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What drives Health Care Expenditure in France since 1950?[1]

A time-series study with structural breaks and non-linearity approaches

Thomas Barnay[2] (Université Paris-Est Créteil, Erudite, TEPP)
and Olivier Damette[3] (Université Paris-Est Créteil, Erudite)

Abstract

Using the French annual database (1950-2009), we conducted a time-series analysis to explain the role of GDP per capita on HCE (Health Care Expenditure) per capita taking into account structural breaks and non-linearity in the long-term economic relationship between HCE and GDP, controlling for price effect, population ageing, innovation proxy and medical density. We show that the non-linearity of the long-run relationship between HCE and GDP comes from both the presence of a structural break and non-linearity explained by a transition variable (by constructing a smooth transition cointegrating regression). More precisely, lower GDP elasticity is explained by an exogenous shock linked to health system policies in the mid 1980's (break analysis) and endogenously driven changes in the health care system *via* medical density in France.

JEL codes: C22, E23, I12, I18

Introduction

With the emergence of the government debt crisis and the consequent challenges facing the Welfare State, analysts are attempting to gain a better understanding of the dynamics of social spending. Securing good health for the whole population is a concern shared by all OECD countries. Health Care Expenditure (HCE) has risen steadily in OECD countries and has been subject to increasing attention in political and scientific debates. HCE as a share of GDP (Gross Domestic Product) varies significantly across countries, reaching an average 8.8% in 2008. The 11.2% share of GDP dedicated to health in France is one of the highest in the world, behind the USA with 16.2%.

Due to weak data, France suffers from a lack of macroeconomic studies able to analyze the determinants of HCE. More specifically, there is a need to understand how various health system reforms and the economic crisis have affected HCE growth in France, taking into account non-stationarity and cointegration (co-movement over the long run) properties between time series. Indeed, recent empirical literature has investigated these classic problems by controlling for structural breaks (co-movement over the short run) and cross-section dependence. For example, Jewell *et al.* (2003) and Carrion-i- Silvestre (2005)

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[2] UPEC, Erudite, TEPP (FR n°3126 – CNRS), 61, avenue du Général de Gaulle - Route de Choisy, Mail des mèches, 94000 Créteil, France. Contact : barnay@u-pec.fr
[3] UPEC, Erudite, 61, avenue du Général de Gaulle - Route de Choisy, Mail des mèches, 94000 Créteil, France. *Corresponding author.* Contact : damette@u-pec.fr

conclude that HCE and GDP are stationary around at least one structural break. Similarly, Narayan and Narayan (2008) advise extending research to the identification of turning points in GDP and HCE time series.

For the first time using French data, we attempt to explain the role of GDP per capita on HCE per capita taking into account the possibility of structural breaks and non-linearity in the long-run economic relationship between HCE and GDP, controlling for price effect, population ageing, innovation proxy and medical density. HCE was determined from annual medical care consumption data for the period 1950-2009 using the 2011 French Health Databases managed by the Institute for Research and Information in Health Economics (IRDES). The paper is organized as follows: section 1 presents a brief review of literature and the specificities of the French Health System, section 2 investigates empirical issues using cointegration analysis, section 3 tests for structural breaks in the cointegrating vector, section 4 deals with the relationships between HCE and GDP using a CSTR (Cointegration Smooth Threshold Regression) non-linear approach and the final section concludes the paper.

Section 1: Brief overview of the literature and the specificities of the French Health System

HCE, particularly in OECD countries, has provided an extensive and varied body of empirical literature (subsection1.1). Many studies have investigated the determinants of HCE, notably income. The French case has not benefited from this field of research notably due to weak data (subsection 1.2).

1.1. HCE Determinants

The literature shows that the macroeconomic determinants of HCE include income effect (Newhouse, 1977), technology (Newhouse, 1992), demographic and epidemiological changes (Culyer, A.J., 1988; Zweifel *et al.*, 1999), price effect (Baumol, 1967), induced demand (Evans, 1974; Fuchs, 1978) and institutional factors (health system reforms, provider payment mechanisms, out of pocket payments (Hitiris, T., Posnett, J., 1992). These determinants have not, however, received equal attention in international studies.

The most robust determinant of HCE is GDP. Following the seminal work of Newhouse (1977), most studies investigate the long-run economic relationship between HCE and income using a panel approach (McCoskey and Selden, 1998; Roberts, 1999; Gerdtham and Lothgren, 2000; Okunade and Karakus, 2001; Jewell et al., 2003; Carrion-i-Silvestre, 2005; Dregen and Reimers, 2005; Freeman, 2003; Wang and Rettenmeier, 2006; Chou, 2007). Some studies examine the stationarity and cointegration properties of HCE (MacDonald and Hopkins, 2002; McCoskey and Selden, 1998; Hitiris, 1997; Jewell et al., 2003; Narayan, 2006). Newhouse showed income elasticity to be significantly greater than unity (1.35), GDP per capita explaining 92% of variations in HCE. Considering the short time dimension of the HCE variable, most studies have conducted non stationary panel tests since the middle of the 2000’s to improve the power of the stationarity and cointegration tests. Recent works particularly insist on cross-section dependence which appears as an important characteristic of health data (Jewell *et al.*, 2003; Freeman, 2003; Carrion-i-Silvestre, 2005; Wang and Rettenmaier, 2006; Chou, 2007). For example, using a panel of 20 OECD countries over a period of 34 years, Baltagi and Moscone (2010) show that health care is a necessity rather than a luxury good, after controlling for cross-country dependence and unobserved heterogeneity. Using a panel of 49 US States over a period of 25 years, Moscone and Tosetti (2010), study the same relationship but cross-section dependence is incorporated in the models using an approximate multifactor structure (Bai and Ng, 2004). More precisely, they adopted a bootstrap method called the Continuous-Path Block Bootstrap (CBB) proposed by Paparoditis and Politis (2001, 2003), and recently used by Fachin (2007) to test for panel co-integration in the presence of cross-section dependence. They find that income elasticity ranges between 0.35 and 0.46. This result is confirmed for the USA by Freeman (2003) with income elasticity equal to 0.82 (using a dynamic OLS approach). Herwatz and Theilen (2010) add nuance to the debate on the nature of health care as a good. They show that, on average, health care is a necessity good in the presence of a relatively young population but seems to become a luxury good in aging economies.

Since Newhouse (1992), technology is also considered as an important driver of HCE. However, it appears very difficult to use an appropriate proxy for changes in medical care technology. This is why several proxies are used such as surgical procedures and specific surgical equipment (Baker and Wheeler, 2000; Weil, 1995), health care R&D spending (Okunade and Murthy, 2002), life expectancy and infant mortality (Dregen and Reimers, 2005) or a time index (Gerdtham and Lothgren, 2000).

Moreover, in what way do demographic or epidemiological changes contribute to HCE growth? Even if the simple correlation between age and HCE appears clear, the relationship becomes less obvious when the contribution of other explanatory factors is taken into account. The relevance of age as an explanatory factor of health expenditure has been discussed by Zweifel *et al.*, (1999) with the conclusion that age is not a stable explanatory variable for HCE since morbidity and mortality vary over time. It is then shown that age has less impact on HCE when health status and "time to death" is taken into account (Yang, Norton *et al.*, 2003, Seshamini and Gray, 2004).

Moreover since Baumol's theory (1967), we know that health sector productivity is low relative to other sectors causing inflation in health spending. However, there is no empirical consensus on the effect of real prices on HCE. Hartwig (2008) and Okunade *et al.* (2004) find a positive and statistically significant effect, whilst Gerdtham *et al.* (1992) and Murthy and Ukpolo (1994) report an insignificant effect. This determinant appears difficult to study particularly in countries where public health expenditures are high.

Arrow's seminal paper (1963) emphasized that unequal information between the health care consumer and the provider is recognized as a key feature of market failure. Supplier induced demand is then defined as the difference between physician-initiated medical services and those that patients would have chosen if they had benefited from the same information as the physician (Rice, 1983). This assumption is plausible when the principle method of physician payment is fee-for-service which is the case in France.

