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Asymmetric effect of income on the US healthcare expenditure: evidence from the nonlinear autoregressive distributed lag (ARDL) approach

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Abstract
Previous research that has investigated the relationship between income and Health Care Expenditure (HCE) assumes that the effect of income variation on HCE is symmetric. Additionally, while HCE consists of twelve different types of health services, most of the studies have only focused on the relationship between income and aggregate HCE. By applying the linear ARDL approach, introduced by Pesaran et al. Bounds testing approaches to the analysis of level relationships. J Appl Econom 16(3):289–326 (2001), this study expands the literature by estimating the income elasticity of HCE for all types of healthcare services. Our findings imply that while for some health services income elasticity is below unity, for some other services health spending tends to grow faster than GDP. We also applied the non-linear ARDL approach of Shin et al. Festschrift in honor of Peter Schmidt (2014), for the first time in the literature, to examine if the adjustment of income variation follows a non-linear path. This paper provides statistically significant and robust evidence that the effect of income variation on healthcare expenditure is not symmetric, despite what previous studies assume.

Keywords Healthcare expenditure · Nonlinear ARDL · Asymmetric effect · Income elasticity of health care

JEL Classification H51 · I10

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1 Introduction

Over the past four decades, healthcare expenditure (HCE) in the USA, and almost all other developed countries, has been growing sharply, at a rate faster than the growth of their economies (Sawyer and Cox 2018). The USA, however, spends more on health care than any other developed or high-income country in the world, despite a global slowdown in health spending growth in recent years. In 2014, the USA devoted 17.5% of its gross domestic product (GDP) to the health sector, which is at least 50% higher than did other countries (PGPF 2016; OECD Health Statistics 2017). It has also been predicted that the health share of GDP will rise to 20.1% by 2025 (CMS 2016). The fast growth of HCE (1.3% faster than GDP growth) concerns economists because such a growth rate is not sustainable in that less money and resources will be available for other important public or private priorities like education and infrastructure (Chernew and Newhouse 2012). Another potential challenge for the US economy is the larger expected out-of-pocket medical expenses, which might force people into poverty (Doorslaer et al. 2006).

The fast growth of HCE could be explained by Baumol's cost disease model. According to this model, the health sector's rising wages in excess of productivity growth is the reason for the sector's cost escalation (Hartwig 2008; Bates and Santerre 2013; Colombier 2017). Yet, still not enough is known empirically about the determinants of the rising health expenses. In order to devise policies to provide US citizens with an efficient healthcare system, it is crucial that major determinants of the rising health expenses in the USA be known and the role of each determinant be investigated. Therefore, using different data sets, various levels of data aggregation, and different econometric methods, many studies have attempted to identify HCE drivers.

Among various determinants of HCE, the strong and positive relationship between HCE and income is well established in the literature (Murthy and Ukpolo 1995; Gerdtham and Lothgren 2000; Okunade and Murthy 2002; Smith et al. 2009; Acemoglu et al. 2013; Caporale et al. 2015; Murthy and Okunade 2016). However, empirical results in the literature are conflicting, especially the size of the income elasticity of health care, which has been the subject of much debate. Some studies estimated that income elasticity exceeds unity and hence concluded that health care is a luxury good (Newhouse 1977; Maxwell 1981; Leu 1986; Gerdtham et al. 1992; Gbesemete and Gerdtham 1992; Murthy and Ukpolo 1995; Getenz 2000; Okunade and Murthy 2002; Hall and Jones 2007). Nordhaus (2003) and Murphy and Topel (2006) also indirectly reinforce the findings of such studies by estimating very high values for improvement in health.[1] On the contrary, others produced estimates below unity for income elasticity, which indicates that health care is a necessity good (Parkin et al. 1987; Matteo 2003; Freeman 2003; Dreger and Reimers 2005; Sen 2005; Costa i font et al. 2009; Baltagi and Moscone 2010; Moscone and Tosetti 2010; Acemoglu et al. 2013; Murthy and Okunade 2016). One common feature of all these studies is that they have assumed that the impact of income variation on HCE is symmetric. However, falling and rising incomes might have an unequal impact on HCE. There-

[1] Improvements in health status would substantially increase the improvement in economic welfare and wealth.

fore, the core objective of the current study is to examine whether or not the impact of income variation on HCE is asymmetric.

One potential theoretical justification for the asymmetric impact of income variation on HCE could be demand irreversibility. Two behavioral factors could explain the irreversible nature of healthcare demand: loss aversion and stockpiling. Loss aversion refers to people's tendency to resent losses more than they enjoy equivalent gains. This phenomenon causes consumers to respond more to income falls than to income rises, which makes demand more elastic given income decreases (Kahneman and Tversky 1984; Kahn and McAlister 1997). Stockpiling refers to people's tendency to raise their demand (in this context for medical products and services) after temporary income rises, especially when people are uncertain about future prices and expenses (Maynard and Subramaniam 2015). Under this hypothesis, healthcare demand would be more elastic given increases in income. Policy inertia and government inability or unwillingness to respond to evidence, especially during economic busts, could be another reason for the asymmetric effect of income on HCE.

Another common feature of past studies is that they have predominantly focused on aggregate HCE. The US aggregate HCE consists of twelve different types of health services, which presumably could be affected differently by income variation.[2] Thus, looking at only aggregate HCE and its relationship with income does not provide a complete picture. Surprisingly, studies on the relationship between income and other components of aggregate HCE are extremely rare. Acemoglu et al. (2013) focused primarily on hospital expenditure, which is the largest component of the US aggregate HCE. By instrumenting for local area income with time-series variation in oil prices interacted with local oil reserves, Acemoglu et al. (2013) estimated an income elasticity of 0.72 for hospital expenditure. Chen et al. (2014) used panel data of the 50 US states to estimate income elasticity of hospital expenditures. Their estimate of 0.42 also implies that income elasticity of hospital expenditures is less than one. Due to the lack of studies on the topic, the second objective of this paper is to disaggregate HCE into constituent services and examine the causal effect of income on aggregate HCE and all its components individually. For each of the services, the existence of an asymmetric relationship between income and health expenses will also be assessed.

The structure of the paper is as follows. The next section provides a brief discussion about the model, outlines both the linear and nonlinear ARDL approaches, and describes the data. The following section presents empirical results and discusses the policy implications of such results. Finally, in the last section we conclude and offer some closing policy suggestions.

2 Model and data

To identify the relationship between HCE and income in the USA, the autoregressive distributed lag (ARDL) approach will be applied in this study.[3] The ARDL approach,

[2] Names and proper explanations of all health services are provided in "Appendix".

[3] The linear ARDL model was used in Murthy and Okunade (2016) for the first time in the literature of *HCE* modeling.

which is developed by Pesaran et al. (2001), has several appealing econometric advantages over previous methods of cointegration analysis. First, unlike other cointegration estimators such as those of Engle and Granger (1987), Johansen (1988), and Johansen and Juselius (1990), the ARDL modeling does not require variables to be integrated in the same order, and hence, there is no need for preunit root test. More informatively, in the ARDL approach the variables set could be a combination of stationary, i.e., $I(0)$, variables and integrated of order one, i.e., $I(1)$, variables, which is the property of almost all macrovariable sets. Second, the economic modeling techniques that are widely employed in the literature, such as ordinary least square (OLS) or the vector autoregression (VAR), only estimate the long-run effect of income changes on HCE. Using the aforementioned methods, in order to obtain the short-run coefficient estimates, error-correction modeling needs to be employed. However, the ARDL modeling provides both the short-run and long-run estimates simultaneously, which simplifies the hypothesis testing. Finally, the ARDL approach, also known as the Pesaran et al. (2001) bound test, has higher statistical power than other cointegration approaches, especially in small samples (Panopoulou and Pittis 2004).

