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# Determinants of U.S. health expenditure: Evidence from autoregressive distributed lag (ARDL) approach to cointegration

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ABSTRACT

Using 1960–2012 annual time-series data for modelling, we apply the Autoregressive Distributed Lag Cointegration (ARDL) approach, to identify some major drivers of per capita real U.S. health spending. The ARDL Bounds testing procedure (Pesaran et al., 1999; 2001) has several econometric advantages compared with the standard Johansen and Juselius cointegration method. One distinguishing feature of this ARDL Bounds testing procedure is its ability to estimate the long-run economic relationship without requiring pre-testing the time-series for the presence of unit roots in the data generating process incorporated in the cointegration model. The empirical findings in this study indicate that per capita real income (INCOME), the population percent above 65 years (AGE) and the level of health care technology (HRD), measured as the level of Research & Development expenditure in health care are cointegrated. INCOME, AGE and HRD exert positive effects on U.S. health expenditure per capita. Unlike prior studies, this paper presents new empirical evidence indicating that the U.S. health care is a necessity, with an income elasticity estimate of around 0.92. We also find that medical technology advances play a major role in the long run rise of the U.S. health expenditure. We discuss implications of these findings.


## 1. Introduction

One of the more recent economic challenges in the U.S. is the resurgence of rising health care spending (Martin et al., 2016). The enactment and gradual implementations of the 2010 Affordable Care Act (ACA) have added more uncertainty in this regard. Many experts claim that the ACA has escalated health spending and they project further rise in future years (Centers for Medicare and Medicaid Services, 2016). The health expenditure percentage of the GDP rose from 5.0% in 1960 to 17.6% in 2016 (CMS, 2016). Moreover, real (in 2009 $) U.S. per capita health expenditure of $8639.65 in 2014 is expected to grow at 6.2% during the years 2015–2022 (CMS, 2016). The annual growth rates of health expenditures (HEXP) in excess of the annual GDP growth rates, not sustainable in the long run, is a major challenge for the U.S. and most of the other OECD (Organization for Economic Cooperation and Developing) countries (see for example, Chernew and Newhouse, 2012). Moreover, the complex set of factors driving U.S. HEXP rise include ageing population, consumer demand expectations for costly high quality care, growing incomes, rising prices of the medical personnel and hospital services, medical innovation diffusion, and the inefficient fragmented health care system including the financing structure. The search for new insights into the understanding of the relationship among rising HEXP and its persistent drivers underlies the timely need to investigate the roles of income, technology and demographic shifts using a different modelling approach.

Consequently, this investigation should interest economists, researchers, and the U.S. health policy decision-makers. Here, for the first time in the literature on the health expenditure modelling in the U.S., we apply a relatively new approach, the Autoregressive Distributed Lag (ARDL), originally developed by Pesaran and Shin (1999), and Pesaran et al. (2001), to identify some of the major drivers of the U.S. aggregate health expenditure. Moreover, this present study extends an earlier study (Okunade and Murthy, 2002) by using a longer time-series data span and a more robust econometric methodology. Specifically, using 1960–2012 time-series data, we test the existence of cointegrating relationship among per capita real health expenditure (HEXP), per capita real GDP (INCOME), health research and development expenditure (HRD), and demographics defined as the elderly population percent 65 years and older (AGE).

The ARDL modelling of the long-run equilibrium economic relationship has a number of attractive econometric advantages. A couple of comments on cointegration are in order. One important requirement for conducting a cointegration analysis is to determine whether the data series in their levels are stationary or nonstationary. Stationarity denotes that the first two moments of a data generating processes do

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not depend on time. In economic modelling, using the Ordinary Least Squares (OLS) technique to regress a non-stationary series on other non-stationary series results in the "spurious regression problem." The ARDL approach, contrary to the other widely employed cointegrating estimators such as the Engle-Granger method (1987) and the Johansen (1988), Johansen and Juselius, 1990), does not require the pre-testing of the orders of integration. As in many instances, the order of integration of the variables used in estimation cannot be determined with certainty Pesaran and Shin (1999). Pesaran et al. (2001) has demonstrated, that the ARDL or the bounds approach can be employed to determine the existence of a long-run equilibrium relationship regardless of the variables used in the cointegration analysis are stationary, I(0), or non-stationary, I(1); or mutually integrated or a combination of I(0) and I(1).

Although the ARDL modelling does not require that all the variables included in Model (1) be integrated of the order of one, I(1), the procedure will not work if the variables are statistically determined to be of the order two, I(2). The endogeneity problem does not arise in the ARDL modelling when estimating both the short-run and long run coefficients simultaneously and with lagged dependent and explanatory variables. The ARDL coefficients estimates are super-consistent even for small samples. The error-correction modelling through the ARDL cointegration procedure facilitates both the short-run and the long-run causality. In addition to simplifying hypothesis testing, the ARDL approach, alternatively referred to as the bounds approach, also has high statistical power and low size distortion even in small samples (see for example, Pesaran and Shin, 1999; Pesaran et al., 2001).