1.2. What about French studies?

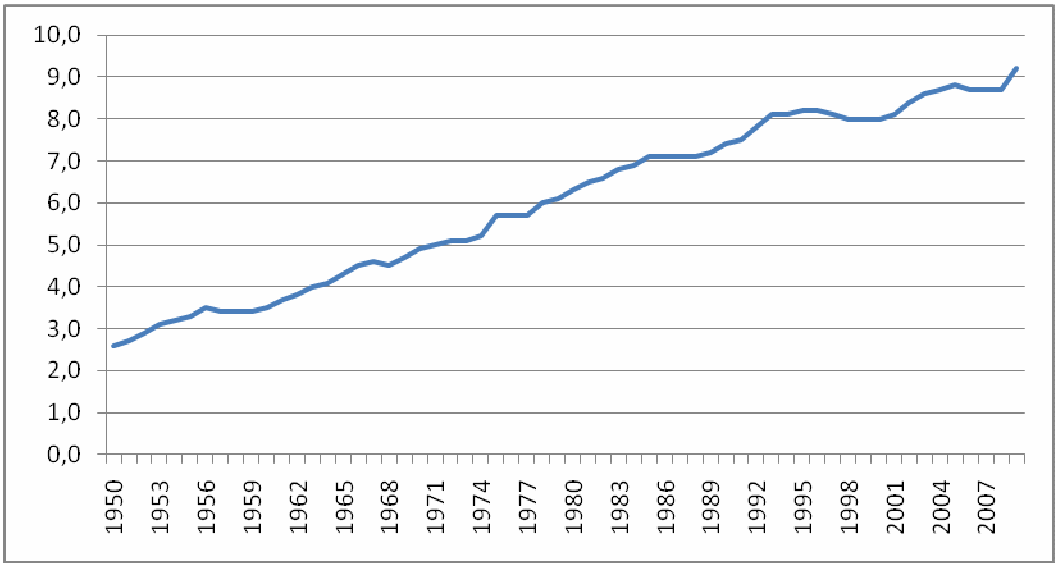
Firstly, in a large majority of comparative studies based on a panel of OCDE countries, France is not retained in the sample. Only French authors have attempted to integrate France in their comparative studies (Mahieu, 2000; Bac and Cornilleau, 2002, Bac, 2004). This can be explained by the lack of long time series data in the French National Health Expenditure index permitting cross-country comparison (according to OECD standards). Moreover, the only studies based on French data are characterized by their small sample size and their failure to use all the appropriate econometric methods to take into account the stationarity and cointegration properties of HCE. These studies also ignore the potential presence of structural breaks and cross-section dependence.

However, we can draw some lessons from the few published studies. The L'Horty *et al.* (1997) study on the 1960-1995 period attempts to explain HCE per capita using Error Correction Models (ECM). After controlling for price effect and introducing linear trend (proxy for the technology effect), they find that health is a necessity good. They conclude that increases in income would explain 50% of HCE growth since 1960. Missegue and Pereira (2005) and Mahieu (2000) corroborate this result (respectively 0.93 and 0.76). Concerning the determinants of HCE, Azizi and Pereira (2005) estimated that between 1970 and 1979 population ageing was annually responsible for 0.82% of spending growth with 0.65 points due to population increase and 0.17 points due to changes in age structure. Dormont *et al.* (2006) found that between 1992 and 2000, demographic changes were responsible for a 0.92% annual increase in spending. Their results showed that the impact of changes in medical practice (including generation and technical progress effects) was 3.8 times higher than for demographic change. Following on the work of Albouy *et al.* (2009), several studies attempt to estimate the relative price elasticity of care supply. The results suggest an elasticity which ranges from -0.6 to -1.0 (Murillo, 1993; L'Horty *et al.*, 1997). The causal interpretation of the volume-price elasticity of care is not a trivial procedure. A demand effect (higher prices result in a lower demand for care) is arguable. In France, due to extensive insurance coverage and the third-party payment mechanism, patients are relatively insensitive to price changes. The existence of a "compensation mechanism" on the supply side cannot be excluded. A decrease in price can cause increase in quantity demand, if physicians want to increase their income and induce demand for extra care.

1.3. The French Health Care System

The French public health care system covers over 99% of the population, independently of age or other socio-economic conditions. HCE reimbursement levels vary considerably according to expenditure item. Over 90% of hospital care expenditures (45% of HCE) are covered by the Social Security whilst ambulatory care, including private practice consultations, is reimbursed at a rate of about 65%. In addition, 93% of the population benefits from complementary health insurance coverage. The French health care system is driven by a regulatory mechanism; health care service volume and price is strictly controlled thereby influencing the rate and structure of HCE growth. Since the 1996 Juppé Law, the Social Security Funding Act and the allocation of a national ceiling for health insurance expenditure (ONDAM) have been set up to act as macroeconomic regulation tools. Upstream, the number of physicians is regulated by quota (*numerus clausus*) restricting the number entries into second year medical studies. The cost of healthcare is also controlled by specific mechanisms depending on the nature of the care provided. This can be illustrated using two examples. The cost of general practice consultations depends on the fee schedule, divided into a regulated (sector 1) and non-regulated (sector 2) payment system. For the 75% of sector 1 GPs, consultation fees are fixed at 23 Euros by the national health system, whereas non-regulated practitioners dependent on sector 2 (established in 1980 and almost abandoned in 1990) are free to set their own fees. In addition, pharmaceutical drug prices are set by agreement between the pharmaceutical industry and the Economic Committee for Health Products. They partly reflect the actual benefits and improvements to the therapeutic arsenal. These specificities not only have an influence on HCE but also on relationship between HCE and GDP. In France HCE has risen steadily since 1950. Over the past 20 years, the rate of increase has, however, decelerated significantly. The share of HCE in GDP, which rose from 3.3% in 1955 to 7.1% in 1985, further increased to 8.7% in 2008. Since the early 80's, the increase in HCE was driven by volume, even if "peak" price increases were recorded (around 3%) in the years 1988-1989 and 2002-2003, in line with the increase in the payroll-related hospital 35 hours and significant revaluations of medical fees.

Chart 1: Share of HCE in GDP – 1950-2009



Section 2: A linear cointegration analysis of HCE/GDP cointegration elasticity

First, we study the elasticity between GDP per capita and HCE per capita using a linear approach taking a number of factors into account. Table 1 presents the Institute for Research and Information in Health Economics (IRDES) data used in this study. The HCE index is based on medical care consumption data from the French national accounts (available since 1950) rather than the National Health Expenditures used in international comparative studies. We introduce several types of explanatory variable on the basis of previous studies. In order to measure price elasticity, we used the nominal price index deflated by the price index for household consumption. We introduce medical density to take into account induced demand as increased physician density lowers the average rate of personal profit and may lead the physician to create unnecessary demand. To account for technical progress we introduce an intermediate input proxy giving the cost impact of innovation (global expenditure in pharmaceutical research) and an output proxy allowing us to measure the benefits of innovation on health status *via* infant mortality rates and life expectancy at 60.

Table 1: Database

Variables	Definition	Availability	Mean	Min	Max
Health Care Expenditure per capita	Medical Care Consumption per capita (deflated € Million – Base 2000)	1950-2009	1 055.0	117.0	2 424.0
Gross Domestic Product per capita	Gross Domestic Product (deflated € Million – Base 2005)	1950-2009	17 654.4	6 260.0	28 233.0
Health Price	Deflated relative health price (Base 100 - 1950)	1950-2005	99.4	88.6	111.9
Population over 65	65+ / total population (%)	1950-2009	13.6%	11.4%	16.8%
Medical Density	Medical density per 100 000 people (Office based practitioners)	1961-2009	148.6	67.5	196.8
Social Security coverage	Share of HCE reimbursed by Social Security (%)	1950-2009	70.9%	51.0%	80.0%
Pharmaceutical research	Global expenditure in pharmaceutical research (deflated € Million - Base 2000)	1965-2007	1 997.3	160.8	4 917.4
Life expectancy	Life expectancy at 60 (male population)	1950-2009	17.8	14.9	22.2
Infant mortality	Infant mortality ratio (per 100 000)	1950-2009	15.9	3.6	51.9

Source: Eco-Santé, Institute for Research and Information in Health Economics

A simple model is as follows:

$$\ln HCE = \alpha_0 + \alpha_1 \ln GDP + Z_t + u_t \quad (1)$$

Where α_0 is a constant term, α_1 represents elasticity and Z_t is a vector of control variables. This vector varies according to the selected model (see table 4) and can incorporate a linear trend, the population over 65, relative health cost and other determinants such as medical density, social security coverage, pharmaceutical research and health indicators (table 1).

2.1 Testing linear cointegration relationship

In a first step, we compute usual unit root tests (Augmented Dickey Fuller, DF-GLS and KPSS) to determine the order of integration for GDP and HCE time series. If both series are integrated in the same order, we then have to test the possibility of cointegration between HCE and GDP. We assume that other variables are excluded from the cointegration vector (see table 2).

Table 2: Usual Unit root tests

Test	**Variables**	**Lags *k***	**Stat**	**Tabulated value (1%)**
ADF	lnHCE	0	-0.27	-4.12
	lnGDP	0	0.27	
KPSS	lnHCE	-	0.25	0.22
	lnGDP	-	0.25	
DF-GLS	lnHCE	9	-3.91	-3.77
	lnGDP	1	0.09	-3.74

Since both series are clearly integrated I(1), considering table 2, we test the possibility of a cointegrating relationship using the Johansen procedure (1988, 1991). Testing a cointegrating relationship is equivalent to showing that the vector of residuals u_t is stationary. There are two main approaches for testing cointegration and then estimating the long-run model (x): the single equation approach and the multivariate VAR approach. The oldest single equation approach is the Engle and Granger two-step method (1987) which consists in testing the stationarity of OLS regression and then using OLS to obtain a cointegrating vector (or a long-run estimate). The Johansen (1988, 1991) procedure is a multivariate VAR approach. This method allows testing the possibility of multiple cointegrating relationships between the series. In this case, the Engle and Granger and Johansen methods are equivalent because only two series may be cointegrated (thus, there is only one potential cointegrating vector).