Following the literature, we assume that US HCE is a function of national income, technological progress, and the age structure of the population. As mentioned, there exists voluminous literature that identifies income as a major driver of HCE (see Introduction). Technological progress is also perceived to escalate the cost of health care because it drives up both the cost of care and the demand for advanced medical treatments. It provokes spending more on medical research and development (R&D) to invent new technologies as well (Weisbrod 1991; Newhouse 1992, 1993; Okunade and Murthy 2002; Murthy and Ketenci 2017). Technological progress, however, is not an easily quantified variable. Different researchers, therefore, have used a variety of measures to proxy technological changes. You and Okunade (2017) perhaps is the first paper that uses several alternative input (economy-wide and hospital R&D expenditures) and output (mortality rate and two medical technology indexes) technology proxies to assess the determinants of HCE. Their results imply that output proxies perform better in estimating the technological effect. Getzen and Okunade (2017) also argue that due to expenditure leakages going from R&D to health care-marketed innovations, output measures could better represent technological progress. In this paper, therefore, instead of widely used R&D expenditures (input proxy), we use life expectancy (output proxy) to represent technological progress.

Finally, since it is generally anticipated that older adults often need more health care, it has been overwhelmingly concluded that an aging population exerts a positive impact on HCE (Hoffman et al. 1996; Zweifel et al. 1999; Keehan et al. 2015; Kaiser Family Foundation 2015). Thus, the following specification is adopted for the analysis of this paper:

$$\mathrm{LnHCE}_t = \alpha + \beta_1 \mathrm{LnGDP}_t + \beta_2 \mathrm{LnLE}_t + \beta_3 \mathrm{LnAGE}_t + \varepsilon_t \tag{1}$$

In Eq. (1), HCE_t. is per capita real healthcare expenditure at time t, GDP_t. represents per capita real national income, AGE_t. is the proportion of population aged 65 years and older, and LE_t. is life expectancy at birth.

Since estimating Eq. (1) only reveals the long-run relationship between variables, the following ARDL specification is conducted to be able to also assess the short-run impacts of exogenous variables on HCE:

$$\begin{aligned}\Delta \text{LnHCE}_t &= \alpha + \sum_{k=1}^{n} \beta_k \Delta \text{Ln HCE}_{t-k} + \sum_{k=0}^{n} \gamma_k \Delta \text{Ln GDP}_{t-k} \\ &\quad + \sum_{k=0}^{n} \theta_k \Delta \text{Ln LE}_{t-k} + \sum_{k=0}^{n} \lambda_k \Delta \text{Ln AGE}_{t-k} + \sigma_1 \text{Ln HCE}_{t-1} \\ &\quad + \sigma_2 \text{Ln GDP}_{t-1} + \sigma_3 \text{Ln LE}_{t-1} + \sigma_4 \text{Ln AGE}_{t-1} + \mu_t \end{aligned} \tag{2}$$

Equation (2) is nothing but a familiar error-correction model in which the lagged error term is calculated from Eq. (1) and replaced by its equivalent. In this setup, the short-run effects could be captured through estimating the coefficients of the first-differenced variables. More specifically, γ, θ, and λ, respectively, represent the short-run impact of changes in the GDP, LE, and the elderly portion of the population (AGE) on HCE. The long-run effects of all variables are inferred from the estimates of $\sigma_2 - \sigma_4$, normalized on σ_1. However, these long-run coefficients are meaningful only if there exists a cointegration relationship among all variables (HCE, GDP, LE, and AGE) in the long run. Thus, following Pesaran et al. (2001), a standard F test, albeit with new tabulated critical values, is conducted to test the null hypothesis of no cointegration (i.e., $\sigma_1 = \sigma_2 = \sigma_3 = \sigma_4 = 0$).

As mentioned, the core objective of this paper is to examine whether or not the impact of income on the HCE is asymmetric. The symmetricity assumption is therefore relaxed to investigate whether the effect of rising income on HCE is different from that of falling income. To this end, following Delatte and Lopez-Villavicencio (2012) and Bahmani-Oskooee and Fariditavana (2014), the movement of *Ln* (GDP) is decomposed into its positive (rise in GDP) and negative (fall in GDP) partial sums. More precisely, $\text{LnGDP} = \text{LnGDP}_0 + \text{Ln GDP}_j^+ + \text{Ln GDP}_j^-$. where Ln GDP_j^+ and $\Delta\text{Ln GDP}_j^-$ are the partial sum processes of positive and negative changes in Ln (GDP).

We then apply the Shin et al. (2014) specification, which is an extension of the Pesaran et al. (2001) ARDL model. First partial sum variables are calculated through Eq. (3), and then, as Eq. (4) makes it apparent, Ln (GDP) in Eq. (2) is replaced by newly created partial sum variables (i.e., POS and NEG).

$$\begin{cases} \text{POS}_t = \sum_{j=1}^{t} \Delta \text{Ln GDP}_j^+ = \sum_{j=1}^{t} \max\left(\Delta \text{Ln GDP}_j, 0\right) \\ \text{NEG}_t = \sum_{j=1}^{t} \Delta \text{Ln GDP}_j^- = \sum_{j=1}^{t} \min\left(\Delta \text{Ln GDP}_j, 0\right) \end{cases} \tag{3}$$

$$\begin{aligned}\Delta \log \text{HCE}_t &= \alpha + \sum_{k=1}^{n} \beta_k \Delta \text{Log HCE}_{t-k} + \sum_{k=0}^{n} \theta_k \Delta \text{Log LE}_{t-k} \\ &\quad + \sum_{k=0}^{n} \lambda_k \Delta \text{Ln AGE}_{t-k} + \sum_{k=0}^{n} \partial_k \text{POS}_{t-k} + \sum_{k=0}^{n} \partial_k' \text{NEG}_{t-k}\end{aligned}$$

$$+ \sigma_1 \text{Log HCE}_{t-1} + \sigma_2 \text{Log LE}_{t-1} + \sigma_3 \text{Log AGE}_{t-1} + \sigma_4 \text{POS}_{t-1} + \sigma_5 \text{NEG}_{t-1} + \mu_t \quad (4)$$

Shin et al. (2014) introduced Eq. (4) as the nonlinear ARDL model. The sign and size of the partial sum coefficients in Eq. (4) will be assessed to judge whether GDP variation has a symmetric or asymmetric impact on the HCE. If both partial sums have the same signs and their sizes are not statistically different from one another either, it could be concluded that income variation has symmetric effects on HCE. Obviously, the effects are asymmetric otherwise. In this paper, we apply the Wald test to check whether or not the partial sums' coefficients are statistically different.

For the empirical analysis, the data on US healthcare expenditure (HCE) came from the Centers for Medicare and Medicaid Services (CMS 2016). The data on GDP, consumer price index (CPI), national population, proportion of population aged 65 years and older (AGE), and life expectancy at birth (LE) are extracted from the Federal Reserve Bank of St. Louis. Table 1 specifies the variables used in the empirical analysis and provides descriptive statistics for the period of 1960–2014. Figure 1, also graphically presents the logarithmically transformed series. As Fig. 1 shows, both GDP and aggregate HCE display an upward trend during the period under study, although HCE shows a tremendous growth.

