. Further, we remark that the properties of the bootstrap method applied to Maddala and Wu test have not yet been explored for the case of N larger than T, as in the study by Wang and Rettenmeir (2006).

5.4 Error correction model

Having established the existence of a cointegration relationship, we now turn to the estimation of the following error correction model

$$\Delta h_{it} = \alpha_i + \theta_i \left(h_{i,t-1} - \hat{\beta} y_{i,t-1} \right) + \vartheta_i \Delta h_{i,t-1} + \delta_i \Delta y_{it} + u_{it}, \qquad (21)$$

where in the parenthesis we have the previous period's cointegrating relation. Again we estimated the above model using 49 US States followed over 25 years. The coefficient θ_i measures the speed of adjustment of health care spending to a deviation from the long-run equilibrium relation between expenditure and disposable income. We first estimate (21) by fixed effects and then by CCE method, where factors are approximated by $\Delta\bar{h}_t, \Delta\bar{h}_{t-1}, \Delta\bar{y}_t$, and $\bar{h}_{t-1} - \hat{\beta}\bar{y}_{t-1}$, where $\hat{\beta}$ is the estimated income elasticity with either the fixed effects, the CCE Mean Group or the CCE Pooled estimator. Table 10 reports the results. For all estimators the coefficient of the error correction term has the expected, negative, sign. However, the fixed effects estimator reveals a speed of adjustment of -0.05, much lower than that assessed by the CCE, respectively -0.31 and -0.20 for the MG and Pooled estimators. The extremely low speed of adjustment of the fixed effects estimator might reflect some distortions due to the fact that it ignores cross the section dependence present in the data.

5.5 Estimating spatial correlation

We now focus on the estimation of the spatial coefficient in model (3). We aim at measuring the amount of spatial correlation due to unobserved spill overs, after adjusting for cross section dependence due to common factors. We consider the residuals $\hat{e}_{it} = h_{it} - \hat{\beta}_{MG} y_{it} - \hat{\mathbf{g}}_i' \bar{\mathbf{z}}_t$, where the common factors have been approximated by $\bar{\mathbf{z}}_t$, the cross section averages of h_{it} and y_{it}, and estimate

$$\hat{e}_{it} = \rho \bar{\hat{e}}_{it} + \varepsilon_{it}.$$

The above model has been estimated by maximum likelihood (Anselin, 1988).

We obtain a significant spatial coefficient $\hat{\rho}$ of 0.30, with a standard error of 0.035, yielding a z-value of 8.571. This result supports the existence of some unobservable risk factors geographically concentrated that affect health spending, or the presence of cross State borders movements of health services beneficiaries (Tiebout, 1956). This also conforms well with the empirical findings in Baicker (2005), who has found that individual State's medical spending has a significant and positive spill over effect on the spending of its neighbours. However, her study shows that each dollar of State spending causes spending in neighboring States to increase by almost 90 cents, a value which is much higher than that found in our analysis. Our smaller spatial coefficient might be explained by the fact that data have been purged by the effect of common shocks.

6 Concluding remarks

In this paper, using a panel of 49 US States followed over 25 years, we have investigated the non-stationarity and cointegration properties of health care expenditure and personal disposable income. We aimed at contributing to the existing debate on whether health care is a luxury or a necessity good. Recent work in this field has recognized that cross section dependence is an important feature of health care spending. However, we argue that correlation across sections has not yet been dealt with in a satisfactory manner. Hence, in this paper we discuss the possible sources of interdependence, namely, the existence of unobservable global shocks, and the presence of spill over effects. We then review the recently advanced CCE approach to study the non-stationarity and cointegration of health spending and income, assuming that cross section dependence is generated by a common factor structure and a spatial process.

Our panel unit root tests suggest that both variables are integrated and that they exhibit a long-run relation. The increase of disposable income and changes in technology and treatment are the likely explanation for the rising of health care expenditures. Further, we estimate an income elasticity below unity, suggesting that health is a necessity good. This evidence is supported by the estimate of both average and State by State elasticities. We remark that our estimated average elasticity is much lower than that detected in other studies at US State level. The relatively low coefficient for disposable income we obtain supports the hypothesis that, while the ability to pay is a determinant of health care spending, the existence of publicly financed programmes such as Medicare and Medicaid weakens the link between income and the standard of care. In our empirical analysis, we have also estimated the amount of spatial correlation in the data, after having controlled for common factors. Results indicate the presence of a significant spatial spill over, though smaller than that identified in other studies.