The rest of this paper proceeds as follows. Section 2 reviews the literature; Section 3 discusses the model and data; Section 4 focuses on empirical findings; and Section 5 concludes.

## 2. Literature review

Past studies[1] have overwhelmingly concluded that INCOME is a major determinant of national health care expenditures. Consequently, INCOME (expressed as the natural logarithm of PRGDP) is one of the major drivers of health expenditure in our paper. Moreover, Hall and Jones (2007) also stress the role of rising income in a household or the economy leading to higher levels of the demand for health care due to the increasing marginal utility from health care rather than from other goods and services. The estimates of high values of health and life provided by Murphy and Topel (2006) and Nordhaus (2003) reinforce income as a core driver of health expenditure (Acemoglu et al., 2013). Moreover, income affects medical technology, insurance and medical prices (Smith et al., 2009). Although it is challenging to estimate the pure income effect and pure income elasticity of demand for health care, in the literature one finds many empirical studies that report what Smith et al. (2009) call expenditure elasticity that may include the effects of other macroeconomic variables. The work of Font et al. (2009) is a concise survey of income elasticity of demand for health care. However, in this paper, we refer to the expenditure elasticity loosely, as income elasticity of demand for health expenditure, $E_{HE.I}$.

Furthermore, health economists loudly contend that technological progress or 'the march of science', in the health sector is a supply side core driver of the persistent rise in the U.S. health spending (see, e.g., Weisbrod, 1991; Newhouse, 1992; Chernew and Newhouse, 2012). The U.S. accounted for 51% of the global biomedical R&D spending, at $131 billion in 2007 and $119 billion, or 45% in 2012 (Research America, 2014). On the demand side, with the changing taste for better and state of the art medical treatment, accompanied by rising income, patients are willing to spend more on health care. On the supply side, changing technology increases the demand for health care inputs, new medical devices and medical research and development expenditures (R&D) leading to cost escalation. Technological progress in health care generally comprises the introduction of innovative chemical entities (or new pharmaceutical agents), medical devices, diagnostic testing methods and surgical procedures, health-monitoring equipments, and other processes and procedures. Okunade and Murthy (2002) and Matteo (2005), for example, theoretically proposed and empirically tested the contribution of technological progress to the escalation of U.S. health expenditures.

Smith et al. (2009) contend that the contribution of medical technology has decreased slightly in recent years but it remains one of the major determinants of the U.S. health expenditure. They found "medical technology to explain roughly 27 to 48% of health spending since 1960, although somewhat a smaller percentage" (p. 1276). Rising income and an enabling health insurance system in the U.S. facilitate advances in medical technology. Moreover, Cutler and McClellan (2001a, 2001b) claim that technological progress in health care escalates health spending in two ways, the "treatment substitution effect" and the "treatment expansion effect". While the former refers to replacing the old medical technology with new and improved treatment technology, the latter is the diffusion of new and improved treatment technologies in the health care system. In light of the above discussions, we hypothesize in this paper that with improved level of technology health expenditure increases (Cutler, 2007).

Another important hypothesis tested in this paper is that AGE exerts a positive impact on HEXP (Anon, 2011; Kaiser Family Foundation, 2015). Population ageing will have a major impact on the U.S. health care spending, as advancing age tends to create a substantial demand for publicly and privately financed health care (Zweifel et al., 1996). As the population ages, incidence of chronic diseases as Alzheimer's, heart attacks, cardiovascular complications, diabetes, elevated blood pressure, fracture-related ailments and osteoporosis would increase. Furthermore, there is a likelihood of chronic illnesses in the old age developing into functional disabilities among the elderly. These developments tend to require greater health expenditures on nursing homes, home health care, personal care, adult day care and multiple visits to the physician and hospital. The literature further documents that persons of 65 years old and above spend about five fold as younger adults and a striking major portion of health expenditure of older Americans is for treating chronic diseases (Hoffman et al., 1996). In fact, Kaiser Family Foundation projects Medicare spending to grow from $555 billion in 2011 to $ 903 billion in 2020 (Kaiser Family Foundation, 2015). Many experts also expect Medicare spending to increase at an annual rate of 6.2% during 2019–2024 (Keehan et al., 2015).

This is the first study on U.S. health expenditure modelling to apply the relatively new ARDL approach, originally developed by Pesaran and Shin (1999, 2001), to identify some major drivers of the U.S. aggregate health expenditure. Appendix Table 1 reviews previous work on other countries (e.g., Malaysia, Tunisia, Pakistan, Turkey, select Asian countries, Nigeria, Finland, Malaysia, and India) applying the time-series ARDL approach to modelling aggregate health expenditure data. We briefly review some of the studies here. Hirnissa et al. (2009), using the ARDL-RECM procedure and 1971–2006 data of select Asian countries, detected a long-run relationship between defense spending, education and health expenditure. Yavuz et al. (2013), using 1975–2007 Turkey data and ARDL bounds testing approach, detected per capita income to have no effect on per capita health expenditure in the long run and that the 0.75 short run income elasticity makes Turkish healthcare a necessity. Nasiru and Usman (2012), using ARDL bounds testing approach and Granger causality test, detected a long-run relationship between health expenditure and economic growth, and found existence of causality relationship in at least one direction. Mushtaq et al. (2013), applying the ARDL bounds testing cointegration procedure to 1975–2001 Pakistan data, found that health expenditures have positive and significant effects on labor force participation rate in the short run. Chaabouni and Abednnadher (2014) used 1961–2008 Tunisia data and the ARDL model to detect a bidirectional causal flow from health