Table 1 Descriptive statistics (all health expenditures are real per capita and in million dollars)

Variable	Mean	SD	Minimum	Maximum
Aggregate healthcare expenditure	19.1	10.7	4.4	38.2
Hospital expenditure	6.8	3.3	1.6	12.9
Physician and clinical expenditure	4.1	2.3	1.01	8.02
Prescription drugs expenditure	1.6	1.2	0.4	3.9
Administration and net cost of health insurance expenditure	1.2	0.9	0.2	3.1
Nursing care facilities and continuing care retirement communities	1.1	0.6	0.14	2.1
Dental care expenditure	0.9	0.4	0.3	1.5
Residential and personal care expenditure	0.8	0.6	0.07	1.9
Non-durable medical equipment expenditure	0.56	0.15	0.3	0.76
Public health activity expenditures	0.55	0.36	0.06	1.12
Other professional services expenditure	0.46	0.36	0.01	1.12
Home healthcare services expenditure	0.42	0.38	0.01	1.1
Durable medical equipment expenditure	0.35	0.16	0.14	0.61
Real per capita national income (million dollars)	182.9	39.01	102.3	241.03
Percentage of population age 65 and above	11.5	1.3	9.1	14.02
Life expectancy at birth	74.5	2.8	69.9	78.8

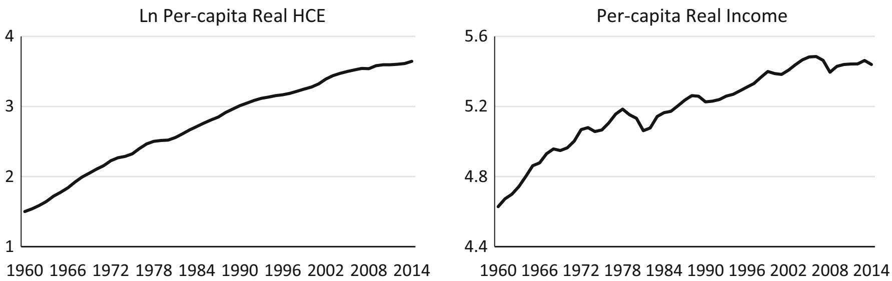

Fig. 1 Graphical representation of the logarithmically transformed series

3 Empirical results

In this section, in order to assess the effect of income variation on aggregate HCE, we first estimate Eq. (2). The Akaike information criterion (AIC) is used to select the optimum number of lags on each first-differenced variable. This is essentially a replication exercise of previous approaches, albeit one with a longer time-series data span and a more appropriate econometric methodology. We then re-estimate Eq. (2) for all different types of health services that form aggregate HCE. This specification will enable us to separately investigate the strength of the link between income and HCE for each type of health service. Finally, to examine whether or not the effect of income is asymmetric, Eq. (4) is estimated for aggregate HCE and all corresponding health services.

The first set of results on aggregate HCE is presented in Table 2, and the results for other health services are presented in Tables 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13 and 14. Each table consists of two parts. Part *I* contains the estimates of the linear ARDL model, i.e., Eq. (2) and Part II contains the estimates of the nonlinear ARDL model, i.e., Eq. (4). Note that each part is divided into three columns. Columns *A*, *B*, and *C*, respectively, report short-run estimates, long-run estimates, and diagnostic statistics.

3.1 Impact of income variation on aggregate HCE

In this section, we focus on Table 2 as a benchmark table, which makes it easy to follow the other tables. From Part I (Columns *A* and *B*), it can be seen that income has a significant positive impact on aggregate HCE both in the short run and in the long run. Our estimate of 0.81 for the long-run coefficient, i.e., income elasticity of HCE, corroborates findings of those researchers who postulated that health care is a necessity good (Parkin et al. 1987; Matteo 2003; Freeman 2003; Dreger and Reimers 2005; Sen 2005; Costa i Font et al. 2009; Baltagi and Moscone 2010; Moscone and Tosetti, 2010, Acemoglu et al. 2013; Caporale et al. 2015; Murthy and Okunade 2016). Nevertheless, in order for these findings to be valid, there must exist a long-run cointegration relationship among HCE, GDP, LE, and AGE. Therefore, the joint significance of lagged-level variables in Eq. (2) is tested. As reported in Column *C*

Table 2 Aggregate healthcare expenditure

Part I: Linear ARDL					
	0	1	2	3	4
Column A: Short-run estimates					
Ln (Aggregate HCE)	0.46** (0.14)				
Ln (GDP)	0.22** (0.07)	−0.22** (0.08)	−0.13 (0.08)		
Ln (AGE)	−1.21** (0.46)	4.42** (1.31)	4.39** (1.33)		
Ln (LE)	0.23 (0.69)				
Column B: Long-run estimates					
Intercept	Ln (Income)	Ln (AGE)	Ln (LE)	ECM_{t-1}	
−8.29 (1.21)	0.81* (0.48)	1.16* (0.63)	5.63* (3.19)	−0.11 (4.61)	
Column C: Diagnostics					
F test	LM test	RESET	R^2	CUSUM (CUSUMSQ)	
4.93	0.45	0.60	0.71	S(S)	
Part II: Nonlinear ARDL					
	0	1	2	3	4
Column A: Short-run estimates					
Ln (Aggregate HCE)	0.39** (0.10)				
POS	0.96** (0.23)	−1.22** (0.28)	−0.62** (0.25)	−0.46* (0.25)	
NEG	0.49* (0.27)				
Ln (AGE)	−1.08** (0.39)	0.21 (0.61)			
Ln (LE)	0.18 (0.61)				
Column B: Long-run estimates					
Intercept	POS	NEG	Ln (AGE)	Ln (LE)	ECM_{t-1}
5.61 (6.25)	4.46** (0.35)	−0.63 (0.53)	−0.09 (0.18)	−0.89 (1.50)	−0.30 (5.94)
Column C: Diagnostics					
F test	LM test	RESET	R^2	CUSUM (CUSUMSQ)	
6.42	1.56	1.86	0.76	S(S)	
Wald-Short (4.11)	Wald-Long (6.24)				

