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DETERMINANTS OF PUBLIC HEALTHCARE INVESTMENT: COINTEGRATION AND CAUSALITY EVIDENCE FROM PAKISTAN

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ABSTRACT

A healthy population and human capital are essential for the emerging countries to achieve faster but more sustainable development, which can only be achieved by investing exclusively in health. The need to probe cause-and-effect relationship between the factors influencing the public health expenditures is the driving force behind this investigation. This study empirically investigates the cointegration and causal relationship between healthcare expenditures (HCE), income, healthcare infrastructure (HCI), and healthcare services (HCS) in Pakistan from 1974 to 2017. Lee-Strazicich and Clemente-Montanes-Reyes structural break unit root tests are employed in addition to standard unit root testing. The Bayer-Hank, Gregory-Hansen, and Hatmei-J cointegration tests consistently show that HCE, income, HCI, and HCS are cointegrated. The short-run Granger causality inferences show unidirectional causalities from HCE to HCI and HCS, from income to HCE, whereas bidirectional causality is observed between HCI and income and between HCI and HCS. Similarly, Long- run casualty results show unidirectional causality from income to HCE, from HCE, income, and HCS to HCI, and bidirectional causality between HCS and HCE. The findings suggest that the government may play an obligatory role in healthcare financing and must pay special attention to the equitable distribution of healthcare facilities, infrastructure, and services across Pakistan.

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INTRODUCTION

Sustainable economic development is a challenging task, especially for developing countries that are striving hard to achieve a higher level of economic development by optimally utilizing the best combination of factors of production and other available resources. Rapid population growth has sparked widespread concern in both developing and developed countries regarding public healthcare systems, and financial sustainability (Khan et al., 2016). Researchers and health economists have debated the importance of examining healthcare expenditures and their drivers over the last few decades. Poverty, higher income inequality, a low standard of life, inadequate healthcare facilities, and market failure in developing countries, justify government intervention in the provision of public services, notably healthcare (World Bank, 1993). It is an ancient adage that health equals wealth, but it is still true, and its relevance has grown through time. People who are in good health are more active and vivacious, and they have a constructive impact on social infrastructure, which in turn has an impact on economic growth and development. Since developing countries are mainly labor-intensive, labor-force productivity is a significant issue for these countries. Economic growth remains a pipe dream for a capital-deficient country in the absence of a productive labour force. The labour productivity is primarily determined by healthier human capital striving to elevate various economic activities (Akram et al., 2008). Improved healthcare facilities have the ability to enhance labor force productivity. Besides, new technology has aided the health sector as a whole by delivering the latest devices and machines for diagnosis and treatment of health-related disorders. As a result of technological advancements in the health sector, population life expectancy grew in both the developing and developed nations over the twentieth century. Furthermore, better diet, increasing awareness of health issues, better sanitary conditions, medical technological developments, and strengthening of public health infrastructure and services have all contributed to a rise in human life expectancy. As a result of improved medical facilities, people's quality of life has improved as well.

Better health brings financial advantages, which leads to economic growth and prosperity, whereas bad health grabs poverty (WHO, 1999). Health and sustainable development are inextricably linked; health acts as a catalyst for achieving long-term goals, as a potential recipient of sustainable development, and as a tool for long-term sustainable development progress (United Nations, 2016). Pakistan is a developing country that is striving hard to improve its level of long-term economic growth. Pakistan has a large labor force, so the country's success is largely dependent on a healthy labor force. Therefore, the significance of the health sector is crucial for both a healthy labor force and Pakistan achieving a higher level of economic development.