[1] Parkin et al., 1987; Murthy and Ukpolo, 1995; Hansen and King, 1996; Newhouse, 1997; Gerdtham and Jonsson, 2000; Gerdtham and Lothgren, 2000; Murthy and Okunade, 2000; Okunade and Murthy, 2002; Dregen and Reimers, 2005; Smith et al., 2009; Font, Gemmil and Rubert, 2009; Baltagi and Moscone, 2010; Moscone and Tosetti, 2010; Acemoglu et al., 2013; Corporale et al., 2015.

expenditure to income in the short and long runs. Finally, Khandelwal (2015) employed the ARDL and VECM approaches to model 1971–2011 India to find a long run causal relationship between energy consumption, fiscal deficit, GDP and public health spending but in the short-run only the GDP was significantly causally related to health care expenditure.

## 3. Model and data

Based on previous studies, received economic theory, and the data availability, we specify the following double-log model:

$$HEXP_t = \alpha + \beta_1 INCOME_t + \beta_2 HRD_t + \beta_3 AGE_t + \mu_t \quad (1)$$

In Eq. (1), HEXP, INCOME, HRD and AGE are, respectively in natural logarithms, per capita real health expenditure, per capita real GDP, real health care research and development (R & D) expenditure, and the percentage of the population aged 65 years and older. Standard theory postulates that in Model (1), $\beta_1 > 0$; $\beta_2 > 0$ and $\beta_3 > 0$. The disturbance term, $\mu_{t,}$ is assumed to be normally distributed. The coefficients $\beta_1$, $\beta_2$ and $\beta_3$ are, respectively, the elasticities of real health expenditure with respect to INCOME, HRD and AGE.

In order to estimate model (1) by the Ordinary Least Squares (OLS), we apply the ARDL bounds approach using the following specified model:

$$\begin{aligned}\Delta \mathrm{HEXP}_t = {} & \alpha_0 + \sum_{i=1}^{n-1} \alpha_{1i}\Delta \mathrm{HEXP}_{t-1} + \sum_{i=1}^{n-1} \alpha_{2i}\Delta \mathrm{INCOME}_{t-1} + \sum_{i=1}^{n-1} \alpha_{3i}\Delta \mathrm{HRD}_{t-1} \\ & + \sum_{i=1}^{n-1} \alpha_{4i}\Delta AGE_{t-1} + \beta_1 HEXP_{t-1} + \beta_2 INCOME_{t-1} + \beta_3 HRD_{t-1} \\ & + \beta_4 AGE_{t-1} + \mu_t \end{aligned} \quad (2)$$

In model (2), $\Delta$ denotes the first difference operator of the respective variable and $\alpha_0$ is the deterministic drift parameter. In order to find out whether there exists a cointegrating relationship among HEXP, INCOME, HRD and AGE in the long run, we test the null that: $H_o: \beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$ and the alternate hypothesis, $H_a: \beta_1 \neq \beta_2 \neq \beta_3 \neq \beta_4 \neq 0$, by conducting a non-standard $F$-test developed by Pesaran et al. (2001) and further modified by Narayan (2005) for small samples. If we reject the null hypothesis of no cointegration in Model (2) statistically, following the procedure in Pesaran et al. (2001), we estimate the following unrestricted error-correction model (ECM):

$$\begin{aligned}\Delta HEXP_{\ t} = {} & \alpha_0 + \sum_{i=1}^{n-1} \alpha_1 \Delta \mathrm{HEXP}_{t-1} + \sum_{i=1}^{n-1} \alpha_2 \Delta \mathrm{INCOME}_{t-1} \\ & + \sum_{i=1}^{n-1} \alpha_3 \Delta \mathrm{HRD}_{t-1} + \sum_{i=1}^{n-1} \alpha_4 \Delta AGE_{\ t-1} + \lambda\ \mathrm{ECT}-1 + \upsilon t \end{aligned} \quad (3)$$

where $\lambda$ is the speed of adjustment parameter and ECT is the residuals from the estimated Model (2) [Details on the ARDL method are Sbia et al., 2014; Alkhathlan, 2013; Jalil et al., 2013].

The data on HEXP, total per capita real health expenditure in U.S. PPP dollars, and AGE, the population percentage aged 65 years and older came from OECD Statistics (2014). Data on INCOME, per capita real GDP in U.S. 2005 PPP dollars, and the health research & development expenditure in U.S. PPP dollars are from OECD (OECD HEALTH, 2010; OECD Statistics Extracts, 2015) and extracts from OECD Library. The population data came from the Economic Report of the President 2013 (U.S. GPO, 2013). Here, we follow Okunade and Murthy (2002) in their proxy-approach to measuring health technology. All of the variables are in natural logs.