***, **,*Statistical significance at the 0.01, 0.05, and 0.10 levels, respectively

Table 3 Physician and clinical expenditure

Part I: Linear ARDL					
	0	1	2	3	4
Column A: Short-run estimates					
Ln (Physician and clinical)	0.32** (0.12)	0.27** (0.13)	0.12 (0.11)		
Ln (GDP)	0.09 (0.85)	− 0.25** (2.36)			
Ln (AGE)	− 1.12* (0.64)	4.17** (1.96)	− 5.91** (2.13)		
Ln (LE)	1.68* (0.97)	0.28 (1.09)	2.26** (1.04)		
Column B: Long-run estimates					
Intercept	Ln (Income)	Ln (AGE)	Ln (LE)	ECM_{t-1}	
− 7.85 (2.87)	− 0.25 (0.65)	2.76** (0.81)	3.83** (3.77)	− 0.16 (5.67)	
Column C: Diagnostics					
F test	LM test	RESET	R^2	CUSUM (CUSUMSQ)	
7.69	0.05	0.59	0.64	S(S)	
Part II: Nonlinear ARDL					
	0	1	2	3	4
Column A: Short-run estimates					
Ln (Physician and clinical)	0.41** (0.09)	0.23** (0.09)	0.31** (0.08)	0.21** (0.08)	
POS	− 0.23 (0.29)	− 1.70** (0.28)	− 0.58* (0.29)	− 1.51** (0.30)	
NEG	0.06 (0.29)	0.70** (0.32)	0.93** (0.31)	0.91** (0.31)	
Ln (AGE)	− 1.43** (0.47)	5.86** (1.125)	8.28** (1.26)		
Ln (LE)	1.55** (0.67)	2.70** (0.73)	3.65** (0.73)		
Column B: Long-run estimates					
Intercept	POS	NEG	Ln (AGE)	Ln (LE)	ECM_{t-1}
3.03 (9.67)	2.91** (0.68)	− 3.73** (0.76)	0.69** (0.31)	− 1.03 (2.32)	− 0.39 (10.02)
Column C: Diagnostics					
F test	LM test	RESET	R^2	CUSUM (CUSUMSQ)	
9.27	4.14	0.07	0.83	S(S)	
Wald-Short (10.82)	Wald-Long (12.14)				

***, **,*Statistical significance at the 0.01, 0.05, and 0.10 levels, respectively

Table 4 Other professional services expenditure

Part I: Linear ARDL					
	0	1	2	3	4
Column A: Short-run estimates					
Ln (Professional services)	− 0.01 (0.13)				
Ln (GDP)	0.25 (0.21)	0.41* (0.21)			
Ln (AGE)	1.11 (1.37)	− 3.40** (1.70)			
Ln (LE)	2.15 (2.17)				
Column B: Long-run estimates					
Intercept	Ln (Income)	Ln (AGE)	Ln (LE)	ECM_{t-1}	
− 6.33 (8.58)	− 0.03 (0.77)	4.53*** (1.04)	6.41** (5.47)	− 0.21 (4.85)	
Column C: Diagnostics					
F test	LM test	RESET	R^2	CUSUM (CUSUMSQ)	
5.44	0.15	5.83	0.42	S(S)	
Part II: Nonlinear ARDL					
	0	1	2	3	4
Column A: Short-run estimates					
Ln (Professional services)	− 0.05 (0.12)				
POS	2.62** (0.69)	1.79** (2.48)			
NEG	− 1.72** (0.82)				
Ln (AGE)	2.05 (1.62)	− 4.33** (1.57)			
Ln (LE)	0.94 (1.94)				
Column B: Long-run estimates					
Intercept	POS	NEG	Ln (AGE)	Ln (LE)	ECM_{t-1}
− 9.95 (3.08)	2.56 (1.98)	− 1.24 (2.81)	5.09*** (1.41)	1.31 (7.02)	− 0.22 (5.40)
Column C: Diagnostics					
F test	LM test	RESET	R^2	CUSUM (CUSUMSQ)	
5.27	0.17	3.26	0.53	S(S)	
Wald-Short (12.33)	Wald-Long (0.34)				

***, **,*Statistical significance at the 0.01, 0.05, and 0.10 levels, respectively

Table 5 Non-durable medical equipment expenditure

Part I: Linear ARDL					
	0	1	2	3	4
Column A: Short-run estimates					
Ln (Non-durable medical equipment)	0.34** (0.13)				
Ln (GDP)	0.18* (0.11)				
Ln (AGE)	0.11 (0.40)				
Ln (LE)	1.83 (1.12)				
Column B: Long-run estimates					
Intercept	Ln (Income)	Ln (AGE)	Ln (LE)	ECM_{t-1}	
− 15.11 (1.47)	0.24 (0.38)	0.98 (0.65)	2.52 (0.81)	− 0.13 (2.28)	
Column C: Diagnostics					
F test	LM test	RESET	R^2	CUSUM (CUSUMSQ)	
1.60	0.11	0.54	0.27	S(S)	
Part II: Nonlinear ARDL					
	0	1	2	3	4
Column A: Short-run estimates					
Ln (Non-durable medical equipment)	0.26* (0.13)				
POS	0.55 (0.42)				
NEG	0.40 (0.54)				
Ln (AGE)	0.09 (0.23)				
Ln (LE)	2.00* (1.13)	− 1.52 (1.16)			
Column B: Long-run estimates					
Intercept	POS	NEG	Ln (AGE)	Ln (LE)	ECM_{t-1}
− 4.95 (1.23)	− 1.50 (4.98)	3.32 (7.79)	− 2.04 (1.49)	8.42 (2.67)	− 0.02 (2.26)
Column C: Diagnostics					
F test	LM test	RESET	R^2	CUSUM (CUSUMSQ)	
1.41	1.87	2.97	0.26	S(S)	
Wald-Short (0.35)	Wald-Long (0.09)				

***, **,*Statistical significance at the 0.01, 0.05, and 0.10 levels, respectively

Table 6 Durable medical equipment expenditure

Part I: Linear ARDL					
	0	1	2	3	4
Column A: Short-run estimates					
Ln (Durable medical equipment)	0.08 (0.13)	0.24** (0.12)			
Ln (GDP)	0.33 (0.23)	0.71** (0.27)			
Ln (AGE)	− 0.74 (0.87)				
Ln (LE)	− 2.16 (2.88)				
Column B: Long-run estimates					
Intercept	Ln (Income)	Ln (AGE)		Ln (LE)	ECM_{t-1}
− 4.26 (4.06)	0.51 (1.62)	0.70 (2.24)		8.52 (0.72)	− 0.11 (2.02)
Column C: Diagnostics					
F test	LM test	RESET	R^2	CUSUM (CUSUMSQ)	
1.06	1.44	4.18	0.29	S(S)	

Part II: Nonlinear ARDL					
	0	1	2	3	4
Column A: Short-run estimates					
Ln (Durable medical equipment)	0.07 (0.12)	0.30** (0.11)			
POS	1.14 (0.98)				
NEG	1.91** (0.92)				
Ln (AGE)	− 1.03 (0.83)				
Ln (LE)	− 3.38 (2.67)				
Column B: Long-run estimates					
Intercept	POS	NEG	Ln (AGE)	Ln (LE)	ECM_{t-1}
5.84 (6.71)	6.11*** (1.51)	− 6.17** (2.51)	− 1.33* (0.76)	− 2.27* (6.45)	− 0.24 (3.36)
Column C: Diagnostics					
F test	LM test	RESET	R^2	CUSUM (CUSUMSQ)	
3.33	0.01	0.39	0.35	S(S)	
Wald-Short (2.16)	Wald-Long (7.53)				