Academics and researchers believe that better healthcare is contingent on better healthcare services and infrastructure, which can only be attained if the government spends more money on delivering them to its inhabitants. Although socioeconomic development can be measured using a variety of indicators, the most significant indicator is total health spending, which is a share of gross domestic product (GDP) spent on health. Since the 1960s, developing countries have seen an increase in the proportion of GDP spent on healthcare. Since then, researchers and practitioners have been interested in investigating the factors influencing HCE. The national income mostly determines HCE. Grossman (1972), Kleiman (1974), and Newhouse (1977) observed that changes in income level influence HCE by approximately 90%. Therefore, income is a primary predictor of HCE, and empirical literature (Culyer et al., 1988; Gerdtham & Jonsson, 1991; Herwartz & Theilen, 2003; Ke, Saksena, & Holly, 2011; Sagarik, 2016) widely acknowledges the significant association between HCE and income. Although Newhouse (1977) proposed income as an exclusive predictor of HCE, it later opened the door for researchers to consider other possibilities. Later, Hitiris and Posnett (1992) used non-income factors to determine HCE in addition to income variables. They examined non-income factors such as mortality rate, population age structure, and share of public spending as main determinants of HCE and found that these factors had a significant impact on HCE. Thereafter, several researchers (Atella & Marini, 2007; Blomqvist & Carter, 1997; Boachie et al., 2014; Chaabouni & Saidi, 2017; Filmer & Pritchett, 1999; Freeman, 2003; Gerdtham et al., 1992; Hitiris, 1997; Matteo, 1998; Murthy & Okunade, 2016; Prieto & Lago, 2012; Schieber & Maeda, 1999; Tchoe & Nam, 2010; Toor & Butt, 2005b) investigated the determinants of HCE. The aforementioned studies included both income and non-income factors like population age structure, health sector employees, women participation ratio in the labor force, income, foreign aid, urbanization as contributing factors in HCE.

In developing countries like Pakistan, where per-person income is low and residents have limited disposable resources for healthcare, healthcare infrastructure (HCI) and healthcare services (HCS) are critical. The majority of the population is infected with various diseases, most likely as a result of the high incidence of poverty and limited access to healthcare facilities. According to the supply-encouraged demand for HCE hypothesis, when the ratio of healthcare personnel and infrastructure to total population grows, patients' access to these facilities improves (Ang, 2010). This, in turn, increases the demand for HCS (Newhouse, 1970) and HCI. As a result, there is a significant increase in HCE. In this regard, Abbas and Hiemenz (2013) argued that increasing HCI improves the quality of HCS provided to the public. Therefore, the provision of better HCS leads to an increase in public HCE. Expectedly, the relationship between HCE and healthcare resources(i.e., infrastructure and services) has been extensively discussed and debated among researchers, few among others are, (Abbas & Hiemenz, 2013; Ang, 2010; Braendle & Colombier, 2016; Giannoni & Hitiris, 2002; Liu, Hsu, & Huang, 2010) and policymakers. In Pakistan, several research on the relationship between HCE and income have been done. These studies concluded mixed results, few studies (Akram et al., 2008; Imran et al., 2012; Raza et al., 2013) found unidirectional causality that runs from HCE to income or income to HCE. While few studies, for example, (Shamsi & Waqas, 2016; Wang et al., 2019) found no causal relationship between income and HCE. However, the cointegrating and causal relationship between healthcare resources and HCE remains overlooked and unclear in the empirical literature in Pakistan. There are two main rationales behind the selection of Pakistan as a case study for investigation. Firstly, Pakistan is a developing country with a large labor force. By making better use of human capital, the country's GDP growth rate can be increased. Its success is dependent on a healthy labor force. Secondly, Pakistan's main hindrances, and opportunities are its high population growth rate, low per capita income, limited healthcare facilities, and less economic development. Investigations between public HCE, per capita income, and healthcare resources are required for proper decision-making in order to reverse the situation.

Accordingly, the main objective of this study is to investigate the cointegrating and causal relationship between public HCE, per capita income, HCI, and HCS in Pakistan. The findings of this study will direct the policymakers towards optimal resource allocation and advice for effective policies to improve healthcare-related services, infrastructure, and expenditures. This work adds to the body of knowledge on HCE in numerous ways: First, we develop indices to incorporate healthcare resources as the main driver of public HCE. To the best of our knowledge, this is Pakistan's first study that examines the causal relationship between HCE and healthcare resources. Second, we investigate the structural shifts in data. The unit root tests for single and double structural breaks are used. The investigation of structural breaks is necessary because the presence of structural break(s) can create biasedness in the hypothesis testing process. Third, in this paper, cointegration tests with single and multiple structural breaks are used. Lastly, we analyze the direction of causality between HCE and its drivers in order to make better decisions and avoid financial resource destruction. Why have we investigated the causal relationship? Because regression simply indicates the interdependence of variables but does not tell us which variable causes which variable(s). Thus, it is important to examine the exact direction of the causality which is a useful tool for policymakers in making the right decision in the right direction. Therefore, this study explores the direction of a causal relationship in both the short and long run. The findings may assist policymakers in developing a comprehensive healthcare policy for accessing healthcare resources and allocating public HCE in Pakistan's economic growth process.