Table 1 presents summary statistics of the variable-series used in the cointegration analysis undertaken here. It is clear from Table 1 that the variables HEXP, INCOME, AGE, and HRD display an upward trend for the 1960–2012 period under study. All the variable-series show a considerable degree of standard deviation. Furthermore, for all the variable-series, we fail to reject the null hypothesis of normal distribution at the 1% level.

**Table 1**
Summary statistics of the main variables.
Source: See the data sources. HEXP and INCOME are in PPP 2005 US dollars and HRD in millions of PPP US dollars.

| Variable | HEXP | INCOME | AGE | HRD |
|---|---|---|---|---|
| Mean | 2897.849 | 20,699.750 | 11.475 | 19,207.38 |
| Median | 1948.000 | 18,427.000 | 12.000 | 14,166.260 |
| Maximum | 8745.000 | 45,350.000 | 13.700 | 44,595.940 |
| Minimum | 148.000 | 2879.000 | 9.200 | 3733.342 |
| Std. deviation | 2717.696 | 14,731.840 | 1.315 | 12,696.880 |
| Jarque-Bera (JB) | 6.282 | 4.576 | 5.175 | 6.848 |
| | *p*-values (0.043) | (0.093) | (0.075) | (0.033) |

## 4. Empirical results

Therefore, we perform unit root tests developed by Lee and Strazicich (2003) that explicitly maintain the presence of a unit root with structural breaks in both the null and alternative hypotheses. The traditional unit root tests such as the augmented Dickey-Fuller and the KPSS ignore the presence of structural breaks in the data generating process. Time-series literature has shown that not considering the presence of structural breaks in the data generating processes will lead to both misleading hypothesis testing results and substantial reduction in the statistical power of traditional unit root tests (see, Perron, 1989, 1997).

Lee and Strazicich (2003) have developed LM unit root tests that allow for endogenously determined structural breaks under both the null and the alternative hypothesis. Considering the time span of our data, we estimate Lee and Strazicich's model A, $[Z_t = 1, t, D_{1t}, D_{2t}]$' incorporating single break in the intercept and the slope. In Model A, $D_{1t}$, $D_{2t}$ denote dummy variables for the intercept and the slope equal to 1, if $t \geq$ the break date plus1 (For details, see Lee and Strazicich, 2003). Unlike other unit root tests that incorporate the presence of a structural break under the null, a rejection of the null hypothesis in the Lee and Strazicich's test indicates strong evidence of stationarity in the data generating process. Table 2 presents the results from the Lee and Strazicich tests (L&S tests, hereafter).

During the 1960–2012 data span studied, structural breaks occurred in the annual U.S. time-series data on health spending, demographics and GDP. Some are likely to be significant.[2] The majority of the structural breaks occurred in the 1980s. More specifically, significant data changes during the 1980s include the fast rise in per capita HEXP due to expansions in private and public insurance, rapid price growth and fundamental changes in the reimbursement systems. Moreover, the largest upward shift in the US elderly population 65 years and older, from 9.9% to 11.3%, occurred in the 1990s (Shrestha and Heisler,

[2] Some structural breaks in healthcare expenditures include compositional changes in the health care goods and services consumed and changes in the payers and legislations that affected the private-public provision (Diamond, 2012). Structural breaks (era, mean annual growth in nominal health spending) in the healthcare expenditure series are, as follows (see, Catlin and Cowan, 2015). The pre-Medicare and Medicaid era (1961–1965, 8.9%); coverage expansion and rapid price growth era (1966–1982, 13%); period of rapid changes in payment systems and moderate price growth (1983–1992, 9.9%); cost containment and managed care backlash era (1993–2002, 6.7%), and a period of relatively slower spending growth (2003–2013, 5.4%). Moreover, while the US population rose by 23 million each decade in the 1960–1990 period, it grew more rapidly by 32.7 million from 1990 to 2000. Structural change towards ageing is a major demographic shift. (Shrestha and Heisler, 2011). Finally, the U.S. annual GDP growth rate underwent major changes during the 1973–74 Arab oil embargo, peaked at 14.46% in 1978, and was in a deep recession due to sharp tax cuts and major reductions in social programs. The economy recovered, and GDP grew 11.4% in 1983 at stable rates until the 2007–2012 global recessionary years when the average annual growth rate fell to 2.126%.