In conclusion, our analysis points out the existence of global and local forms of cross section dependence in health spending and income, that, if not taken into account in the study of health expenditure, are likely to provide policy makers with misleading results. It would be interesting to use this approach to analyse health spending for the OECD countries, to see if the same conclusions hold in the case of a group of heterogenous, cross sectionally dependent countries.

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Table 1: Grouping of States in BEA Regions[A]

Region	States
New England (NENG)	Connecticut,Maine,Massachusetts New Hampshire,Rhode Island,Vermont
Mideast (MEST)	Delaware,District of Columbia,Maryland New Jersey,New York,Pennsylvania
Southeast (SEST)	Alabama,Arkansas,Florida,Georgia,Kentucky Louisiana,Mississippi,North Carolina South Carolina,Tennessee,Virginia,West Virginia
Great Lake (GLAK)	Illinois,Indiana,Michigan,Ohio,Wisconsin
Plains (PLNS)	Iowa,Kansas,Minnesota,Missouri Nebraska,North Dakota,South Dakota
Southwest (SWST)	Arizona,New Mexico,Oklahoma,Texas
Rocky Mountain (RKMT)	Colorado,Idaho,Montana,Utah,Wyoming
Far West (FWST)	Alaska,California,Hawaii,Nevada,Oregon,Washington

[A]: Source: Bureau of Economic Analysis.

Table 2: Cross section dependence in the first differences of the logarithm of real per-capita health expenditure and of the logarithm of real per-capita disposable income.

	$\overline{\rho}$	CD_P	CD_{LM}
Δh_{it}	0.851	142.98	399.64
Δy_{it}	0.621	104.30	221.36

Notes: $\overline{\rho}$, CD_P,CD_{LM} are computed as in (17),(18) and (19), respectively.

Table 3: Average of pairwise correlation coefficients within and between BEA regions of first differences of log of real health expenditure and of log of real per-capita disposable income

	NENG	MEST	SEST	GLAK	PLNS	SWST	RKMT	FWST
	Health expenditure							
NENG	0.869							
MEST	0.871	0.894						
SEST	0.862	0.884	0.900					
GLAK	0.858	0.882	0.890	0.888				
PLNS	0.824	0.844	0.870	0.866	0.861			
SWST	0.801	0.841	0.851	0.834	0.822	0.825		
RKMT	0.806	0.840	0.860	0.844	0.835	0.839	0.862	
FWST	0.795	0.823	0.809	0.815	0.806	0.788	0.809	0.825
	Disposable income							
NENG	0.850							
MEST	0.738	0.762						
SEST	0.668	0.713	0.750					
GLAK	0.739	0.700	0.765	0.845				
PLNS	0.492	0.517	0.619	0.644	0.654			
SWST	0.515	0.594	0.627	0.623	0.513	0.509		
RKMT	0.374	0.539	0.543	0.514	0.453	0.551	0.549	
FWST	0.618	0.644	0.621	0.658	0.494	0.575	0.511	0.697

Notes: See Table 1 for definition of regions. The figures are average of sample pairwise correlation coefficients (see notes to Table 2).

Table 4: CIPS panel unit roots tests

	CADF(0)	CADF(1)	CADF(2)	CADF(3)
	With an intercept only			
h_{it}	-1.761	-1.978	-1.941	-1.828
y_{it}	-2.167*	-2.337*	-2.348*	-2.159*
	With an intercept and trend			
h_{it}	-2.353	-2.548	-2.374	-2.319
y_{it}	-2.117	-2.349	-2.485	-2.238

Notes: The 5% critical value for the intercept only case is -2.11; the 5% critical value for the intercept and trend case is -2.62. The superscript "*" indicates that the test is significant at the 5% level.

Table 5: Cross section dependence in residuals from CADF regression

	CADF(0)	CADF(1)	CADF(2)	CADF(3)
(A): Use of $\hat{u}_{it}$				
	$\bar{\rho}$			
h_{it}	0.555	0.550	0.530	0.571
y_{it}	0.406	0.390	0.352	0.294
	CD_P			
h_{it}	87.151	86.376	83.250	89.808
y_{it}	63.729	61.241	55.381	46.215
	CD_{LM}			
h_{it}	157.388	155.520	155.758	168.132
y_{it}	91.698	88.010	82.715	71.475
(B): Use of $\hat{e}_{it}$				
	$\bar{\rho}$			
h_{it}	-0.019	-0.019	-0.017	-0.015
y_{it}	-0.000	0.004	0.008	0.023
	CD_P			
h_{it}	-3.021	-3.008	-2.703	-2.402
y_{it}	-0.018	0.606	1.211	3.615
	CD_{LM}			
h_{it}	10.649	11.593	12.196	16.748
y_{it}	19.666	18.255	18.691	19.843
	$Moran$			
h_{it}	1.323	1.329	1.089	1.214
y_{it}	2.470	2.436	2.160	1.503

(A): The CD statistics are computed on $\hat{u}_{it}= \Delta q_{it}-\hat{a}_i-\hat{b}_i q_{i,t-1}-\hat{c}_i t$ for CADF(0) and on $\hat{u}_{it}= \Delta q_{it}-\hat{a}_i-\hat{b}_i q_{i,t-1}-\hat{c}_i t-\sum_{j=1}^{p}\hat{d}_{ij}\Delta q_{i,t-j}$ for CADF(p), with p=1,2,3.