The Johansen methodology (see table 3 results of the Trace and Eigen value tests) reveals a clear cointegrating relationship between HCE and GDP per capita with or without supplement trend (except when the trend is quadratic specified). All in all, it indicates a clear-cut equilibrium in the relationship between the two series.

Table 3: Cointegration tests in a bivariate system

	Eigenvalue	Hypothesis	Alternative Hypothesis	Statistics (Prob)
Trace test	0.445	r=0	r=1	37.80 (0.00)
	0.060	r=1	r=2	3.60 (0.06)
Eigen Value test	0.445	r=0	r=1	14.26 (0.00)
	0.060	r=1	r=2	3.84 (0.06)

The table 3 gives evidence of the existence of a cointegrating relationship when a linear deterministic trend is considered. The other results of Eigen Value and Trace tests (not reproduced here to save place), leads to rejecting the null of no cointegration except in the case of a quadratic trend. In the following models therefore, quadratic trend is not integrated (contrary to Pereira and Missegue's study). It is quite possible that this trend reflects the extension of the French populations' health insurance coverage in the first part of the period (1950-1980) followed by deceleration thereby explaining a major part of the relationship between GDP and HCE.

2.2 Model Estimation

In the first phase, we estimate the model (1) by OLS. Indeed, OLS provides super consistent estimates when the data seems to support the assumption of a single cointegration vector. However, we have to assume that all regressors are exogenous. An estimation method taking into account the possible endogeneity of the regressors, and improving the Engle and Granger single equation approach is thus needed. We choose to provide a step-by-step method of specification in order to better understand the role of different variables on GDP elasticity. We then test various specifications.

Table 4: OLS estimates

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-5.38	-5.06	-4.54	-5.30	5.00	-1.93
LnGDP per capita	**1.80**	**1.61**	**1.48**	**1.42**	**0.39**	**1.14**
LnPrice	-1.18	-0.90	-0.61	-0.42	-0.95	-0.64
Linear Trend		0.01	0.02	0.01	0.02	
Population over 65			-6.52	-3.46	-0.58	
Medical Density				0.00	0.00	0.00
Social Security					1.90	
Pharmaceutical research						-0.02
Life expectancy at 60 (men)						0.02
Period	*1950-2009*	*1950-2009*	*1950-2009*	*1961-2009*	*1961-2009*	*1965-2007*

Variable	(7)	(8)	(9)	(10)	(11)
Constant	2.31	-1.33	-0.48	-0.14	-2.34
LnGDP per capita	**1.24**	**1.56**	**1.33**	**0.72**	**1.24**
LnPrice	-1.71	-1.46	-1.35	-0.65	-0.73
Linear Trend					
Population over 65	2.63	0.41			0.99
Medical Density				0.00	0.00
Social Security		-0.52		1.58	-0.06
Pharmaceutical research	-0.01	-0.01	-0.01	-0.01	-0.01
Life expectancy at 60 (men)			0.03	0.08	
Period	*1965-2007*	*1965-2007*	*1965-2007*	*1965-2007*	*1965-2007*

We thus performed the DOLS method proposed by Saikkonen (1991) and Stock and Watson (1993) *via* a dynamic OLS (DOLS) regression. Indeed, in a small sample, the DOLS estimator is more precise, as it has a smaller mean squared-error than the MLE (see Stock and Watson, 1993).

Table 5: DOLS estimates

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-5.67***	-5.64***	-5.64***	-7.44***	0.73	-8.82***
LnGDP per capita	**1.85*** **	**1.83*** **	**1.83*** **	**1.60*** **	**0.79*** **	**1.89*** **
LnPrice	-1.23***	-1.20***	-1.20	-0.36	-0.67***	-0.64***
Linear Trend		0.00	0.00	0.01	0.02***	
Population over 65			-0.06	-1.41*	-2.78***	
Medical Density				0.00***	0.00***	0.00***
Social Security					0.98***	
Pharmaceutical research						0.01*
Life expectancy at 60 (men)[4]						-0.00
Period	*1950-2009*	*1950-2009*	*1950-2009*	*1961-2009*	*1961-2009*	*1965-2007*

Variable	(7)	(8)	(9)	(10)	(11)
Constant	-12.71***	-10.72***	-10.95	-6.95***	-8.75***
LnGDP per capita	**2.41*** **	**2.27*** **	**2.39*** **	**1.63*** **	**1.84*** **
LnPrice	-0.89***	-1.11***	-1.20	-0.85***	-0.70**
Linear Trend					

[4] We try to introduce infant mortality but this variable doesn't explain HCE so we only keep life expectancy at 60.

Population over 65	-1.40**	-0.39			0.49
Medical Density				0.00***	0.00***
Social Security		0.36*		0.87***	0.34
Pharmaceutical research	0.02***	0.02***	0.02***	0.01***	0.02**
Life expectancy at 60 (men)			-0.02***	0.03***	
Period	*1965-2007*	*1965-2007*	*1965-2007*	*1965-2007*	*1965-2007*

Determinants of HCE are analyzed from several explanatory models. Since 1950, the relationship between HCE per capita and GDP per capita is obvious and strongly significant. According to the specification used, HCE always appears as a luxury good (with elasticity ranging between 1.6 to 2.4) except for model 5 (with social security coverage). The price elasticity of health spending is significantly negative (from -1.9 to -0.4). The decrease in the relative price of health observed in France is mainly due to drug prices. It contributes to the growth of health spending notably through a supply effect (price regulation may lead to increased volumes). The period 1960-1980 is characterized by strong growth in HCE that can *a priori* be imputed to demand factors but also supply of care (GPs).

The extension of health insurance cover (extension of social security to farmers in 1961, the self-employed in 1966, voluntary insurance in 1967) significantly contributed to the growth of HCE in the 60's and 70's by allowing demand to be sustainable for health care. A comparison between models (5) and (6) on one hand, and models (7) and (8) on the other, shows that a large part of HCE growth can be explained by social security coverage. As expected, the pharmaceutical research coefficient is significant and positive for all specifications (from 6 to 11) which corroborates the literature.

More surprising is the negative role played by population aging on health spending. Macroeconomic literature on this subject shows that aging has a very slight positive effect on HCE. Our results do not support these findings. It is possible that the age structure incorporates contrasting confounding factors. Age and generation effects contribute to increasing health costs. However, a better health status at each age level reduces health costs[5]. We think it possible that this is a non-linear time series that possibly includes a break, which can affect coefficients. The negative coefficient could be explained by a low related to the First World War that could disrupt the long-term influence of age structure on health spending (see appendix).

The phenomenon of supplier induced demand is approached using the index of medical density. Finally, we show that density plays a positive role on HCE per capita, corroborating this assumption.

2.3 An unstable linear relationship?

At this point, it is necessary to check the stability of the relationship between GDP and HCE. We could indeed expect a time varying relationship between HCE and income per capita: after the introduction of major structural reforms or during an economic crisis, households are likely to change their consumption behavior. The French health care system's regulation

[5] Increased Life Expectancy at 60 contributes to decreasing HCE in model 9. This assumption is nevertheless inconsistent with model 8 results.

policy (level of coverage provided by compulsory and complementary health insurance, increase of out of pocket spending *via* deductibles) could influence health care access behaviors and HCE trends. Moreover, there are many factors that could affect HCE growth (in value and volume): therapeutic decisions favoring the use of medicines; per case prospective payment; increased use of generic drugs; modification of relative prices; intensification of the demand for healthcare (cultural or innovation reasons, ageing population).

We check the stability of the previously estimated linear cointegrating relationship by performing CUSUM stability tests (see Brown *et al.*, 1975), Ploberger and Kramer (1992) for OLS regressions and Xiao and Philipps (2002) for the case of cointegrating regressions). The CUSUM test is constructed based on the sum of recursive residuals (w_t) as follows:

$$w_t = \frac{e_t = y_t - \hat{y}_t}{S_e} = \frac{y_t - \hat{y}_t}{\sqrt{(1 + x_t^{'}(X_{t-1}^{'} X_{t-1})^{-1} x_t)}}$$