The rest of the paper is laid out as follows: Section 2 is devoted to a review of the literature. Methodology, model specification, and econometric techniques are all described in Section 3. Section 4 discusses the study's empirical findings, while Section 5 is specified for the conclusion, policy implications, and future research directions.

The literature on the determinants of HCE has been intensively investigated in recent years. However, the researchers are divided on the relationship between per capita GDP and HCE. Previous studies on HCE and per capita GDP growth are classified into four groups. One is a health expenditure-led growth perspective (Keynes, 1937). Two, growth-led health expenditure perspective (Wagner, 1890).Three, feedback or bi-directional perspective, and four, no relationship between the two. As a result, there are three possibilities for the causal relationship between HCE and its determinants: (1) unidirectional hypothesis (2) feedback hypothesis (3) neutrality hypothesis.

Unidirectional Hypothesis

Many researchers, few among others are, Tang and Lai (2011), Tang (2011), and Taskaya and Demirkiran (2016) found unidirectional causality between healthcare variables and per capita GDP growth. Tang and Lai (2011) examined the short and long run causal relationship between education expenditures and HCE in Malaysia. The results showed that education expenditures cause HCE both in the short and long run. Tang (2011) investigated the relationship between relative price, income, and HCE in Malaysia from 1970 to 2009 using multivariate cointegration and causality tests. The findings revealed one-way causality from relative price to HCE in the short run and two-way causality between income and relative price. Long-run two-way causality between HCE and income was also discovered, as well as one-way causality from relative price to HCE and income. The cointegration and causal relationship between HCI, HCS, HCE, and per capita GDP was investigated by Taskaya and Demirkiran (2016) . Their findings supported unidirectional causality running from HCE to income,and from HCS to HCE. In the same vein, Apergis et al. (2018) applied panel techniques to investigate the relationships between CO_2, per capita GDP, renewable energy, and HCE. The findings revealed a long-run cointegration relationship amid variables and one-way causality from per capita GDP to HCE in the short run. Hartwig (2010) investigated whether health capital formation promotes GDP growth in OECD countries using the panel Granger causality test. The findings did not support the notion that health capital formation improves long-term GDP growth in the OECD region. Likewise, Boz and Ozsarı (2020) investigated the causal relationship between aging and HCE for Turkey over the period 1975-2016 using Toda and Yamamoto causality technique. The results showed one-way causality running from population aging to HCE. Fasoranti (2015) examined the determinants of Public HCE in Nigeria using annual data from 1970 to 2012. The causality finding showed a one-way casualty from public HCE to the population aged 65 and up, and the life expectancy rate. On the other hand, there was a two-way causality between the literacy rate and the population aged 65 and up. Haseeb, Kot, Hussain, and Jermsittiparsert (2019) analyzed the short and long run effects of energy consumption, pollution, and economic growth on R&D and HCE in ASEAN countries. The findings revealed a long-term one-way causality from the CO2 emissions, GDP growth, and energy consumption to HCE.