***, **,*Statistical significance at the 0.01, 0.05, and 0.10 levels, respectively

Table 7 Prescription drugs expenditure

Part I: Linear ARDL					
	0	1	2	3	4
Column A: Short-run estimates					
Ln (Prescription drug)	0.49** (0.14)				
Ln (GDP)	0.59** (0.14)	− 0.31* (0.17)	0.21 (0.15)		
Ln (AGE)	− 4.79** (0.88)	2.86 (2.48)	5.75 (4.01)	− 6.91** (2.62)	
Ln (LE)	− 0.69 (1.30)	− 1.49 (1.32)	− 0.78 (1.38)	− 3.23** (1.31)	
Column B: Long-run estimate					
Intercept	Ln (Income)	Ln (AGE)	Ln (LE)	ECM_{t-1}	
− 15.09 (2.83)	− 0.62 (1.72)	− 3.39 (2.30)	3.88** (2.74)	− 0.08 (3.31)	
Column C: Diagnostics					
F test	LM test	RESET	R^2	CUSUM (CUSUMSQ)	
2.50	1.12	0.07	0.78	S(S)	
Part II: Nonlinear ARDL					
	0	1	2	3	4
Column A: Short-run estimates					
Ln (Prescription drug)	0.55** (0.15)				
POS	3.15** (0.58)	− 1.31** (0.65)	1.07* (0.55)	0.56 (0.46)	
NEG	− 0.03 (0.52)				
Ln (AGE)	− 4.54** (0.81)	− 2.97 (2.40)	2.29** (4.43)	− 7.17** (2.67)	
Ln (LE)	− 2.04* (1.19)				
Column B: Long-run estimates					
Intercept	POS	NEG	Ln (AGE)	Ln (LE)	ECM_{t-1}
7.28 (1.04)	9.87* (5.12)	− 5.08** (4.70)	− 4.64* (2.50)	− 4.50 (5.75)	− 0.07 (3.54)
Column C: Diagnostics					
F test	LM test	RESET	R^2	CUSUM (CUSUMSQ)	
2.28	0.14	0.81	0.80	S(S)	
Wald-Short (3.94)	Wald-Long (9.78)				

***, **,*Statistical significance at the 0.01, 0.05, and 0.10 levels, respectively

Table 8 Dental expenditure

Part I: Linear ARDL					
	0	1	2	3	4
Column A: Short-run estimates					
Ln (Dental services)	− 0.05 (0.13)				
Ln (GDP)	0.30** (0.14)	0.01 (0.13)	− 0.26** (2.06)		
Ln (AGE)	− 1.03 (0.78)	3.37 (2.37)	− 1.26 (3.68)	− 4.32* (2.51)	
Ln (LE)	3.41** (1.22)	− 2.53* (1.32)			
Column B: Long-run estimates					
Intercept	Ln (Income)	Ln(AGE)	Ln(LE)	ECM_{t-1}	
− 23.98 (7.79)	0.82** (0.40)	0.06 (0.50)	4.56** (2.26)	− 0.29 (4.62)	
Column C: Diagnostics					
F test	LM test	RESET	R^2	CUSUM (CUSUMSQ)	
5.05	0.60	0.78	0.46	S(S)	

Part II: Nonlinear ARDL					
	0	1	2	3	4
Column A: Short-run estimates					
Ln (Dental services)	0.07 (0.11)				
POS	1.25** (0.37)	− 1.91** (0.50)	− 0.99** (0.42)	− 1.16** (0.41)	
NEG	0.65 (0.43)	1.24** (0.41)			
Ln (AGE)	− 1.60** (0.34)				
Ln (LE)	2.68** (1.03)				
Column B: Long-run estimates					
Intercept	POS	NEG	Ln (AGE)	Ln (LE)	ECM_{t-1}
4.73 (0.54)	4.14*** (0.32)	0.22 (0.46)	− 1.06*** (0.16)	− 0.79 (1.32)	− 0.64 (6.51)
Column C: Diagnostics					
F test	LM test	RESET	R^2	CUSUM (CUSUMSQ)	
7.63	0.14	0.03	0.62	S(S)	
Wald-Short (7.62)	Wald-Long (11.34)				

***, **,*Statistical significance at the 0.01, 0.05, and 0.10 levels, respectively

Table 9 Administration and net cost of health insurance expenditure

Part I: Linear ARDL					
	0	1	2	3	4
Column A: Short-run estimates					
Ln (Administration and net cost of health insurance)	0.51** (0.15)	−0.24* (0.13)	−0.04 (0.12)		
Ln (GDP)	0.58 (0.38)	0.56 (0.44)	−1.14** (0.42)		
Ln (AGE)	−1.17 (1.26)				
Ln (LE)	−1.21 (3.83)	−1.36 (4.48)	−7.63* (4.29)		
Column B: Long-run estimates					
Intercept	Ln (Income)	Ln (AGE)	Ln (LE)	ECM_{t-1}	
−7.75 (4.35)	1.07* (0.56)	−1.64** (0.73)	6.23** (4.19)	−0.43 (3.56)	
Column C: Diagnostics					
F test	LM test	RESET	R^2	CUSUM (CUSUMSQ)	
3.48	0.66	0.24	0.60	S(s)	
Part II: Nonlinear ARDL					
	0	1	2	3	4
Column A: Short-run estimates					
Ln (Administration and net cost of health insurance)	0.49** (0.11)				
POS	2.39* (1.32)	1.33 (1.44)	−3.97** (1.36)		
NEG	0.72 (1.52)				
Ln (AGE)	−1.41 (1.18)				
Ln (LE)	−2.65 (3.64)				
Column B: Long-run estimates					
Intercept	POS	NEG	Ln (AGE)	Ln (LE)	ECM_{t-1}
−4.97 (1.42)	4.30*** (1.06)	−0.21 (1.70)	−1.84** (0.56)	5.71** (4.71)	−0.37 (3.85)
Column C: Diagnostics					
F test	LM test	RESET	R^2	CUSUM (CUSUMSQ)	
6.53	0.03	0.002	0.62	S(S)	
Wald-Short (0.14)	Wald-Long (4.45)				

***, **,*Statistical significance at the 0.01, 0.05, and 0.10 levels, respectively

Table 10 Hospital care expenditures

Part I: Linear ARDL					
	0	1	2	3	4
Column A: Short-run estimates					
Ln (Hospital)	0.34** (0.16)	0.31* (0.18)	0.08 (0.13)		
Ln (GDP)	0.34** (0.08)	− 0.51** (0.09)	− 0.42** (0.11)		
Ln (AGE)	0.97** (0.27)				
Ln (LE)	0.63 (0.82)				
Column B: Long-run estimates					
Intercept	Ln (Income)	Ln (AGE)	Ln (LE)	ECM_{t-1}	
− 12.28 (4.86)	1.55*** (0.19)	1.43** (0.28)	0.61 (1.40)	− 0.27 (6.36)	
Column C: Diagnostics					
F test	LM test	RESET	R^2	CUSUM (CUSUMSQ)	
11.28	3.71	6.68	0.71	S(S)	
Part II: Nonlinear ARDL					
	0	1	2	3	4
Column A: Short-run estimates					
Ln (Hospital)	0.15 (0.11)	0.16 (0.10)	0.39** (0.10)		
POS	2.28*** (0.27)	− 1.93** (0.28)	− 0.83** (0.30)		
NEG	0.38 (0.25)	− 1.01** (0.25)	− 1.44** (0.31)	− 0.81** (2.44)	
Ln (AGE)	0.15 (0.43)	− 3.98** (1.12)	5.32** (1.09)		
Ln (LE)	− 0.68 (0.59)	− 0.05 (0.62)	1.14* (0.62)	2.80** (0.64)	
Column B: Long-run estimates					
Intercept	POS	NEG	Ln (AGE)	Ln (LE)	ECM_{t-1}
8.59 (7.32)	5.52*** (0.52)	1.28* (0.64)	1.17*** (0.27)	− 7.26** (1.67)	− 0.42 (8.32)
Column C: Diagnostics					
F test	LM test	RESET	R^2	CUSUM (CUSUMSQ)	
12.57	0.01	0.79	0.88		
Wald-Short (2.23)	Wald-Long (11.04)				