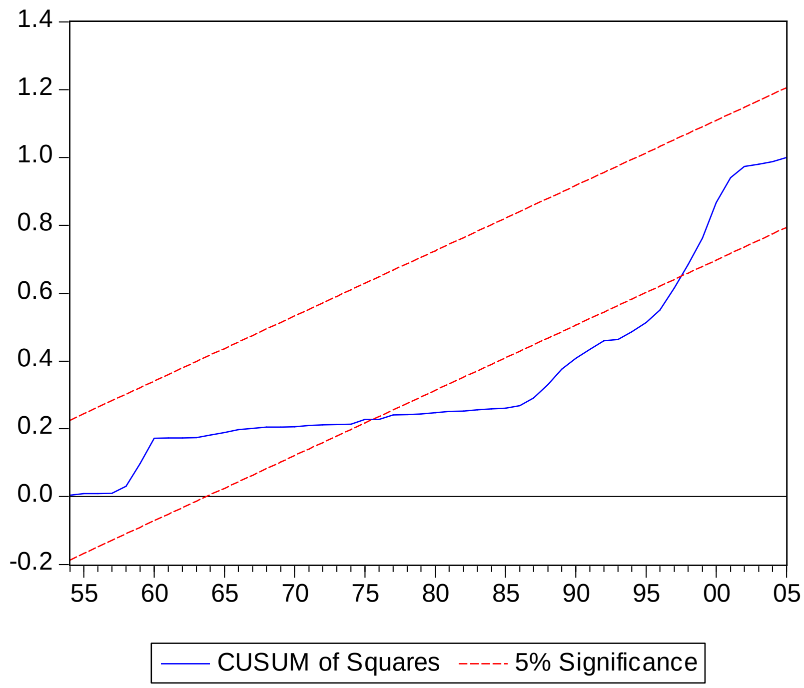
$$t = K+2, K+3, \ldots, n$$

$$S_t = \frac{n-k}{SCR} \sum_{j=K+2}^{t} w_j$$

$$\left[K, \pm\alpha\sqrt{n-K}\right] et \left[n, \pm 3\alpha\sqrt{n-K}\right]$$

The CUSUM of squares test related to the OLS regression in model (4) is reported below:

Chart 2: CUSUM of squares



The linear model clearly exhibits non constant coefficients over time and there is evidence of a structural change in the elasticity. The linear model clearly appears unstable, and we can probably assume the existence of a non-linear phenomenon and/or structural change to time between 1975 and 1995. This point is treated in greater depth in the next two sections. The instability of the relationship is probably due to non-linearities (either through structural breaks, or regime shifts). This relationship seems misspecified because linear co-integration tests reject the existence of an equilibrium relationship between HCE and GDP with such a trend. Therefore, OLS or DOLS estimates are completely biased in this case and cause a spurious regression as indicated by Yule.

Section 3: Accounting for structural breaks

In this section, we examine the instability of the co-integration relationship outlined in the previous section by considering the possibility of a structural break in the co-integrating relationship or in the deterministic trend. In others words, we consider some form of structural and brutal non linearity in the link between HCE and GDP. Since 1950, the French health system has undergone several reforms potentially explaining breaks in the GDP/HCE relationship. The general form of non-linearity is not tested at this stage because, as raised by Koop and Potter (2001), a linear relationship with breaks could be mistakenly approximated to a non-linear model. Controlling for the existence of breaks thus needs to be effectuated prior to testing a more general form of non-linearity.

3.1 Unit root tests with endogenous structural breaks

In a first step, we need to reevaluate the properties of our time series by taking into account potential structural breaks: are they really non stationary or stationary around some structural breaks?

Since the seminal paper of Perron (1989), it is well known that the usual unit root tests (based on the Dickey Fuller principle) fail to reject the null hypothesis of a unit root when structural breaks are not take into account in the procedure. More especially, the power of usual ADF unit root tests diminishes when there is a break in the trend. Since structural change may be a characteristic of HCE dynamics, we examine the stationarity (or the absence of a unit root) of the HCE variable by performing the so called Lee and Strazicich (2003) LM unit root tests. The main advantage of this kind of test is that they are not subject to spurious rejections under the null hypothesis and allow for the detection of breaks.

In this kind of test, based on the Dickey Fuller principle[6], the break points are detected endogenously from the data *via* a grid search. However, this test is outperformed by the Lee and Strazicich minimum LM unit root tests based on the seminal work of Schmidt and Phillips (1992). Indeed, they are not affected by the incorrect placement of breaks, contrary to other tests; the invariance property outlined by Lee and Strazicich (2003). This is very important because the finite-sample distribution of unit root with structural breaks tests depends on the location of the breaks. Furthermore, the Lee and Strazicich test allows for the possibility of one or two potential breaks in the time series, taking into account zero.

[6] See also the Zivot Andrews (1992) and Lumsdaine and Papell (1997) tests. Note that the LM test proposed by Lee and Strazicich (2003) exhibits greater power than the former.

Moreover, in contrast to other break unit root tests, the Lee and Strazicich (2003) test incorporates structural change both under the null and alternative hypothesis. It is thus not subject to the problem of spurious rejection. More precisely, Lee and Strazicich (2003) considered three models in line with other unit root tests allowing for structural breaks: a crash model (A), a changing growth model (B) and a model allowing both changes (C). In our study, we expect two potential breaks in both level and trend and consequently used model C. If we observe both GDP and HCE trends (see charts 3 and 4), we notice a trend change in HCE between 1975 and 1980 and again in the early 1990s. Regarding the GDP trend, the potential breaks are well known and correspond to the 1973 oil crisis and the economic crisis of 1993.

Chart 3: LnHCE – 1950-2009

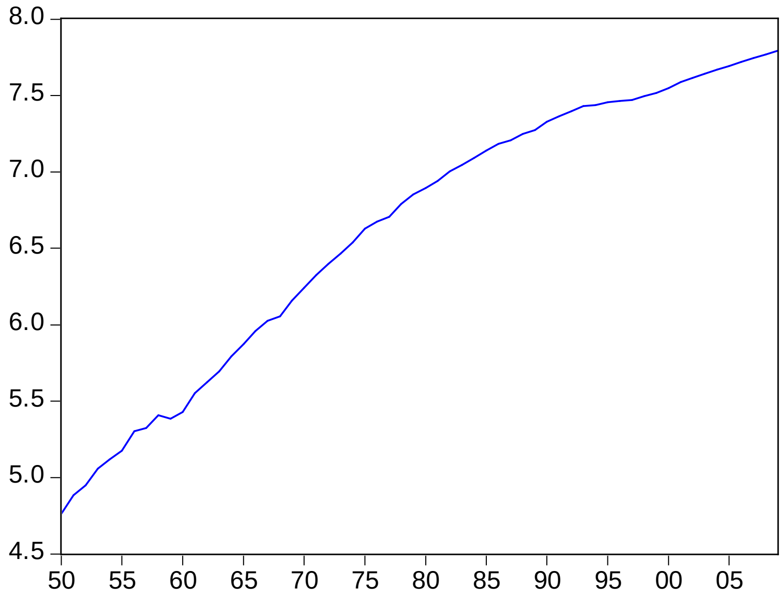
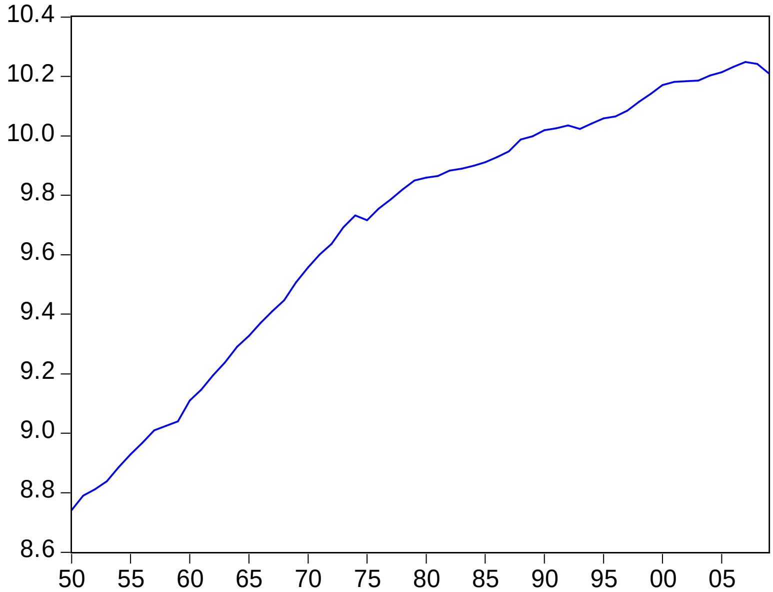


Chart 4: LnGDP – 1950-2009



Following the authors' seminal paper, the so called LM unit root test is obtained from the following GDP:

$$y_t = d'Z_t + e_t \quad t = 1,\ldots,T \qquad (2)$$
$$e_t = \beta e_{t-1} + \varepsilon_t$$

where Z_t is a vector of exogenous variables and ε_t is nid.

In model C with the two breaks in level and trend used here, the vector of exogenous variables Z_t is given as $Z_t = [1, t, D_{1t}, D_{2t}, DT^*_{1t}, DT^*_{2t}]'$ where $D_{jt} = 1$ for $t \geq T_{Bj} + 1, j = 1, 2,$ and 0 otherwise and where $DT_{jt} = t - T_{Bj}$ for $t \geq T_{Bj} + 1, j = 1, 2$ and 0 otherwise. T_{Bj} denotes the time period when the break occurs.