Feedback Hypothesis

A few researchers have found the feedback hypothesis in healthcare expenditures literature. In this respect, Chaabouni and Saidi (2017) examined the cointegration and causal association between HCE, CO_2 emissions, and per capita GDP growth in 51 countries from 1995 to 2013. For all three panels, causality inferences demonstrate that there is two-way causality between GDP growth and CO_2 emissions, and between GDP growth and HCE. In the same way, Zaidi and Saidi (2018) examined the relationship between CO_2 emissions, per capita GDP growth, and HEC in Sub-Saharan African countries using yearly data over the period 1990- 2015. The causality inferences showed two-way causality between per capita GDP growth and CO_2 emissions, and between CO_2 emissions and HCE. Chaabouni et al. (2016) applied dynamic simultaneous-equations models to investigate the causal relationship between per capita GDP, CO_2 emissions, and HCE for a global panel of 51 nations from 1995 to 2013. The finding showed bidirectional causality between HCE and per capita GDP for the global panel. Amiri and Ventelou (2012) examined the relationship between per capita GDP and HCE in OECD countries. The findings demonstrated that bidirectional Granger causality prevails. Chaabouni and Abednnadher (2014) examined the determinants of HCE in Tunisia from 1961 to 2008 using ARDL approach and Granger causality test. The causality inferences showed bidirectional causality between per capita GDP and HCE in both the short and long run. Erdil and Yetkiner (2009) examined the causal relationship between GDP and HCE per capita using panel data set. According to causality inferences, in low and middle income countries, there is unidirectional causality from income to HCE, but the opposite is true for high-income countries.

Neutrality Hypothesis

The empirical researchers have also investigated the health-related neutrality hypothesis. In this connection, Devlin and Hansen (2001) investigated the causal association between HCE and income for the organization of economic cooperation and development (OECD) countries. They argued that the relationship between income and HCE is highly complex and country-specific since the observed relationship varies across countries. However, the authors came to the conclusion that there is no causal association between HCE and income. Tsaurai (2014) examined Wagner's theory as a possible explanation for the HCE in Botswana. The findings revealed that there is no causal association between per capita GDP and HCE, ruling out the applicability of Wagner's hypothesis. Taskaya and Demirkiran (2016) and Chaabouni and Abednnadher (2014) found no causal relationship between HCE and HCI, and medical densities and HCE, respectively.

Mixed Results

Though, some research studies have yielded contradictory findings. In this respect, Kiymaz et al. (2006) investigated the cointegration and causal association between per capita GDP, per capita public, private, and total HCE, and population growth in Turkey. The result showed cointegration among the variables, while causality inferences revealed one-way causality from per capita GDP to various definitions of HCE. Rana et al. (2020) investigated the causal relationship between GDP growth and HCE for a panel of 161 countries. The results showed that bidirectional causality exists in high-income countries, whereas unidirectional causality exists in low-income countries from GDP growth to HCE.

The Case of Pakistan

There is a scarcity of research in Pakistan addressing the causal relationship between HCE and its determinants. In this regard, relatively few studies have examined the relationship between income and HCE. Shamsi and Waqas (2016) analyzed the causal relationship between HCE and its socioeconomic determinants from 1980 to 2009. Their findings revealed no causality between GDP and HCE per capita. Imran et al. (2012) investigated the relationship between human capital and GDP growth from 1973 to 2002. The findings revealed cointegration among variables as well as one-way causality from public HCE to GDP growth. Akram et al. (2008) examined the short and long run effects of health human capital on economic growth. The findings demonstrate that health human capital has no association with economic growth. Hassan and Kalim (2012) examined the triangle causality between per capita HCE, per capita education, and per capita GDP in Pakistan from 1972 to 2009. The causality findings showed that there is no causal link between real per capita HCE and per capita GDP. Wang et al. (2019) investigated how economic growth and CO_2 emissions affect public HCE in Pakistan. The findings showed that in the short run, there is one-way causality from CO_2 emissions to HCE, but in the long run, two-way causality between CO_2 emissions and HCE and between economic growth and HCE has been discovered.

We found inconclusive results on the causal relationship between HCE and its determinants based on extensive empirical literature review described above. The aforementioned studies found bidirectional or unidirectional causality between HCE and income/per capita GDP. While few studies suggested the absence of causality between income and HCE or showed inconclusive results and propose the neutrality hypothesis. We observed inordinate differences in the empirical literature on the causal association between HCE and its determinants. The differences in results may be due to the use of different time series, variations in used techniques, and different variables being investigated by researchers. Therefore, it is empirically impossible to investigate the causal relationship of the larger set of health determinants in a single study. The present study, thus, is not supposed to be a comprehensive study on the issue. However, this is the first study that tries to examine the relationship between HCE, HCI, HCS, and income with respect to Pakistan.