**Table 2**
The Lee & Strazicich minimum LM unit root tests with a single break.

| Series | Constant, | $S_{t-1,}$ | k | $D_t$ | $D_{t,}$ | Break date |
|---|---|---|---|---|---|---|
| HEXP | −0.098 | −0.122 | 4 | −0.21 | −0.021 | 1985 |
| | (20.870)* | (−3.171) | | (−2.451) | (−2.451) | |
| Δ HEXP | 0.028 | −0.638 | 4 | 0.018 | −0.029 | 1983 |
| | (3.751)** | (−3.814)*** | | (1.318) | (−3.886)** | |
| INCOME | 0.055 | −0.185 | 4 | 0.032 | 0.008 | 1982 |
| | (6.804)* | (−2.891) | | (1.175) | (0.462) | |
| Δ INCOME | 0.030 | −1.001 | 2 | 0.063 | −0.053 | 1980 |
| | (4.023)* | (−4.681)* | | (2.914)** | (−4.553)* | |
| HRD | 0.083 | −0.136 | 2 | −0.032 | −0.038 | 1972 |
| | (4.144)* | (−2.195) | | (−0.763) | (−1.961)** | |
| Δ HRD | −0.045 | −0.835 | 1 | −0.109 | 0.122 | 1969 |
| | (−2.899)** | (−4.708)* | | (−2.526)** | (4.756)* | |
| AGE | 0.007 | −3.309 | 4 | 0.073 | −0.015 | 1993 |
| | (3.364)** | (−3.364) | | (3.558)** | (−3.265)** | |
| Δ AGE | 0.001 | −1.352 | 1 | 0.019 | −0.021 | 1990 |
| | (0.469) | (−5.685)* | | (1.550) | (−4.071)* | |

Note: *k* is the lag length. $S_{t-1}$ is the coefficient of the unit root parameter. *T*-values are in parentheses. Critical values are from Lee and Strazicich (2003; Table2). The critical values applied to the dummy variables follow the standard normal distribution.
Symbols *, **, *** denote significance at the 1%,5% and 10% levels, respectively.

2011). The recessionary U.S. economy of the late 1970s began recovering around 1983 when GDP grew at the annual rate of 11.4%.

The tests on the unit root parameter, $S_{t-1,}$ also indicate that we fail to reject the null hypothesis of the presence of a unit root with a structural break present in both the level and trend even at the 10% level of significance. Thus, the Lee and Strazicich unit root tests confirm that the variables included in the model (1) are non-stationary in levels. Using the even the 10% critical value provided by L&S, for the series in levels, we fail to reject the null hypothesis of the presence of a unit root. While we reject the null for first-differenced series of INCOME, HRD, and AGE series, at the 1%, we reject the null for the HEXP series at the 10%. Using two breaks, we obtained consistent results. However, in order to know if the no break unit root tests can establish whether the time-series used in the analysis are I(0) or I(1), we conduct the Schmidt and Phillips (1992) no-break LM tests. We present the Schmidt and Phillips (1992) test results in Table 3. The results clearly show that all the series in levels are I (1), with the exception of first-differenced HEXP series. This finding is consistent with the results of the one-break L&S unit root tests. As the HEXP, series has undergone a structural break, the Schmidt & Phillips LM test fails to statistically discern that the series is I(1). Thus, we have to look at both Tables 2 and 3 to determine the integration order of the series. The results in Tables 2 and 3, overwhelmingly confirm that the series used in this paper are integrated of order one, I (1), but, not of order two, I (2). Since the order of the series is not I (2), we can apply the ARDL bounds testing approach to test the existence of cointegration among the variables, HEXP, INCOME, HRD, and AGE.[3]

Table 4 reports the results of the Pesaran's ARDL bounds tests. We use both the critical values for determining the long-run forcing variable, found in Pesaran et al. (2001), and modified by Narayan (2005) for small samples. The deterministic term included in the model is an unrestricted intercept. Using the critical values, we reject the null hypothesis of no cointegration at the 1% level of significance when only HEXP is the dependent variable. When we conducted the bounds tests specifying INCOME, HRD, and AGE individually as the dependent variable, we fail to reject the null hypothesis of no cointegration. Thus, from the results presented in Table 4, we statistically confirm that there is a long-run economic relationship among HEXP, INCOME, HRD, and AGE.

Table 5 reports the results of the estimated long-run ARDL cointegration model (2, 0, 5, 1), selected automatically by applying the Akaike Information Criterion (AIC) out of 1080 models. The AIC criterion automatically determined the lag to be five. As the restricted trend term included in the model initially, was not significant, we further specified an unrestricted constant as the deterministic term. In Table 5, the estimated constant term is negative and highly significant at the 1% level. The coefficients of INCOME, HRD, and AGE are both correctly signed and statistically significant at the 1% level.

The result from the Wald test on the coefficient of INCOME indicates that the income elasticity of health expenditure is statistically different from unity, confirming that over time, in the U.S., health care has become a necessity. This finding of a lower point estimate of the income elasticity of demand for health care is consistent with that in Acemoglu et al. (2013) and the theoretical arguments of Zhang (2013). Zhang (2013) hypothesized that as the level of wealth increases in an economy, basic health needs are satisfied and therefore, increases in income will have relatively less effect on health care. It is interesting to note here that while Acemoglu et al.'s estimated income elasticity of demand for hospital expenditure, this paper estimates the income elasticity of demand for total health expenditure including public health expenditure (Medicare and Medicaid). Furthermore, Acemoglu et al. used a slightly different data span and employed the Instrumental Variable