It is important to note that the GDP includes breaks under both the null ($\beta = 1$) and alternative ($\beta < 1$) hypothesis in contrast to other endogenous break tests such as those proposed by Zivot Andrews (1992) and Lumsdaine and Papell (1997). Indeed, Nunes et al. (1997) and Lee and Strazicich (2001) demonstrate that assuming no break under the null hypothesis causes the test statistic to diverge and leads to significant rejections of the unit root null hypothesis. We thus have:

Null hypothesis: $y_t = \mu_0 + d_1 B_{1t} + d_2 B_{2t} + d_3 D_{1t} + d_4 D_{2t} + y_{t-1} + \upsilon_{1t}$

Alternative hypothesis: $y_t = \mu_1 + \gamma_t + d_1 B_{1t} + d_2 B_{2t} + d_3 D_{1t} + d_4 D_{2t} + (1-\alpha) y_{t-1} + \upsilon_{2t}$

Finally, the two breaks LM statistic is generated from the following regression:

$$\Delta y_t = \delta' \Delta Z_t + \phi \tilde{S}_{t-i} + u_t \quad t = 1,\ldots,T \qquad (3)$$

In the equation (x), $\tilde{S}_t$ is a detrended series defined as $\tilde{S}_t = y_t - \tilde{\psi}_x - Z_t\tilde{\delta},\ t = 2,...,T$ with $\tilde{\psi}_x = y_1 - Z_1\hat{\delta}$. $\tilde{\delta}$ are coefficients in the regression of Δy_t on ΔZ_t and y_1 and Z_1 are the first observations of y_t and Z_t. Usually, testing the unit root is equivalent to testing $\phi = 0$ in equation (X):

$$\tilde{\rho} = T\tilde{\phi}$$
$$LM_\tau = \inf_\lambda \tilde{\tau}(\lambda)$$

In addition, note that lagged terms may be included to correct serial autocorrelation as in the usual Augmented Dickey Fuller. We use this specification and the equation (x) is then rewritten as:

$$\Delta y_t = \delta' \Delta Z_t + \phi \tilde{S}_{t-i} + \sum_{i=1}^{p} \gamma_i \Delta \tilde{S}_{t-i} + u_t \quad t = 1,...,T \qquad (4)$$

To endogenously determine the location of breaks, the following grid search is used:

$$LM_\rho = \inf_\lambda \tilde{\rho}(\lambda)$$
$$LM_\tau = \inf_\lambda \overline{\tau}(\lambda)$$

Table 6 displays the Lee and Strazicich unit root tests. Allowing for breaks in the unit root tests provide significant evidence in favour of segmented trend stationarity for the lnGDP series. We chose to introduce two structural breaks. Concerning both series, the Lee and Strazicich test indicates non-stationarity (for lnHCE : -5.99 and for lnGDP -4.26) in the HCE series where two significant breaks are identified: a break level in 1976 and a trend break in 1994 (both are negative and show a decrease in HCE growth). 1976 corresponds to a drastic austerity budget introduced by the Raymond Barre government in 1976 seeking to limit HCE, whereas 1994 marks an important break in the pace of HCE growth in France due to economic recession in 1993 with a negative GDP of -0.9%. Concerning the lnGDP series, we test one and six lags (better properties to control autocorrelation) and we identify a break in 1967 (1968 represents a main social crisis in France) and the first oil crisis. These results corroborate the non-stationarity of time series when taking into account two breaks.

Table 6: Lee and Strazicich Unit root tests with two structural breaks

Variables	k	St-1	Stat	B1	B2	DT1	DT2	$T\hat{B}$
lnHCE	5	-0,72	- 5.99	-0.05 (-2.52)	0.01 (0.73)	0.01 (1.19)	-0.07 (-6.51)	1976, 1994
lnGDP	6	-0.55	- 4,26	-0.06 (0.68)	-0.02 (1.48)	0.01 (2.60)	-0.00 (-6.41)	1974, 1995

Lecture: k is the number of lags to correct autocorrelation concerns and $T\hat{B}$ *consists in estimated structural breaks. The significance of the LM test statistic is realized via comparison with the critical values of table 3 of Lee and Strazicich (2003) and the significance of the derived breaks points is established using t-statistic at the 5% level of significance.*

3.2 Cointegration test with endogenous structural breaks

Since we outlined some breaks in our univariate time series, we also test the existence of possible breaks in the co-integrating relationship that is in the GDP/HCE elasticity. We use the Carrion-i-silvestre and Sanso (2006) co-integration test[7]. We thus test for the null hypothesis of co-integration against the alternative of no co-integration in the presence of a potential break under both hypotheses. The test is derived for a known and an unknown break with exogenous or endogenous regressors. This Lagrange Multiplier test is very interesting to challenge linear results leading to rejecting the co-integration and outlining some breaks in the co-integrating relationship. The main advantage of this test over the others used in the literature (see for instance Johansen *et al.* (2000)) is that it allows breaks in the slope parameters of the co-integrating vector and not only in the constant and time trend terms. Under the null, the co-integrating vector may shift from one long run regime into another.

The model considered by the authors is a multivariate extension of Kwiatkowski *et al.* (1992) where deterministic and/or stochastic trends might change at a point of time (TB). The data generating process considered takes the following form[8]:

$$
\begin{aligned}
&y_t = \alpha_t + \xi_t + x_t^{'}\beta_1 + \varepsilon_t \ (1)\\
&x_t = x_{t-1} + \varsigma_t \ (2)\\
&\alpha_t = f(t) + \alpha_{t-1} + \eta_t \ (3)
\end{aligned}
$$

$\eta_t \sim iid(0,\sigma_\eta^2)$, x is vector of k I(1) process (lnHCE and lnGDP here), α_t is a constant and $f(t)$, the heart of the model, is a function collecting deterministic and/or stochastic components.

The definition of the function f(t) leads to the consideration of six different specifications (An to E). In the way of Perron (1989, 1990), the models An to C affect the deterministic trend component:

$$
\begin{aligned}
&An: \xi = 0,\ f(t) = \theta D(T_b)_t\\
&A: \xi \neq 0,\ f(t) = \theta D(T_b)_t\\
&B: \xi \neq 0,\ f(t) = \gamma DU_t\\
&C: \xi \neq 0,\ f(t) = \theta D(T_b)_t + \gamma DU_t
\end{aligned}
$$

where $D(T_b)_t = 1 \text{ for } t = T_b + 1 \text{ and } 0 \text{ otherwise}$, $DU_t = 1 \text{ for } t > T_b \text{ and } 0 \text{ otherwise}$ with $T_b = \lambda T$ indicating the estimated date of break ($0 < \lambda < 1$).

This test is based on the KPSS stationarity test (1992) for which under the null hypothesis, the variance of the autoregressive process (equation (3)) is null: $\sigma_\eta^2 = 0$. Under the alternative hypotheses $\sigma_\eta^2 > 0$. Consequently, under the null hypothesis, the model given by (1), (2) and (3) can be rewritten as:

$$
\begin{aligned}
&y_t = g_i(t) + x_t^{'}\beta + \varepsilon_t \ (4)\\
&\text{with } i = \{A, An, B, C\}
\end{aligned}
$$

[7] We used the gauss code kindly provided by Carrion-i-Silvestre.

[8] This part draws heavily on the work of Carrion-i-Silvestre and Sanso (2006).

These four models An to C account for structural breaks in the long run deterministic relationship but the co-integrating vector remains unchanged. In model An, we consider a level shift without time trend, in model A, we consider a trend and a break in level, model B captures a change in the slope of the time trend but not in the level and finally, model C captures level and slope shifts. In models D and E, the specification allows for a structural break that not only shifts the deterministic component but also changes the co-integrating vector. Thus, in some situations, practitioners would be interested in modeling a co-integration relationship that at a point in time might have shifted from one long-run path to another one (see Carrion and Sanso, 2006). Consequently, a dummy now affects the co-integrating vector (indeed see that $x_t^{'}\beta$ is affected by $DU(t)$ in the model (5)). The differences between D and E are that model D does not take time trend into consideration.

$$
\begin{aligned}
&D: \xi = 0,\ f(t) = \theta D(T_b)_t + x_t^{'}\beta_2 D(T_b)_t \\
&E: \xi \neq 0,\ f(t) = \theta D(T_b)_t + \gamma DU_t + x_t^{'}\beta_2 D(T_b)_t
\end{aligned}
$$

$$
\begin{aligned}
&y_t = g_i(t) + x_t^{'}\beta_1 + x_t^{'}\beta_2 DU(t) + \varepsilon_t \quad (5) \\
&i = \{D, E\} \\
&g_D(t) = \alpha + \theta DU(t) \\
&g_E(t) = \alpha + \theta DU(t) + \gamma DT^*(t)
\end{aligned}
$$

Carrion-i-Silvestre and Sanso (2006) distinguish between models with strictly exogenous regressors and models with non-strictly exogenous regressors. In the second case, which is our preferred case, the asymptotic theory no longer holds. Indeed, estimating the cointegration vector is inefficient using endogenous regressors, and Dynamic OLS estimators (see Saikkonen (1991) and Stock and Watson (1993) are needed. Thus, OLS estimation of (4) and (5) are substituted by DOLS estimation in the following equations (note the lead and lag term difference in both equations in line with Stock and Watson (1993)):

$$y_t = g_i(t) + x_t^{'}\beta + \sum_{j=-k}^{k} \Delta x_t^{'}\gamma_j + \varepsilon_t \ (6) \text{ if } i = \{An, A, B, C\}$$

$$y_t = g_i(t) + x_t^{'}\beta_1 + x_t^{'}\beta_2 DU_t + \sum_{j=-k}^{k} \Delta x_t^{'}\gamma_j + \varepsilon_t \ (7) \text{ if } i = \{D, E\}$$

After getting the estimated residuals denoted as $\hat{e}_{i,t}$, the test statistic is computed as:

$$SC_i^+(\lambda) = T^{-2}\hat{w}_1^{-2}\sum_{t=1}^{T}(S_{i,t}^+)^2$$

where $\hat{w}_1^2$ is a consistent estimation of the long run variance of ε_t using $\hat{e}_{it}$ and $S_{i,t}^+ = \sum_{j=1}^{t}\hat{e}_{i,t}$.