Based on the above-cited literature and gaps in the empirical literature we formulate the following testable alternative hypotheses for Pakistan.

1. $H_{1\,A,\,B}$: HCI Granger causes HCE.
2. $H_{2\,A,\,B}$: HCI Granger causes HCS.
3. $H_{3\,A,\,B}$: HCS Granger causes Income.
4. $H_{4\,A,\,B}$: HCE Granger causes Income.
5. $H_{5\,A,\,B}$: HCE Granger causes HCS.
6. $H_{6\,A,\,B}$: HCI Granger causes Income.

We have provided a conceptual diagram that illustrates the details of the hypotheses and the possible patterns of the relationships being explored in this study. Figure 1 shows six hypotheses being examined in Pakistan to investigate the causality phenomena in income, healthcare resources, and HCE.

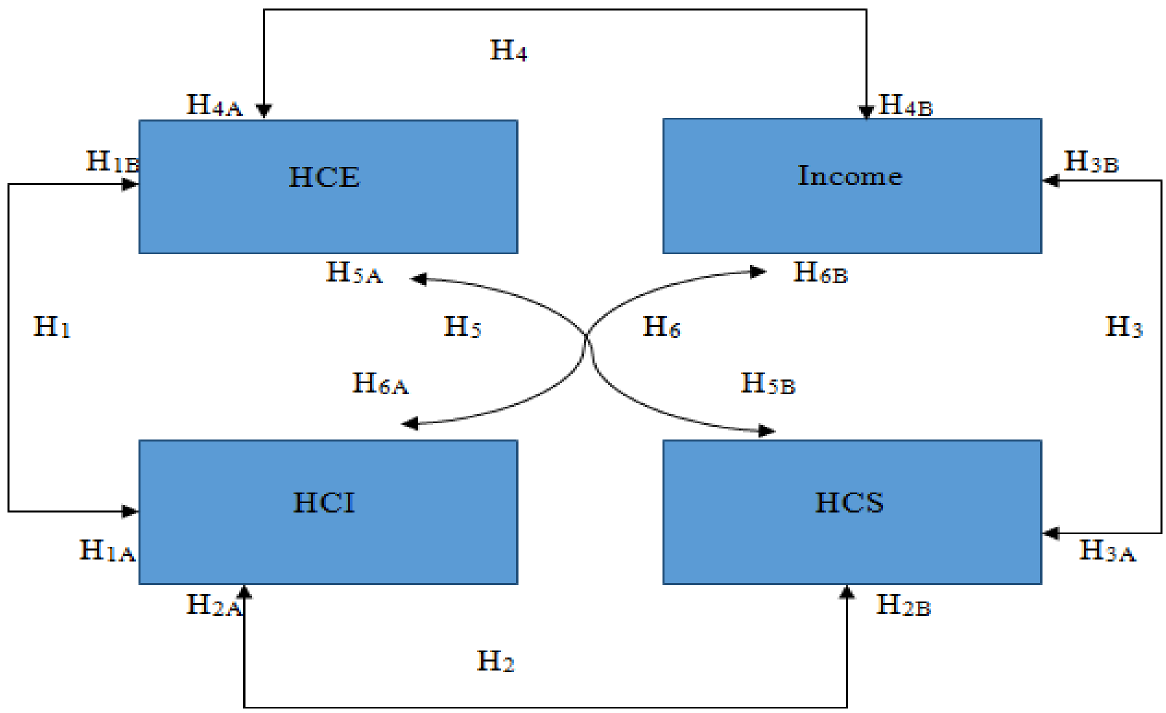

Figure 1. Possible causality patterns between the variables.