(B): The CD statistics are computed on $\hat{e}_{it}= \Delta q_{it} - \hat{a}_i - \hat{b}_i q_{i,t-1} - \hat{c}_i t-\hat{\mathbf{g}}_i'\bar{\mathbf{z}}_t$ for CADF(0) and on $\hat{e}_{it}= \Delta q_{it} - \hat{a}_i - \hat{b}_i q_{i,t-1} - \hat{c}_i t - \sum_{j=1}^{p}\hat{d}_{ij}\Delta q_{i,t-j}-\hat{\mathbf{g}}_i'\bar{\mathbf{z}}_t$ for CADF(p), with p=1,2,3, where $\bar{z}_t= (\bar{q}_{t-1}, \Delta\bar{q}_t, \Delta\bar{q}_{t-1}, ..., \Delta\bar{q}_{t-p})'$, q_{it} being h_{it} or y_{it}

We report $Moran =\frac{I-E(I)}{std(I)}$, where I is given by (20).

Table 6: CCE estimate of the coefficients by State

State	Coeff.	Std. err.	State	Coeff.	Std. err.
Washington	1.514*	0.263	Ohio	-0.021	0.184
Montana	0.512*	0.140	Illinois	-0.168	0.377
Maine	-0.926*	0.353	District of Columbia	-0.689*	0.311
North Dakota	-0.125*	0.039	Delaware	0.053	0.212
South Dakota	0.765*	0.309	West Virginia	0.781*	0.132
Wyoming	0.347*	0.046	Maryland	0.157	0.142
Wisconsin	1.311*	0.141	Colorado	0.348	0.462
Idaho	0.185	0.105	Kentucky	1.304*	0.280
Vermont	-0.258	0.722	Kansas	0.653	0.450
Minnesota	0.244	0.248	Virginia	0.264	0.184
Oregon	0.386	0.259	Missouri	0.252	0.290
New Hampshire	0.793*	0.166	Arizona	-0.199	0.381
Iowa	0.588*	0.289	Oklahoma	0.730*	0.140
Massachusetts	0.366*	0.056	North Carolina	0.245	0.334
Nebraska	0.145	0.454	Tennessee	0.615*	0.118
New York	-0.103	0.092	Texas	0.187	0.139
Pennsylvania	0.688*	0.163	New Mexico	0.950*	0.377
Connecticut	1.137*	0.171	Alabama	0.933*	0.134
Rhode Island	0.344	0.238	Mississippi	1.002*	0.493
New Jersey	0.804*	0.346	Georgia	1.145*	0.394
Indiana	0.110	0.133	South Carolina	1.744*	0.350
Nevada	0.019	0.190	Arkansas	-0.126	0.183
Utah	0.804*	0.701	Louisiana	-0.238	0.249
California	0.116	0.253	Florida	1.429*	0.181
			Michigan	0.856*	0.192
Average slope	0.448*	0.080			

Notes: The individual coefficients have been computed according to formula (9), and their variance as in (**??**). The superscript "*" means that the coefficient is significant at 5% level.

Table 7: Estimation results: income elasticity of health expenditure

	Fixed Effects$^{(+)}$		CCE Mean Group		CCE Pooled	
	Coeff.	Std.err.	Coeff.	Std.err.	Coeff.	Std.err.
y	0.908^{*}	0.033	0.448^{*}	0.080	0.363^{*}	0.097
CD statistics						
(A): Use of $\hat{u}_{it}$						
$\overline{\rho}$			0.814		0.826	
CD_P			139.505		141.607	
CD_{LM}			380.972		392.515	
(B): Use of $\hat{e}_{it}$						
$\overline{\rho}$	-		-0.019		-0.020	
CD_P	-		-3.273		-3.336	
CD_{LM}	-		21.305		21.049	
$Moran$	-		4.754		4.706	

Notes: $^{(+)}$: time dummies were included. The superscript "*" indicates that the coefficient is significant at the 5% level.
(A): The CD statistics are computed on $\hat{u}_{it}= h_{it}-\hat{\alpha}_i-\hat{\beta}y_{it}$,
(B): The CD statistics are computed on $\hat{e}_{it}= h_{it}-\hat{\alpha}_i-\hat{\beta}y_{it}-\hat{\mathbf{g}}_i'\bar{\mathbf{z}}_t$
where $\bar{\mathbf{z}}_t= \left(\bar{h}_t, \bar{y}_t\right)'$. For the Moran statistic see the notes to Table 5.