Finally, the date break is estimated by minimizing the sequence of squared errors, or equivalently by minimizing the sequence of the Bayesian Information Criterion (BIC), obtained when computing the test for all possible structural breaks (see Carrion-i-Silvestre and Sanso for more details):

$$\hat{T}_b = \arg\min_{\lambda \in \wedge} \left[SSR(\lambda) \right]$$

where $SSR(\lambda)$ denotes the sum of squared residuals and λ is a closed subset of the interval (0,1) redefined as $\left[2/T,(T-1)/T\right]$ to minimize the loss of information.

Table 7 outlines the results obtained by performing Carrion and Sanso's test for models An to E. The results of the An model are not very interesting in our case given the absence of time trend but the results are included for comparison purposes. The D and E models are our preferred models.

The results are very similar in the B and C models leading to the conclusion that the null of cointegration with a break in 1985 (C) and 1986 (D) in the slope of the time trend cannot be rejected. Very similar results are also derived when we based the test on models D and E although the break date is now 1985 instead 1989. D and E results are of particular interest because structural breaks in the deterministic part and also in the co-integrating vector are allowed. The results of table 7 show that the co-integrating vector has shifted in 1984-1985, we can see this rupture in chart 1.

Whatever the specification of the test we used, the break dates seem located in the middle of the 1980's. The period 1984-1985 is the most consistent to identify break date. The beginning of the 80s was marked by a measure likely to increase health spending, the creation of the sector 2 fee schedule allowing GPs to set their own fees. Between 1980 and 1985, there is a 4 point difference in GDP and health spending growth rates (HCE: +5.5% GDP: +1.5%). Given this weak economic growth, the 80's starting in 1982, are marked by numerous measures to control HCE, especially regarding hospital expenditures (main driver of HCE). Thus, the annual growth rate in hospital spending declined from 18% in 1982 to 7% in 1985. The Bérégovoy Plan (1982) initiated these measures with the creation of hospital deductibles, increased of out of pocket payments for certain drugs and the non-revaluation of sickness benefits. The Dufoix Plan (1985) reduced reimbursement rates for 379 drugs. Finally, in 1987, the Seguin Plan revised and extended the list of 25 diseases exempt from out-of-pocket payments and increased hospital deductibles.

Table 7: Carrion and Sanso co-integration test

Model	Break test (1)	Break date (1)	Break test (2)	Break date (2)
An	0.071	1987	0.039	**1984**
	0.083	**1984**	0.039	**1984**
A	0.068	1980	0.039	**1984**
	0.090	1997	0.039	**1984**
B	0.037	1986	0.030	1989
	0.037	1986	0.030	1989
C	0.036	**1985**	0.034	1988
	0.036	**1985**	0.035	1991
D	0.061	1980	0.035	**1985**

	0.061	1980	0.037	**1984**
E	0.040 0.041	**1985** 1987	- -	- -

Note: Null hypothesis: cointegration with break at unkown time. Exogeneous (1) and endogenous (2) regressors are considered. Critical values come from the table 3 of Carrion-i-Silvestre and Sansó's (2006).

To illustrate the existence of a break in the middle of the 1980's we again computed the DOLS regressions outlined in the previous section by adding a dummy in 1984 and 1985. We only show results for the 1984 dummy, in level (table 8)[9].

Coefficients are now more consistent relative to the simple linear approach. Whatever the specification and the break date used, the dummy is always strongly significant, positive and constant (from 0.03 to 0.06). The results of this analysis show that introduction of the structural break validates the luxury good assumption in all specifications and normalizes income elasticity (comprised from 1.02 to 1.98). In particular, models 1, 2, 3 and 4 are highly convergent with respect to GDP elasticity.

Introducing a dummy reinforces the role of health insurance on health spending. It is now clearly established that an important part of the relationship between GDP and HCE is explained by the rise in health insurance. For instance, the pathway from (4) to (5) is explicit with a decrease of elasticity from 1.9 to 1. We think that the role played by social security on HCE was very strong particularly during the first period from 1950-1985 (see appendix).

Contrary to the linear model, ageing does not have a significant effect on health spending, all other things being equal. Pharmaceutical research leads to increased health spending but these aggregate data do not indicate the positive impact of innovation (life expectancy at 60 seems to be positively correlated with HCE). Finally, medical density has a positive impact on HCE for all specifications.

Table 8: DOLS estimates with dummy in 1984 (in level[10])

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-8.83***	-9.11***	-8.91***	-11.03***	-3.88***	-9.65***
LnGDP per capita	**1.91*** **	**1.94*** **	**1.92*** **	**1.90*** **	**1.02*** **	**1.61*** **
LnPrice	-0.67**	-0.68**	-0.68**	-0.20	-1.01	-0.04
Linear Trend		-0.00***	0.00	-0.01	0.01**	
Population over 65			-0.14	1.02		1.14
Medical Density				0.00***	0.00***	0.00***
Social Security					0.80***	0.52**
Pharmaceutical research						0.01**
Life Expectancy at 60 (men)						
Dummy 1984	**0.07*** **	**0.07*** **	**0.07*** **	**0.06*** **	**0.05*** **	**0.06*** **
Period	*1950-2009*	*1950-2009*	*1950-2009*	*1961-2009*	*1961-2009*	*1965-2007*

Variable	(7)	(8)	(9)	(10)	(11)
Constant	-9.28**	-6.61***	-9.17	-8.51***	-9.65***
LnGDP per capita	**1.98*** **	**1.94*** **	**1.97*** **	**1.52*** **	**1.61*** **

[9] Results are very similar for dummy 1985 model; these are available upon request.
[10] Unfortunately, we do not have sufficient observations to simultaneously introduce dummy in level and trend.

LnPrice	-0.74**	-1.34***	-0.74**	-0.22	-0.04
Linear Trend					
Population over 65	-0.18	0.64			1.14
Medical Density				0.00***	0.00***
Social Security		0.41*		0.76***	0.52**
Pharmaceutical research	0.00	0.00	0.00	0.01***	0.01**
Life Expectancy at 60 (men)			-0.00	0.03***	
Dummy 1984	**0.06****	**0.03**	**0.06****	**0.05*****	**0.06*****
Period	*1965-2007*	*1965-2007*	*1965-2007*	*1965-2007*	*1965-2007*

We can conclude that a long-term equilibrium exists between GDP and HCE with a co-integrating relationship. We highlight a structural break in the cointegration vector, linked to the concentration of health policies in the middle of the 1980's. Nevertheless, as the nature of cointegration changed after 1984, we have now to identify the change pathways which can be linked to specific variables such as induced demand, innovation, ageing population, health status or social security. In the next section, we attempt to analyze the possibility of a non-linear model.

Section 4: Structural breaks or smooth non linearity?

In the previous section, we tested linear co-integration and co-integration with breaks, i.e. the hypothesis that the link between GDP and HCE might be instable due to the existence of a break. However, structural breaks imply durable and "abrupt" changes without possible ways-back. The true relationship can transit from one regime to another in both directions and may be completely non-linear.

4.1 Testing for non-linearity

There is a recent body of literature dealing with non-linear econometric models. One major direction focused on modeling and testing non-linear adjustments in deviations from linear long run equilibrium: see Balke and Fomby (1997), Hansen and Seo (2002)… The other direction considers that the equilibrium relationship itself may be non-linear. In other words, equilibrium among our interest variables depends on the state of the health system as represented by one or several transition variables. This approach is more convincing in this context.

We test the possibility that the relationship linking GDP and HCE (both variables being I(1)) undergoes regime shifts. Indeed, if the assumption of linearity is invalid, a re-examination of GDP elasticity is needed. To this aim, the Choi and Saikkonen (2004) smooth transition cointegrating regression model is used (CSTR). The major interest of this approach is to identify the transition or threshold variable to capture the non-linearity of the long run relationship between consumption and expenditures by explicitly considering the I(1) processes of these variables. The general methodology consists in identifying a transition value for an explanatory variable (exogeneous to the model or lagged endogeneous) to deal with the dependence of the parameters (here elasticity coefficients) to the dynamics of the "health environment". Consequently, the long-run equilibrium relationship might change smoothly depending on the transition (or threshold) variable that is dependent on where the covariates x_t are located relative to the threshold parameter *c*.