***, **,*Statistical significance at the 0.01, 0.05, and 0.10 levels, respectively

Table 11 Nursing care facilities and continuing care retirement communities expenditure

Part I: Linear ARDL

	0	1	2	3	4
Column A: Short-run estimates					
Ln (Nursing care facilities)	0.41** (0.12)				
Ln (GDP)	0.49** (0.11)	−0.41** (0.12)			
Ln (AGE)	−0.71* (0.38)				
Ln (LE)	−0.94 (1.17)				
Column B: Long-run estimates					
Intercept	Ln (Income)	Ln (AGE)	Ln (LE)	ECM_{t-1}	
(3.84)	2.51** (4.51)	2.34** (0.73)	−6.12 (4.06)	−0.13 (5.83)	
Column C: Diagnostics					
F test	LM test	RESET	R^2	CUSUM (CUSUMSQ)	
8.07	0.08	3.75	0.85	S(S)	

Part II: Nonlinear ARDL

	0	1	2	3	4
Column A: Short-run estimates					
Ln (Nursing care facilities)	0.35** (0.12)				
POS	1.74** (0.39)	−1.34** (0.49)	0.58 (0.43)		
NEG	−0.44 (0.45)				
Ln (AGE)	−1.06** (0.40)				
Ln (LE)	−1.39 (1.09)	5.34** (1.36)	1.98 (1.49)	2.15* (1.13)	
Column B: Long-run estimates					
Intercept	POS	NEG	Ln (AGE)	Ln (LE)	ECM_{t-1}
1.41** (3.89)	8.46*** (1.18)	−3.60 (2.64)	2.24** (0.57)	−5.44*** (6.19)	−0.17 (5.28)
Column C: Diagnostics					
F test	LM test	RESET	R^2	CUSUM (CUSUMSQ)	
5.01	0.05	2.42	0.88	S(S)	
Wald-Short (1.20)	Wald-Long (13.94)				

***, **,*Statistical significance at the 0.01, 0.05, and 0.10 levels, respectively

Table 12 Home healthcare expenditure

Part I: Linear ARDL					
	0	1	2	3	4
Column A: Short-run estimates					
Ln (Home health care)	0.74** (0.11)	−0.01 (0.13)			
Ln (GDP)	0.47 (0.34)				
Ln (AGE)	0.84 (2.50)	−5.43** (3.76)			
Ln (LE)	4.22 (3.73)				
Column B: Long-run estimates					
Intercept	Ln (Income)	Ln (AGE)	Ln (LE)	ECM_{t-1}	
−8.30 (3.97)	1.31** (0.54)	6.19*** (0.81)	4.12** (3.44)	−0.43 (4.98)	
Column C: Diagnostics					
F test	LM test	RESET	R^2	CUSUM (CUSUMSQ)	
5.80	0.30	0.44	0.67	S(S)	
Part II: Nonlinear ARDL					
	0	1	2	3	4
Column A: Short-run estimates					
Ln (Home health care)	0.83** (0.12)				
POS	5.21** (1.30)	−2.22 (1.33)			
NEG	−2.16 (1.61)				
Ln (AGE)	1.74 (2.38)	−5.51** (3.50)			
Ln (LE)	−0.25 (3.62)				
Column B: Long-run estimates					
Intercept	POS	NEG	Ln (AGE)	Ln (LE)	ECM_{t-1}
−4.01 (6.02)	5.03** (1.56)	1.92 (2.23)	6.33** (0.81)	5.93 (6.26)	−0.45 (5.55)
Column C: Diagnostics					
F test	LM test	RESET	R^2	CUSUM (CUSUMSQ)	
5.65	0.04	0.19	0.71	S(S)	
Wald-Short (1.35)	Wald-Long (4.24)				

***, **,*Statistical significance at the 0.01, 0.05, and 0.10 levels, respectively

Table 13 Residential and personal care expenditure

Part I: Linear ARDL

	0	1	2	3	4
Column A: Short-run estimates					
Ln (Residential and personal care)	0.35** (0.12)				
Ln (GDP)	0.75** (0.14)	− 0.68** (0.17)			
Ln (AGE)	− 2.09** (0.59)				
Ln (LE)	− 0.86 (1.40)	− 0.80 (0.53)	2.89** (2.17)		
Column B: Long-run estimates					
Intercept	Ln (Income)	Ln (AGE)	Ln (LE)	ECM_{t-1}	
− 7.62 (1.71)	1.76*** (0.34)	0.74 (0.48)	3.04** (2.91)	− 0.27 (5.26)	
Column C: Diagnostics					
F test	LM test	RESET	R^2	CUSUM (CUSUMSQ)	
6.41	0.02	1.36	0.65	S(S)	

Part II: Nonlinear ARDL

	0	1	2	3	4
Column A: Short-run estimates					
Ln (Residential and personal care)	0.38** (0.11)				
POS	0.99** (0.46)				
NEG	1.28** (0.56)				
Ln (AGE)	− 0.82 (0.88)	2.27 (2.43)	− 4.97** (2.35)		
Ln (LE)	1.08 (1.41)				
Column B: Long-run estimates					
Intercept	POS	NEG	Ln (AGE)	Ln (LE)	ECM_{t-1}
− 7.99 (4.74)	2.56** (0.96)	4.72** (1.74)	1.57** (0.52)	6.74*** (3.46)	− 0.33 (5.93)
Column C: Diagnostics					
F test	LM test	RESET	R^2	CUSUM (CUSUMSQ)	
6.42	0.04	1.09	0.65	S(S)	
Wald-Short (2.10)	Wald-Long (1.01)				

***, **,*Statistical significance at the 0.01, 0.05, and 0.10 levels, respectively

Table 14 Public health activity expenditures

Part I: Linear ARDL					
	0	1	2	3	4
Column A: Short-run estimates					
Ln (Public health activity)	0.01 (0.12)				
Ln (GDP)	0.12 (0.14)	− 0.49** (0.17)	− 0.39** (0.18)		
Ln (AGE)	1.35 (1.01)	2.01 (2.63)	− 7.15** (2.65)		
Ln (LE)	1.20 (1.49)				
Column B: Long-run estimates					
Intercept	Ln (Income)	Ln (AGE)	Ln (LE)	ECM_{t-1}	
0.26 (1.79)	2.19*** (0.36)	3.58*** (0.58)	− 4.87 (2.99)	− 0.31 (6.59)	
Column C: Diagnostics					
F test	LM test	RESET	R^2	CUSUM (CUSUMSQ)	
10.17	1.88	0.41	0.63	S(S)	
Part II: Nonlinear ARDL					
	0	1	2	3	4
Column A: Short-run estimates					
Ln (Public health activity)	− 0.23* (0.14)	− 0.31** (0.12)	− 0.38** (2.71)		
POS	− 0.48 (0.57)				
NEG	0.30 (0.67)	− 2.96** (0.68)	− 2.39** (3.31)		
Ln (AGE)	1.63 (1.01)	8.73** (2.90)	− 4.62 (3.17)		
Ln (LE)	− 1.25 (1.55)				
Column B: Long-run estimates					
Intercept	POS	NEG	Ln (AGE)	Ln (LE)	ECM_{t-1}
7.97 (4.87)	6.06** (2.17)	8.32** (2.82)	6.99*** (2.19)	− 2.02 (3.73)	− 0.19 (7.36)
Column C: Diagnostics					
F test	LM test	RESET	R^2	CUSUM (CUSUMSQ)	
9.76	0.42	0.49	0.68	S(s)	
Wald-Short (6.59)	Wald-Long (0.45)				

***, **,*Statistical significance at the 0.01, 0.05, and 0.10 levels, respectively

of Part I, the calculated F-statistic is greater than its upper bound critical value, i.e., 4.70 (Pesaran et al. 2001; Narayan 2005), which rejects the null hypothesis of no cointegration with a 95% level of confidence.