Table 8: Income elasticity of health expenditure, controlling for other regressors

	Fixed Effects$^{(+)}$		CCE MG		Fixed Effects$^{(+)}$		CCE MG		Fixed Effects$^{(+)}$		CCE MG	
	Coeff.	Std.err.	Coeff.	Std.err.	Coeff.	Std.err.	Coeff.	Std.err.	Coeff.	Std.err.	Coeff.	Std.err.
y	0.7698*	0.0419	0.3645*	0.0685	0.9683*	0.0416	0.4385*	0.0577	0.9612*	0.0397	0.4246*	0.0596
% over 65	0.3405*	0.0421	0.1444	0.1262	0.7297*	0.0435	0.0576	0.0847	0.5598*	0.0443	0.0057	0.0957
n. doctor	-		-		0.9669*	0.0345	0.0823	0.0738	0.8933*	0.0336	0.0653	0.0771
n. beds	-		-		-0.0659*	0.0131	0.0718*	0.0317	-0.0410	0.0127	0.0375	0.0363
% public exp.	-								0.2148*	0.0199	-0.1082*	0.0347

Notes: $^{(+)}$: time dummies were included. The superscript "*" indicates that the coefficient is significant at the 5% level.

Table 9: CIPS panel unit roots tests on residuals from CCE estimation (intercept only case)

	CADF(0)	CADF(1)	CADF(2)	CADF(3)
	Fixed Effects			
$\hat{u}_{it}$	-2.496*	-2.639*	-2.081	-1.594
	CCE Mean Group			
$\hat{u}_{it}$	-2.210*	-2.175*	-2.121*	-1.827
	CCE Pooled			
$\hat{u}_{it}$	-2.225*	-2.174*	-2.130*	-1.999

Notes: Residual from CCE Mean Group estimation in Table 7. Critical value for the intercept only case -2.11. The superscript "*" indicates that the test is significant a the 5% level.

Table 10: Error correction model

	Fixed Effects$^{(+)}$		CCE Mean Group		CCE Pooled	
	Coeff.	Std.err.	Coeff.	Std.err.	Coeff.	Std.err.
$h_{i,t-1} - \widehat{\beta} y_{i,t-1}$	-0.004*	0.002	-0.3031*	0.033	-0.205*	0.048
$\Delta h_{i,t-1}$	0.008	0.029	0.002	0.034	-0.019	0.035
Δy_{it}	0.261*	0.030	0.396*	0.046	0.307*	0.069
	CD statistics					
	(A): Use of $\hat{u}_{it}$					
ρ	-		0.9175		0.853	
CD_P	-		147.583		137.149	
CD_{LM}	-		427.515		369.283	
	(B): Use of $\hat{e}_{it}$					
ρ	-		-0.019		-0.020	
CD_P	-		-3.112		-3.164	
CD_{LM}	-		18.771		13.697	
$Moran$	-		3.772		3.698	

Notes: the superscript "*" indicates that the coefficient is significant at the 5% level.
$^{(+)}$: time dummies were included.

(A): The CD statistics are computed on $\hat{u}_{it} = \Delta h_{it} - \hat{\alpha}_i - \hat{\theta}\left(h_{it} - \widehat{\beta} y_{it}\right) - \hat{\vartheta}\Delta h_{i,t-1} - \hat{\delta}\Delta y_{i,t-1}$,

(B): The CD statistics are computed on $\hat{e}_{it} = \Delta h_{it} - \hat{\alpha}_i - \hat{\theta}\left(h_{it} - \widehat{\beta} y_{it}\right) - \hat{\vartheta}\Delta h_{i,t-1} - \hat{\delta}\Delta y_{i,t-1} - \hat{\mathbf{g}}_i' \bar{\mathbf{z}}_t$

where $\bar{\mathbf{z}}_t = \left(\Delta \bar{h}_t, \bar{h}_{t-1} - \widehat{\beta}\bar{y}_{t-1}, \Delta \bar{h}_{t-1}, \Delta \bar{y}_{t-1}\right)'$. For the Moran statistic see the notes to Table 5.