Following to the review of literature (section 1), we consider five possible transition variables:

1. ***Population over 65***. Even if population ageing is not significant in explaining HCE in a structural break model (table 8), we try to test it. We know there is a positive link between age and health status, but understanding the role of ageing on the GDP/HCE relationship is more complex. An increase in the elderly population causes a profound epidemiological transformation. New neuropsychiatric disorders appear requiring an appropriate care supply. This variable may introduce changes in the GDP/HCE relationship even if the acceleration of population ageing does that from 2005 with a strong potential impact on health spending.

2. ***Medical density***. This indicator of Health Care supply can be a good proxy of induced demand.

3. ***Pharmaceutical research.*** Technological progress may correspond to medical innovations affecting both small appliances (hearing aids, for example) and heavy equipment (scanners, Medical imaging).

4. ***Health.*** Technological progress also refers to the development of medical techniques to improve the quality of life of patients suffering from chronic diseases (including widespread use of home dialysis, transplants...). We then introduce life expectancy at 60 (in the male population).

5. ***Social Security.*** As shown, the extension of health insurance coverage can explain a large part of HCE and then the relationship between GDP and HCE.

Following the approach recently developed by Choi and Saikkonen (2004), we test linearity against non-linearity of the STR form. The non-linear model is given by[11]:

$$\begin{aligned} & y_t = \delta + \alpha x_t + \beta x_t g(s_t, \gamma, c) + \sum_{j=-K}^{K} \pi_j^{'} \Delta x_{t-j} + u_t \\ & t = K+1, \ldots, T-K \end{aligned} \qquad (8)$$

where u_t is a zero mean stationary error term, the function *g* is a logistic function bounded between 0 to 1 that only affects the regressor x_t, *c* is a threshold (or location) parameter and γ denotes the smoothness i.e. the slope of the change. It should be noted that y_t may be substituted by $\ln HCE$ here and that x_t is a vector of explanatory variables that may contain both $w_t^{'} = \left(1, y_{t-1}, \ldots, y_{t-p}\right)^{'}$ and $z_t = \left(z_{1t}, \ldots, z_{kt}\right)^{'}$ exogenous or weakly exogenous variables. The last term of the equation (8) allows us to resolve the serial correlation between regressors and error terms by adding *K* leads and lags. The logistic transition function makes the regression coefficient for x_t (which includes at least $\ln GDP$ in our

[11] Five econometric restrictions are needed for the transition variable *g*, see Choi and Saikkonen (2004) for more details.

context) vary smoothly between α and $\alpha+\beta$. In this paper, we assume a standard logistic function of order one: $g=\frac{1}{1+e^{[-\gamma(z_t-c)]}}$.

When the value of the transition function exceeds the threshold value, the coefficient of the regressor x_t takes a value close to α but when the value of the density decreases and is far below the threshold value, the coefficient for elasticity changes and approaches $\alpha+\beta$. Furthermore, if $\beta=0$, the non-linear STR becomes a conventional linear model.

Thus, in line with Choi and Saikkonen (2004), we test for linearity in equation (8) by assuming the null hypothesis: $H_0:\gamma=0 \text{ or } \beta=0$. However, conventional hypothesis testing is complicated because the cointegrating STR model contains unidentified nuisance parameters under the null corresponding to the transition value *c* and the slope parameter γ. Hence, a possible solution is to employ the first-order (T1) and the third-order (T2) in order to replace the transition function *g*. The Choi and Saikkonen statistic follows a Chi Square distribution under the null with *p* degrees of freedom where *p* is the number of covariates related to the transition function.

The results of the LM linearity tests are illustrated in table 9. Two specifications (denoted by (1) and (2)) are distinguished: in the first, only the cointegrating relationship between HCE and GDP is considered; in the second, we also include the log of the relative price in the long-run relationship (i.e. in the vector of cointegration[12]) to check the robustness of our results. Choi and Saikkonen (2004) consider that we may reject the null hypothesis of linearity if the LM test leads to rejection for at least one value of *K*. As outlined in table 9, we can conclude that the evidence supports non-linearity when the density is considered but supports linearity when other transition variables are considered. The results concerning Social Security are less clear-cut: non-linearity is supported only when at least 2 lags and leads are included in the DOLS. All in all, our results are also robust in the specification of the long-run relationship.

Table 9: LM Linearity tests from Choi and Saikkonen

Transition variable	T1			T2		
	K=1	K=2	K=3	K=1	K=2	K=3
Past Health expenditures	0.00	0.08	0.00	2.18	1.62	0.97
Pharmaceutical research	0.24	0.39	0.48	3.41	4.57	5.33*
Population over 65	0.25	0.35	0.34	0.64	0.62	0.55
Medical density (1)	5.98**	6.55**	6.85***	5.98*	6.55**	6.86**
Medical density (2)	6.23*	11.20**	11.68***	6.28	12.23**	12.76**
Life Expectancy at 60 (1)[13]	2.20	2.30	2.20	4.46	4.40	4.06
Life Expectancy at 60 (2)	2.82	0.04	0.43	4.52	1.78	1.11

[12] Therefore, given P_t the log of the relative price, the equation (8) can be rewritten as

$$\ln HCE_t - \ln GDP - \ln P_t = \beta_1^{'} x_t + \beta_2^{'} x_t g(z_t,\gamma,c) + \sum_{j=-K}^{K} \pi_j^{'} \Delta x_{t-j} + u_t .$$

[13] Tests with Infant mortality are not consistent

Social Security (1)	2.48	2.74*	2.73*	2.71	2.74	3.06
Social Security (2)	2.84	0.34	0.32	2.98	4.88	7.32

Notes: K denotes the leads and lags in the auxiliary regression model (8). T1 (first order expansion) and T2 (second order expansion) are distributed as asymptotic Chi2 statistic under the null with one and two degrees of freedom respectively (specification (1)) and with two and three degrees of freedom respectively (specification (2)). ***, ** and *: significant at 10%, 5% and 1% level respectively.

4.2 Estimation of the CSTR model

Since the null of non-linearity can be rejected for at least two different transition variables, medical density and social security, a cointegrating STR model has to be estimated. The estimation procedure is based on the work of Saikkonen and Choi (2004)[14]. It consists in giving a consistent and efficient estimator of the following parameters: $\delta, \alpha, \beta, \gamma, c$. They consider a two-step estimator based on NLLS (nonlinear least-squares). For convenience, we set the vector of estimates at $\theta = \left(\delta, \alpha, \beta, \gamma, c\right)^{'}$.

The first step of the estimation consists in obtaining a conventional NLLS estimator[15] θ_N with respect to θ. Since there is error dependence, the NLLS is not efficient although it is consistent. Based on the DOLS principle, the authors suggest adding short-run dynamics of the explanatory variables ($\Delta \ln GDP$ in our case) in the estimated model to deal with this issue. The estimation model then conforms to equation (8).

The second step of the estimation consists in obtaining one-step Gauss-Newton and two-step Gauss-Newton estimators. Indeed, using the Gauss-Newton procedure with the previous NLLS estimator lead to an efficient one-step Gauss-Newton estimator of θ and of the short run dynamics parameters $\pi = \left(\pi_{-K}, ..., \pi_{K}\right)^{'}$:

$$\begin{bmatrix} \theta_T^1 \\ \pi_T^1 \end{bmatrix} = \begin{bmatrix} \theta_N \\ 0 \end{bmatrix} + \left(\sum_{t=K+1}^{T-k} \tilde{p}_t \tilde{p}_t^{'} \right)^{-1} \left(\sum_{t=K+1}^{T-k} \tilde{p}_t^{'} \tilde{u}_t \right)^{-1}$$

where θ_T^1 is the one-step Gauss-Newton estimator of θ and $\tilde{u}_t$ denotes the fitted residuals obtained by the NLLS estimation of the equation (1). Then, the last term of the equation

[14] Note that it is a different article than the previous reference to Choi and Saikkonen (2004).
[15] This estimator is usually performed when the variables are stationary.

denotes the least squares estimator obtained from a regression of $\tilde{u}_t$ on $\tilde{p}_t$. More precisely, we have $\tilde{p}_t = \left[\tilde{K}(x_t)^{'} V_t^{'}\right]$ with $V_t = \left[\Delta x_{t-k}^{'}, ..., \Delta x_{t+k}^{'}\right]^{'}$ and $\tilde{K}(x_t) = \begin{bmatrix} 1 \\ x_t \\ x_t g\left(s_t, \tilde{\gamma}, \tilde{c}\right) \\ \beta x_t \dfrac{\delta g(.)}{\delta \gamma} \\ \beta x_t \dfrac{\delta g(.)}{\delta c} \end{bmatrix}$.

Finally, the two-step Gauss-Newton estimator is also computed considering the first-step estimator as the initial estimator instead of the NLLS one.