In Column C, a few other diagnostic tests are also presented. The adjusted R^2 value of 71% and the results of the Lagrange multiplier (LM) test and Ramsey's RESET test imply that an optimum model is specified, all coefficients are stable, and residuals are free of autocorrelation. Following Pesaran et al. (2001), we also conduct CUSUM and CUSUMSQ tests to assess the parameter's stability (Brown et al. 1975). Coefficients are represented by "*S*" if they are stable and by "*US*" if they are unstable. As presented, results of both tests imply that stable coefficients are estimated.[4]

Findings reported in Part II show whether or not changes in national income affect HCE asymmetrically. Looking at the long-run coefficient estimates of Eq. (4), reported in Column B, one could conclude that contrary to what previous studies assume, the impact of income variation on aggregate HCE is not symmetric. While a highly significant positive coefficient is estimated for POS variable, the NEG variable does not carry a significant coefficient. The Wald test, reported in Column C of Part II, also clearly confirms that estimated coefficients of POS and NEG are statistically different. These findings imply that a long-run increase in national income does expand aggregate HCE, but there is no statistical support for the diminishing role of declining income.

Other diagnostic statistics remain at the same level to those of the linear model, meaning that the nonlinear ARDL model is well specified and all coefficients are stable. For instance, a reported estimate of 6.42 for F-statistics makes it evident that similar to Eq. (2), variables in Eq. (4) are also cointegrated in the long run, which means that long-run coefficient estimates are meaningful.

3.2 Impact of income variation on different health services

As noted, there has been a contentious debate over the size of income elasticity of HCE, the central question being whether health spending is a necessity or a luxury good. Thus, to have better insight into the understanding of the relationship between income and health spending, in this section we break aggregate HCE down into 12 different types of health services, assessing the impact of income changes on each of the services' expenses (Tables 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14).

Our estimates of the linear ARDL model (reported in Part I, Column B) suggest that contrary to what the literature assumes, a strong and positive relationship between HCE and income does not exist for many (5 out of 12) types of health services. That is, other factors must be driving rising expenses of such health services (Tables 3, 4, 5, 6, 7).[5] For instance, according to our estimates, for "prescription drugs" technological progress is the major driver of such expenditure. For "physician and clinical" and "other professional" services, again technological progress is a major determinate, but the age structure of population also plays an important role in the cost escalation

[4] S(s) means both CUSUM and CUSUMSQ are stable.

[5] Physician and clinical expenditure; professional services expenditure; home healthcare expenditure; non-durable medical products expenditure; prescription drug expenditure; administration; and net cost of health insurance.

of such expenditures. For durable and non-durable medical equipment, our estimates imply that none of the conventional factors widely used in the literature could explain the rising cost of such expenditures.

For other services in which income variation does have a significant impact, the size of income elasticity varies across different types of health services. Among them, "dental" expenditure is the only health service for which income elasticity is less than unity (Table 8). For "administrative expenditure," the income elasticity is very close to one (Table 9); for "hospital care," "nursing care facilities," "home health care," "residential and personal care," and "public health activity," the income elasticity becomes greater than one (Tables 10, 11, 12, 13, 14). These outcomes imply that, as expected, various health services respond differently to income changes.

The outcomes of the nonlinear ARDL model are reported in Part II. Except for "other professional services," "non-durable medical equipment," "residential and personal care," and "public health activity," the estimated coefficients of POS and NEG are statistically different from each other. This confirms that for the majority of health services, income variation does not have a symmetric impact on health expenses. Our findings on the asymmetric relationship between income and health expenses provide valuable policy implications, which we will briefly discuss below.

3.3 Policy implication

Past studies, by only assessing aggregate HCE, place great emphasis on the role of government in the delivery of health care only if health care is a necessity good. They conclude that if health care is known as a luxury good, it would be a commodity much like any other and should be left to market forces alone (Getzen 2000; Farag et al. 2012; Murthy and Okunade 2016). However, this distinction is only true when the effect of income on health expenses is symmetric. For example, our results of the linear ARDL model imply that hospital care is a luxury good and hence, according to the literature, should be left to market forces alone. However, the results of the nonlinear ARDL model show that the effect of income on hospital spending is asymmetric, implying that hospital expenses are more responsive to income increases; that is, demand irreversibility could potentially be the reason that the linear model produces a greater-than-one income elasticity. In other words, our results indicate that people tend to purchase more hospital services when income is growing, but they do not purchase less when income is declining. People may behave like this because they are uncertain about future prices, not because hospital care is a luxury service. Thus, in this paper, instead of necessity and luxury, we divide health services into three different categories: services that are not affected by income changes at all, services in which the effect of income is asymmetric, and services in which the effect of income is symmetric.

According to our estimates, 5 out of 12 health services ("physician and clinical services," "other professional services," "durable medical equipment," "non-durable medical equipment," and "prescription drugs") form the first group. Since expenses for these health services rise regardless of the level of income, public involvement is indispensable. Government and policy makers should find a mechanism to control prices of these services, which are rising much faster than inflation (Patton 2015).

Our second group is formed by “dental,” “administrative,” “hospital care,” “nursing care,” and “home healthcare” services, which are affected asymmetrically by income variation. It could be inferred from the estimates of the nonlinear ARDL model that these expenditures are more elastic given income increases, i.e., the stockpiling behavior is predominant among consumers of such health services. The stockpiling behavior motivates healthcare retailers to adopt a more responsive pricing strategy (Maynard and Subramaniam 2015).[6] Thus, for health services in the second group, government intervention is required regardless of the numerical size of the income elasticity. More specifically, government should adopt policies to increase competition on the demand side of health care.[7] For instance, government policies should make healthcare prices more transparent so that patients can clearly see the price of a treatment and determine how much they will pay out of pocket before receiving care.

“Residential care” and “public health” services are the only services that are affected symmetrically by income variation form our third group. For these services, we could rely on the literature and judge about the public intervention based on the numerical size of their income elasticity. According to the results of the linear ARDL model, both of these services have a greater-than-one income elasticity, i.e., they are both considered luxury commodities. According to the literature, finding a health service luxury could mean that it has more of a calming effect and would provide comfort and convenience rather than actual physiological treatment. Thus, it should be left to the market forces.

4 Conclusion and discussion

The main objective of this study has been to explore the relationship between income and HCE in the USA. One common feature of all past studies is to assume that the effect of income changes on HCE is symmetric. However, while a rise in income could expand HCE, a similar income fall may not decline the HCE equally, i.e., the effect of income on HCE is not symmetric. In order to examine this hypothesis, the nonlinear ARDL model is employed to deconstruct the movement of national income into its positive (rise in GDP) and negative (fall in GDP) partial sums. Another common feature of most past studies is that they have only focused on aggregate HCE and its determinants. Thus, in this study, we break aggregate HCE down into 12 different types of services, and for each type of service, income elasticity of HCE is estimated.