METHODOLOGY

Model Specification

According to the literature and discussion cited above, the major drivers of public HCE are per capita income, HCI, and HCS. McGuire et al. (1993) argued that the study of healthcare is discreditable since it lacks a solid theoretical framework. The demand function approach is frequently used in the empirical literature to investigate the determinants of HCE, where HCE is predicted to be a function of income as well as a number of other factors. Health care demand is affected by changes in income, and it can be classified as an inferior, normal, or superior good depending on the size and magnitude of the change (McGuire et al., 1993). Several research studies have found that per capita income has a beneficial effect on HCE (Ang, 2010; Gbesemete & Gerdtham, 1992; Gerdtham et al., 1992; Hitiris & Posnett, 1992; Newhouse, 1977). Taking supply-induced demand for HCE theory into consideration, academics and researchers have extensively examined and analyzed the relationship between HCE and healthcare resources (i.e., infrastructure and services) (Abbas & Hiemenz, 2013; Ang, 2010; Braendle & Colombier, 2016; Giannoni & Hitiris, 2002; Liu et al., 2010). Based on the above arguments, this study utilizes a multivariate framework method and follows Grossman (1972), who developed the theoretical model on health, and his work has been extensively used to investigate the economic and non-economic drivers of HCE. Many researchers (Ang, 2010; Gerdtham & Jonsson, 1991; Grossman, 1972; Matteo, 1998; Newhouse, 1977; Tang, 2011; Taskaya & Demirkiran, 2016; Toor & Butt, 2005a) have used a similar framework in their empirical studies. The model's functional form is as follows:

$$HCE = f\ (Y, HCI, HCS) \tag{1}$$

Where Y stands for per capita GDP/ income, HCI is the health care infrastructure and HCS is the healthcare services while healthcare expenditures are represented by HCE. The empirical specification of the healthcare demand equation is as follows:

$$HCE = f(Y, HCI, HCS) \tag{2}$$

We used the semi-log model for estimation, as shown in Equation (3).

$$lnHCEt = \alpha_0 + \alpha_1 \ln Y_t + \alpha_2 HCI_t + \alpha_3 HCS_t + \varepsilon t \tag{3}$$

Where ln, α_o, t, and ε_t respectively stand for natural log, intercept, year, and residual term, respectively.

Figure 2 depicts the structural framework illustrating the possible linkage(s) under investigation. The graph depicts the potential relationships between per capita GDP, HCE, HCI, and HCS.

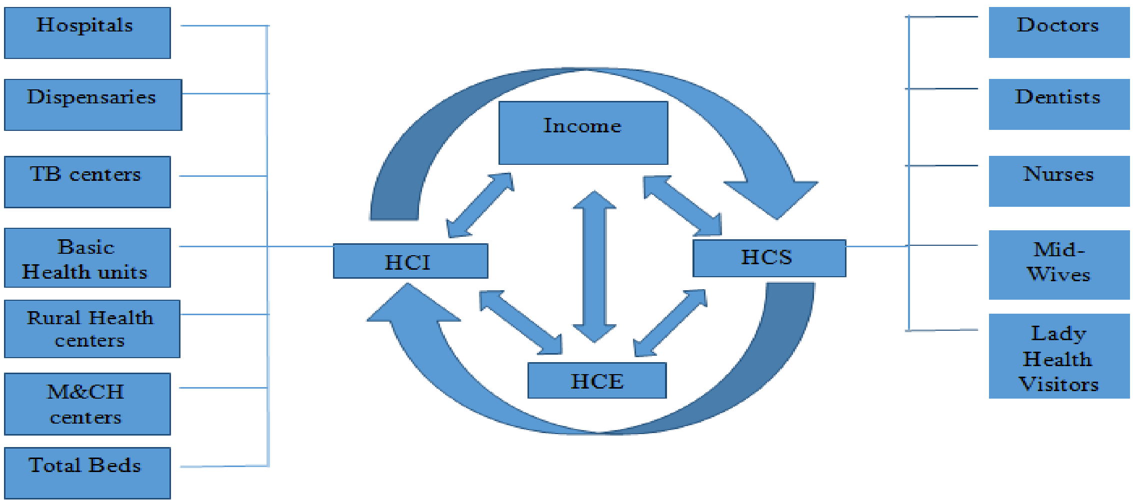

Figure 2. The structural framework of possible linkages.