**Table 3**
The Schmidt & Phillips LM unit root tests with no break.

| | Constant, | $S_{t-1,}$ | k |
|---|---|---|---|
| EXP | −0.081 | −0.010 | 0 |
| | (11.042)* | (−0.508) | |
| Δ HEXP | 0.0058 | −0.113 | 0 |
| | (1.382) | (−1.712) | |
| INCOME | 0.056 | −0.013 | 0 |
| | (7.705)* | (−0.577) | |
| Δ INCOME | 0.012 | −0.327 | 0 |
| | (2.418)* | (−3.10)** | |
| HRD | 0.069 | −0.107 | 0 |
| | (4.490)* | (−1.684) | |
| Δ HRD | −0.045[a] | −0.075 | 0 |
| | (−2.899)** | (−3.849)** | |
| AGE | 0.008 | −0.0536 | 0 |
| | (4.394)** | (−1.173) | |
| Δ AGE | −0.012 | −0.927 | 0 |
| | (−4.182)* | (−6.508)* | |

[a] With a trend of 0.002 ($t = -3.429$*). Lag length automatically determined by Schwert value of L4 and L12 = 10. The test outcomes are not sensitive to lag length. * and ** denote significance at the 1% and 5% levels, respectively.

[3] We have not included health care prices in our modelling as they overstate the growth of medical prices and are biased due to other problems (see, Smith et al., 2009). The effect of health care prices are included indirectly in the expenditure. In this paper, health expenditure is real total health expenditure per capita.

**Table 4**
The Bounds test for cointegrating relationship.

| Model observed *F*-value lags significance level | | | |
|---|---|---|---|
| HEXP = F (INCOME, AGE, HRD) | 6.958* | 3 | 1% |
| INCOME = F (HEXP, AGE, HRD) | 3.205 | 3 | – |
| HRD = F (HEXP, AGE, INCOME) | 3.967 | 3 | – |
| AGE = F (HEXP, AGE, INCOME) | 2.173 | 3 | – |

Symbol * shows significant at the 1% level. The critical values for unrestricted intercept and no trend (Case III) are I (0) 4.865 and I (1) 6.360 [from Narayan (2005): Critical values for $k = 3$].

**Table 5**
The long-run ARDL cointegration model (2, 0, 5, 1).

| Variable | Coefficient | Std, error | *t*-Statistic |
|---|---|---|---|
| INCOME | 0.918 | 0.084 | 10.873* |
| HRD | 0.398 | 0.063 | 6.297* |
| AGE | 1.744 | 0.400 | 4.352* |
| *Diagnostic tests* | | | |
| Adjusted $R^2$ | | 0.98 | |
| JB normality test | | 1.621(0445) | |
| Breusch-Godfrey serial correlation *F*-test | | 0.577(0.567) | |
| Breusch-Pagan-Godfrey heteroscedasticity F-test | | 0.836(0.606) | |
| Wald test on the coefficient of INCOME = 1 | | 25.506($\chi$2, $DF = 1$) | |

Note: Symbol * shows significance at the 1% level.

Approach (IV) approach. It is interesting to note that Okunade and Murthy (2002), using the Johansen and the Phillips-Fully-Modified cointegrating (FMOLS) estimators, report income elasticity of health expenditure spending to be around 1.55 for the period 1960–1997, indicating that health care was a luxury in the U.S.

The bottom part of Table 5 contains diagnostic test results of the selected ARDL (2, 0, 5, and 1) model. The adjusted $R^2$ value of 89% suggests that INCOME, HRD and AGE jointly explain a significant part of the variation in health care spending. The JB test for normality indicates that the residuals are distributed non-normal. Furthermore, from the results of the Breusch-Godfrey serial correlation *F*- test and the Breusch-Pagan-Godfrey heteroscedasticity *F*-test, we fail to reject the null-hypotheses of no serial correlation and no heteroscedasticity of the residuals.

Table 6 presents an estimate of elasticity of health expenditure with respect to health R&D (i.e., technology elasticity). The technology elasticity of health expenditure is 0.398, which is slightly greater than that reported by Okunade and Murthy (2002). Their estimated technology elasticities, based on the Johansen method and FMOLS, were 0.18 and 0.39, respectively for economy wide and health R&D proxies. These estimated relied on a much shorter 1960–1997 time-series data length and different cointegrating estimators. Moreover, their specified model excluded the AGE variable. The present study covers a much larger period, 1960–2012, during which high rates of diffusion and usage of the existing health technology, the introduction of many new medical technologies, devices and much improved prescription drugs have taken place. During the 2000–2008 period for the U.S., significant health technology improvements occurred. Some landmark technological innovations that occurred include: The FDA approval of the first robotic system for general laparoscopic surgery; the first PET (Positron Emission Tomography); CT (Computed Tomography) hybrid scanner; drug-eluting stent for clearing clogged arteries; the 64-slice CT scanner; the first vaccine for human papillomavirus (HPV) to protect against cervical cancer; and the commercial hybrid PET/Magnetic Resonance Imaging, MRI (National Center for Health Statistics, 2010). In light of these developments, we expect the coefficients of INCOME, AGE and HRD to differ from Okunade and Murthy (2002). Furthermore, this study employs a very different estimation procedure than applied in their investigation.