All in all, the Saikkonen and Choi (2004) procedure has two advantages: in large samples, the Gauss-Newton estimator is more efficient than NLLS estimators and eliminates NLLS bias and the t-test follows a conventional standard normal distribution in the limit. Simulations conducted by the authors show that when the sample size grows, the RMSEs (Root Mean Squared Error) of one-step and two-step Gauss-Newton estimators decrease. In our paper, the sample is, however, somewhat small and so we compute bootstrap t-stats. Note in addition that we will report both one-step and two-step estimators; the two-step tends to improve the RMSE of the one-step Gauss-Newton estimator in terms of RMSE when the errors are serially and contemporaneously correlated but on occasions, the two-step estimator may be more biased than the one-step.

As in Saikkonen and Choi (2004), we did not estimate the smooth parameter but instead tested different values of γ. Indeed, it is difficult to accurately estimate the parameter by the NLSS (see Saikkonen and Choi, 2004) estimator unless either sample sizes are very large or the location parameter is located close to the median of the explanatory variable, in this case the GDP per capita logarithm. In addition, the choice of the initial values is crucial to avoid multiple local maxima issues. Note also that the other parameters are adversely affected by a poor estimate of γ. Consequently, we set some values of γ and only report results yielding the least sum of squared errors for the two-step Gauss-Newton estimator. Finally, we choose $\gamma = 1$. However, it should be noted that choosing other values of gamma between 0.9 and 1.1 do not qualitatively and quantitatively change our results. The results of the two-step Gauss-Newton estimation of model (8) with the medical density as a transition variable[16] are reported in table 10.

Our results show that the sum of the coefficients $\alpha + \beta$ is always greater than α. Hence, non-linear elasticity diminishes implying that density has negative effects on GDP elasticity value. We identify the same threshold value (135.2) in the three specifications (K=1, K=2 and

[16] We also test the social security variable as a transition variable and we get non significant estimates.

K=4); in other words, in all specifications, the non linear part comes to play when the medical density is over 135.2. When we look at the historical data, this threshold can be related to the start of the 1980's. Furthermore, we gradually reached this threshold, the transition speed is relatively small. Although the level of the medical density is diminishing since 1997, we are nowadays above the threshold. Regarding the elasticity, it comes that the coefficient of the linear part (about 1.79 with one and two leads/lags) turns to be smaller (about 1.77) when the nonlinear part comes to play. Therefore, our findings need to be cautiously interpreted because the coefficient β is low. In an econometric point of view, this fact may be explained by the drawbacks of the non linear estimators we must perform to estimate the CSTR model. Indeed, the performance of this kind of estimator is relative in finite samples. We hope that the availability of a longer sample will improve these first results in the future[17].

We prove that the nonlinearity part comes from medical density's threshold. Thus, the CSRT analysis complements and confirms structural breaks findings by showing that non-linearity also comes from supply care medical at the end of 70's.

Table 10: Two-Step Gauss-Newton estimation results

		δ	α	β	c
$\gamma=1$	K=1	-10.55	1.787 (1.426; 2.148)	-0.018 (-0.05; 0.019)	135.2
	K=2	-10.57	1.790 (1.213; 2.366)	-0.016 (-0.07; 0.04)	135.2
	K=4	-11.31	1.865 (0.794; 2.936)	-0.011 (-0.09; 0.07)	135.2

Notes: K denotes the leads and lags in the auxiliary regression model (8). The number in parentheses denotes the 95% confidence interval using the long-run variance estimated through Andrews's (1991) method with an AR(4) approximation for the prefilter. We used the prcg as the solution algorithm as in Saikkonen and Choi (2004).

Conclusion

In the first part of this study (section 2), we conduct a linear analysis after checking cointegration properties. Results seem robust in comparison with other French studies. Health care is considered as a luxury good except after introducing social security coverage. Price effect has a negative impact on HCE because of its role in increasing care volume. This first analysis nevertheless shows that it is not a satisfactory cause of the relationships' instability.

We then re-examine the bound between GDP and HCE by taking into account structural breaks and the possibility of non-linear phenomena. We show (section 3) that a structural break changed the nature of cointegration in the middle of the 1980's. After introducing dummy variables in the models, health care always appears as a luxury good. We can

[17] Note that we proceed by linear interpolation to fill in the missing observations of the density variable at the beginning of our sample.

assume that between 1950 and 1980, health expenditures were explained by an increase in health insurance coverage. However from the mid 80's, the pace of growth in health spending slowed due to an exogenous shock related to health expenditure regulation (Bérégovoy Plan, Dufoix Plan).

We also verify the stability of general elasticity by testing the possibility of nonlinear dynamics due to changes in certain variables (section 4). Medical density should explain the new GDP/HCE dynamic because it captures the non-linearity of the long run relationship between consumption and expenditures.

All in all, we find evidence that the non-linearity of the long term relationship between HCE and GDP comes from both the presence of a structural break (1984, 1985) and non-linearity explained by a medical density (by constructing a cointegrating smooth transition regression) at the end of 70's. Lower GDP elasticity is explained by an exogenous shock linked to health system policies in the middle of the 1980's and the endogenously driven changes in the health system *via* medical density in France.

Our results highlight the specificities of the French health system at the origin of a high level of health expenditure compared to other countries. Health expenditures are mainly explained by a volume effect due to regulated prices, GPs fee-for-service payment system and over-medication in France. The theory of induced demand by supply appears to be particularly checked. The recent reforms in France introducing the pay-for-performance system is likely to limit moral hazard on the side of health care supply.

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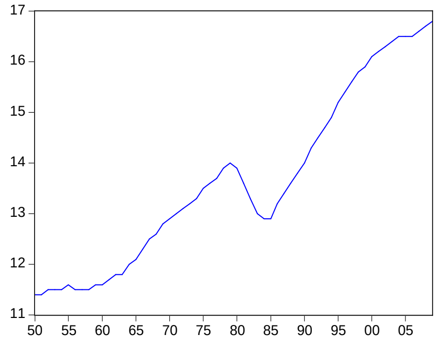
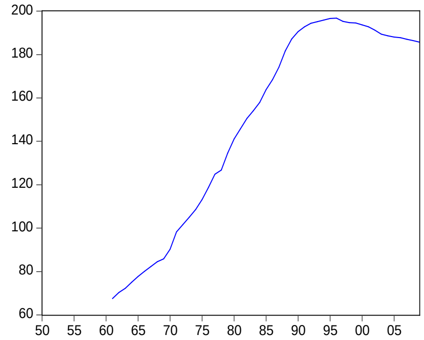
APPENDIX

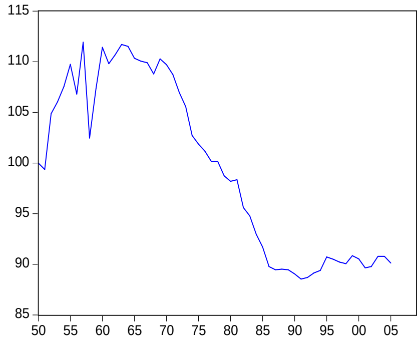
POPULATION OVER 65 (%) / 1950-2009



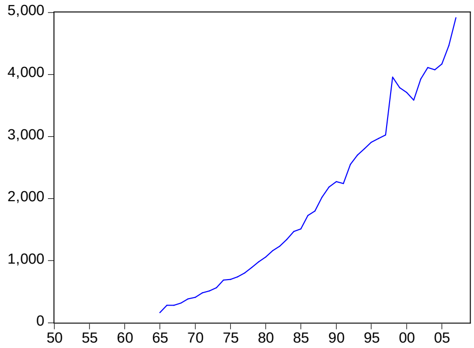
MEDICAL DENSITY / 1961-2009



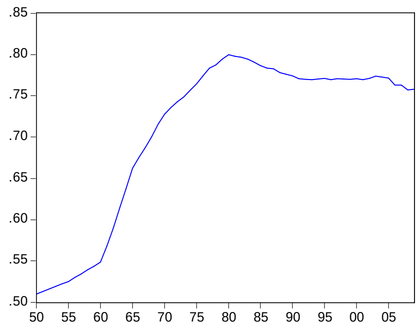
RELATIVE PRICE OF HEALTH / 1950-2005



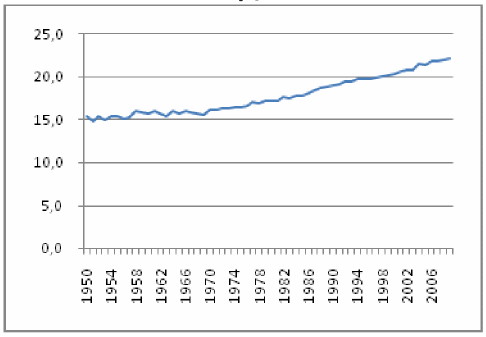
PHARMAC. RESEARCH / 1965-2007



SOCIAL SECURITY (%) / 1950-2009



LIFE EXPECTANCY AT 60 (MALE POPULATION) / 1950-2009



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