Similar to many recent studies, we also estimate a positive and significant income elasticity for aggregate HCE, which is less than one (Corporale et al. 2015; Murthy and Okunade 2016). However, findings imply that the size of income elasticity varies across different types of health services. While for some health services, income elasticity is below unity, other spending tends to grow faster than the GDP. Results

[6] In responsive pricing strategy, prices are decided after demand information is revealed.

[7] Despite the fact that income elasticities for “hospital” and “nursing care” expenditures are above one, government involvement is recommended.

also indicate that for many health services, income does not have a significant impact on their expenditures. These results reinforce findings of the papers (Acemoglu et al. 2013; Murthy and Okunade 2016), which concluded that factors other than income (e.g., aging or technological progress) must be driving rising health expenses. Our estimates of the nonlinear ARDL model imply that for aggregate HCE as well as most of its associated health services, the impact of income variation on HCE is not symmetric; that is, a rise in income expands HCE, but falling income does not lead to an equal decline in HCE. Our results emphasize on a greater government participation for the financing and distribution of healthcare resources in the USA.

There are many healthcare policies that have been established or are being established at federal, state, and local levels of government with the intention to improve the US healthcare system. However, not all healthcare policies are successful. The Supplemental Nutrition Assistance Program (SNAP), which offers nutrition assistance to eligible, low-income individuals, and Medicaid expansion in 2014 are examples of good policies, which are associated with significant healthcare savings (Pines et al. 2016; Zielinskie et al. 2017). Some policies, on the other hand, have unintended consequences and foster other problems and some fail by worsening the problems they are intended to address. For example, in 2004, California required that specific minimum nurse-to-patient ratios must be established for all units in acute care hospitals in the state. "Minimum nurse staffing ratios" were implemented to improve patient outcomes. However, while there is no evidence that this resulted from the policy change, growth in nurse's wages led to a significant growth in hospital expenditures (Longest 1998; Aiken et al. 2010).

Based on our findings, health services are divided into three groups: services that are not affected by income changes at all, services in which the effect of income is asymmetric, and services in which the effect of income is symmetric. We believe that in order for policies to be successful, appropriate policies should be adopted for each group individually. For example, in the first group as health expenses rise regardless of the level of income, government should find a mechanism to control prices. Policies that could prevent hospital mergers and/or reduce hospital market powers are among the most essential policies for achieving this purpose.[8] There is substantial evidence that shows that mergers lead to higher prices, though without any measured impact on quality (Gaynor et al. 2015; Ginsburg 2016).

For the second group, as health expenditures are more elastic given income increases, healthcare providers are motivated to increase prices, while income is growing. Therefore, policies that could make prices more transparent should reduce the expenditure spent on these services (Boynton and Robinson 2015). Making hospitals' prices public, like what has been done in Massachusetts, could help patients to clearly see and compare the prices of a particular treatment and make more informed decisions.[9] Building more public hospitals and expansion of public health activity could also help to create reference prices and will put a downward price pressure on more expensive hospitals. Ironically, statistics show that the number of public hospitals has

[8] Hospital mergers are growing very fast during last 20 year in the USA (CDC 2017; AHA 2017).

[9] Since 2014, Massachusetts physicians and hospitals are required by law to provide cost information for procedures and services to patients who request it (Massachusetts Medical Society 2017).

been declining dramatically since 1975 (CDC 2017; AHA 2017).[10] With regard to the third group, since its health services are affected symmetrically by income variation and their income elasticity is greater than one, government intervention is not justifiable.

Appendix

In this section, according to Centers for Medicare and Medicaid Services (CMS), explanations are provided for the 12 health services that are studied in this paper.

Hospital care

It includes revenue received for all services provided in hospitals to patients. Therefore, expenditures include revenues received to cover room and board, ancillary services such as operating room fees, inpatient and outpatient care, services of resident physicians, inpatient pharmacy, hospital-based nursing home care, hospital-based home health care, and fees for any other services billed by the hospital such as hospice.

Physicians and clinical services

They include offices of physicians (including Doctors of Medicine (M.D.) and Doctors of Osteopathy (D.O.), and outpatient care centers) as well as the portion of medical and diagnostic laboratory services that are billed independently by the laboratories.

Other professional services

They include services provided in offices of other health practitioners.

Dental services

They include services provided by Offices of Doctors of Dental Surgery (D.D.S.), Doctors of Dental Medicine (D.M.D.), or Doctors of Dental Science (D.D.Sc.).

[10] From 1975 to 2015, the number of federal hospitals has dropped from 382 to 212 and the number of state–local hospitals has dropped from 1761 to 983.

Residential and personal care

It includes spending for school health, worksite health care, Medicaid home- and community-based waivers, some ambulance services, residential mental health and substance abuse facilities, and other types of health care. Generally, these services are provided in non-traditional settings.

Home health care

It includes expenditures on medical care services delivered in the home by freestanding home health agencies (HHAs). Home healthcare providers are private-sector establishments primarily engaged in providing skilled nursing services in the home, along with a range of the following: personal care services, homemaker and companion services, physical therapy, medical social services, medications, medical equipment and supplies, counseling, 24-h home care, occupational and vocational therapy, dietary and nutritional services, speech therapy, audiology, and high-tech care such as intravenous therapy.

Nursing care facilities and continuing care retirement communities

Expenditures reported in this category are for services provided in freestanding nursing homes and continuing care retirement communities. These facilities are defined as private-sector establishments primarily engaged in providing inpatient nursing, rehabilitative, continuous personal care services to persons requiring nursing care, and continuing care retirement communities with onsite nursing care facilities.

Prescription drugs

Expenditures on prescription drugs include retail sales of human-use, dosage-form drugs, biological drugs, and diagnostic products that are available only by a prescription. These include retail prescription drug purchases that occur in pharmacies and drug stores (including both chain and independent), supermarkets and other grocery store pharmacies, mail order and other direct-selling establishments, department stores, warehouse clubs and supercenters, and all other general mass-merchandising establishments.

Durable medical equipment

Durable medical equipment generally has a useful life of over 3 years. Expenditures in this category represent retail sales of items such as contact lenses, eyeglasses and other ophthalmic products, surgical and orthopedic products, medical equipment rental, oxygen and hearing aids.

Non-durable medical equipment

Non-durable medical equipment generally has a useful life of less than 3 years. Expenditures in this category include nonprescription drugs (products purchased over the counter such as analgesics and cough and allergy medications) and medical sundries (items such as surgical and medical instruments and surgical dressings, and diagnostic products such as needles and thermometers.

Administration and net cost of health insurance

This category includes the administrative costs of healthcare programs such as Medicare and Medicaid as well as the net cost of private health insurance. Net cost is the difference between private health insurance expenditures and benefits incurred and includes administrative costs, additions to reserves, rate credits and dividends, premium taxes and fees, and net underwriting gains or losses.

Public health activity

In addition to funding the care of individual citizens, the government is involved in organizing and delivering publicly provided health services such as epidemiological surveillance, inoculations, immunization/vaccination services, disease prevention programs, the operation of public health laboratories, and other such functions.

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