The results reported in Tables 5 and 6 of this study, reveal that technological advance in health care is still an important (statistically significant) driver of U.S. health care expenditure. As stated by Smith et al. (2009), the relative generosity of health insurance and the increasing level of income have induced more technological change in the health care area (see, Acemoglu et al., 2013). Moreover, on the demand side, increasing real per capita income and the prevalence of relatively liberal insurance system, has facilitated health consumers' taste for opting for state of the art treatment. The AGE coefficient, denoting the elasticity of health expenditure with respect to AGE, is 1.744, showing that a rise in the population percentage above 65 years of age raises health care costs. This finding on age elasticity is not surprising as most of the health spending occurs in the old age, especially during the final years of life.

Table 7 presents results of the estimated ARDL short-run error-correction model. The intercept (Constant) term and the coefficients of Δ HEXP (−1), Δ INCOME, and Δ HRD, are positive and significant. The short income elasticity is less than one, indicating that in the very short run, the demand for health care is highly inelastic. The coefficients of Δ HRD, Δ HRD (−2), and Δ HRD (−4) and Δ AGE are significant at the 1% level. As we expect these variables, do not change much at all in the short period. The error –correction term, ECT (−1), is significant at the 1% percent level and exhibits the expected negative sign. The error-correction term, besides confirming the existence of a

**Table 6**
Elasticity estimates of health expenditure.

| | |
|---|---|
| Income Elasticity ($E_{HE.I}$) | 0.92*a |
| Technology Elasticity ($E_{HE\cdot HRD}$) | 0.39* |
| Age Elasticity ($E_{HE}$.AGE) | 1.74* |

Note: Asterisk *shows significance at the 1% level. [a]Is significantly different from 1 at the 1% level.

**Table 7**
The ARDL cointegrating short-run error–correction model (2, 0, 5, 1).

| Variable | Coefficient | *t*-Statistics | *p*-value |
|---|---|---|---|
| Δ HEXP (−1) | 0.789 | 11.885 | 0.000* |
| Δ INCOME | 0.193 | 2.974 | 0.005* |
| Δ HRD | 0.049 | 1.291 | 0.0.205 |
| Δ HRD (−1) | −0.019 | −0.468 | 0.643 |
| Δ HRD (−2) | −0.095 | −2.320 | 0.026** |
| Δ HRD (−3) | −0.053 | −1.309 | 0.198 |
| Δ HRD (−4) | −0.075 | −2.174 | 0.030** |
| Δ AGE | 0.184 | 0.116 | 0.123 |
| CONSTANT | −2.585 | −5.638 | 0.000* |
| ECT (−1) | −0.271 | −5.644 | 0.000* |

Note: The symbols * and ** show significance at the 1% and 5% levels.

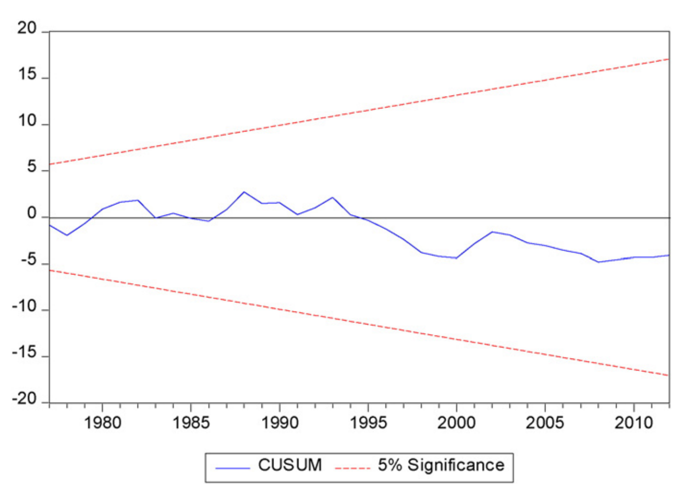


**Fig. 1.** CUSUM test of recursive residuals.

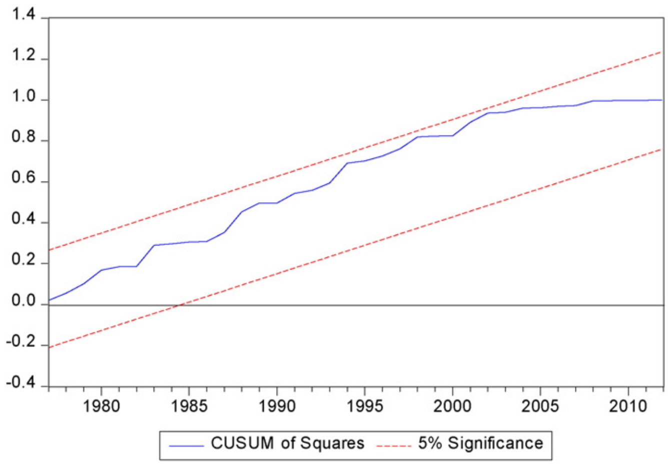


**Fig. 2.** CUSUM square stability test of recursive residuals.

cointegrating relationship based on the ARDL model, shows that roughly 27% correction to the disequilibria in the health expenditure originating from past shocks in the current period takes place, although the speed of adjustment is relatively slower. Given the complexities and rigidities of the health care sector, this speed of adjustment is normal.

One of the econometric requirements for a well-specified and performed ARDL model is the presence of parameter stability. In order to test for the stability of the short-run and long run coefficients estimated by the ARDL model, we perform the cumulative sum (CUSUM) and cumulative sum of squares (CUSUM Square) tests, applied to recursive residuals from the ARDL model estimated in this paper, for stability (see, Brown et al., 1975). In Figs. 1 and 2, the plots of the CUSUM and CUSUM Square do lie inside the critical boundaries of 5% level. Thus, we have empirical evidence to support that the estimated coefficients of the ARDL cointegration model (2, 0, 5, 1) display parameter stability.

## 5. Conclusions and policy implications

This paper is the first study to apply the Autoregressive Distributed Lag (ARDL) approach developed by Pesaran and Shin (1999), Pesaran et al., 2001) to empirically identify some major drivers of U.S. health expenditure (HEXP) during the period 1960–2012. By extending the U.S. healthcare expenditure model and time-series data length estimated by Okunade and Murthy (2002) and using a novel and simple cointegration procedure, our paper demonstrates that the major drivers of health expenditure are income (INCOME), health research and development expenditure (HRD), and the percentage of population that is above 65 years of age and older (AGE). Furthermore, the paper econometrically determines that although all the variables used in the study have experienced structural breaks, they are non-stationary in levels and stationary in first-differences. Hence, they are integrated of the order one I (1). However, together they form a long-run link exhibiting a cointegrating relationship among HEXP, INCOME, HRD and AGE. Our estimated ARDL cointegration model passed all of the diagnostic econometric tests, besides yielding stable coefficients. It is interesting to compare findings of our ARDL model with those of studies from other countries using the same procedure. However, it is interesting to note here that none of the studies reviewed (see, Appendix Table 1) are of higher dimension. However, a direct comparison of our study findings with those from other structurally different countries is challenging, as they used time-series data of varying lengths and estimated ARDL models with lower dimensions. Nevertheless, previous ARDL models of health care expenditure and income (or economic growth) together with one or more other variable(s) include Nasiru and Usman (2012) for Nigeria, Halicioglu (2013) for Finland, and Khandelwal (2015) for India. Moreover, similar to our current study finding for the U.S. (a high-income economy), Chaabouni and Abednnadher (2014) found Tunisia (a middle-income economy) health care to be a technical necessity, although the implications of this finding would differ for the U.S.

While previous studies found the U.S. health care to be a luxury good, the current study findings indicate that the statistically significant estimate of the income elasticity of health expenditure is less than unity; therefore, healthcare is presumed to be a necessity. The aggregate U.S. health care as a necessity justifies arguments for more inevitable government intervention in subsidizing insurance premiums of the underinsured (especially, for small business operators and their employees) and expanding access of the indigent population groups and the elderly to the redesigned Medicaid and Medicaid public insurance programs, expected in the near future.

The findings of this paper that the observed income elasticity of demand for health care is less than one has the important implication that additional factors are driving the recent increases in the U.S. health expenditure. Therefore, in this paper, we have furnished evidence to support 'the march of science' hypothesis in health care that continues as an important long run driver (on both the supply and demand sides) of the escalating healthcare costs. Moreover, it is possible that economic growth and the prevalence of relatively liberal insurance, including Medicare and Medicaid, facilitated the role of medical technology in health care. Another core driver of health expenditure is population ageing. Improving the Medicare program, increasing health-literacy among the old by providing health-related information, and facilitating preventive health care can be efficient strategies for containing elderly health care costs.

One of the implications of the study findings is that health spending would grow continuously with increases in future economic prosperity, improvements in medical care technologies and the ageing demographic structure. Moreover, as recently projected in the U.S. Congressional Budget Office document on *Budget Projections: 2015–2025* (2015), future health expenditures are likely to rise due to increases in Medicaid enrollments and public subsidies for health insurance coverage purchased through the exchanges under implementations of the 2010 Affordable Care Act. Interestingly, recent growths in both private and public sector insurance coverage are an important funding source for health care technologies. During 2012, the U.S. accounted for 41% (or $119 billion) of total global research spending. Moreover, from 2010 to 2012, the U.S. R&D spending by industry (e.g., biotechnology and medical technology sub-sectors) and other non-federal R&D (e.g., independent research institutes, foundations and voluntary health associations) entities rose significantly (Research America, 2014). Therefore, reliable healthcare expenditure projections can be based on future forecasts of health R&D expenditures, the GDP, population ageing, and other drivers of health care expenditure that form long-term cointegration relationships detected in this study. Perhaps equally important, because innovative technologies could be health care cost-increasing, cost-saving or cost-neutral (Weisbrod, 1991) future studies of the cointegration relationships might consider using separate proxies capable of capturing these different technology dimensions on the aggregate healthcare spending to assess whether they yield better health care values for the society in the long term.

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