Data and Data Sources

This study uses annual time series data on per capita public HCE, per capita GDP as a proxy of income, HCI, and HCS from 1974 to 2017 in Pakistan. The time period is determined by the availability of data. The data is derived from several issues of the Pakistan Economic Survey and International Financial Statistics (IFS). We have constructed the indices of HCI and HCS. Both indices have been constructed by using the principal component analysis (PCA) technique. We developed the HCI index using variables related to healthcare infrastructure, such as the number of beds, hospitals, tuberculosis centers, dispensaries, rural health centers, maternity and child health centers, and basic health units. These variables enhance the efficiency of HCI. In contrast, the HCS index uses indicators such as the number of doctors, dentists, nurses, midwives, and lady health visitors. All variables are in logarithmic form, with the exception of the HCI and HCS indices, which are developed using PCA technique and contain some negative values, making log transformation impossible (Rafindadi & Yusof, 2015).

HCI and HCS Indices Construction through PCA

This study has discussed a number of healthcare infrastructure and services indicators. All of these indicators are important in determining a clear and comprehensive picture of healthcare infrastructure and services. Since indicators from both categories are extremely collinear with one another, incorporating all of these indicators into a single equation at the same time is neither reliable nor feasible. Besides, due to the issue of multicollinearity, the results produced by regression will not be robust and reliable. Following Stock and Watson (2002a, 2002b), this study employs PCA technique to develop an index that is the best and most comprehensive representation of all of these indicators. It attempts to find a pattern in the data, reduces dimensionality, and therefore collects all of the information from indicators. Thus, this study uses PCA technique to construct the indices of HCI and HCS. The indices that are developed will be a comprehensive representation of the indicators used in HCI and HCS. The general arrangement of PCA is represented in Eq. (4).[1]

$$PCn = a1\ x1 + a2\ x2 + \ldots\ldots + an\ xn \qquad (4)$$

Where the weights assigned to variable 'x' are represented by 'a_i'. We ensure the factorability of the indicators under consideration before using PCA technique. In this study, two tests are performed to confirm the factorability of variables. The two tests are the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity[2]. The findings of these tests are summarised in Table 1. In both cases, the KMO test statistics are greater than the benchmark value of 0.6. The Bartlett test rejects the null hypothesis that there is no intercorrelation. This indicates that these tests have validated the factorability and sphericity in the data. Thus, the findings support the notion that PCA is an acceptable approach for constructing indices. Table 2 displays descriptive statistics for the variables used in this analysis. The Jarque-Bera test findings demonstrate that HCE, income, HCI, and HCS are normally distributed. The standard deviation results show that the income is more volatile while HCS are relatively less volatile. The data is negatively skewed for HCS while other variables are positively skewed.

Unit Root Tests Without and With Structural Breaks

Before examining cointegration, the integration order of variables must be checked. This study primarily utilizes the Augmented Dickey-Fuller (ADF) and Phillips Perron (PP) unit root tests for this aim. The aforementioned unit root tests, however, ignore the presence of a structural break in the time series. In such a case, the possibility of spurious results increases, especially if the series is trend stationary and has a structural break (Perron, 1989). There are numerous unit root tests in the literature that detect the presence of structural breaks. For example, Zivot and Andrews (1992) and Lumsdaine and Papell (1997) tests. In these tests, the structural break is considered only in the alternative hypothesis, which is the major drawback of these tests. It is not necessary that rejection of null of no structural break also rejects the presence of unit root per se (Lee & Strazicich, 2003). On the other side, the alternative hypothesis suggests the presence of a structural break but it does not disclose anything about the absence of unit root. To circumvent this issue, Lee and Strazicich (2003) suggest a unit root test that permits structural breaks in both the null hypothesis and alternative hypotheses. Therefore, rejection of the null hypothesis in the Lee and Strazicich (2003) test shows that the variable is stationary with a structural break. This study also uses the Clemente et al. (1998) unit root test for robustness. This test is a better option for determining unit roots in the presence of structural breaks. It is more powerful than the tests developed by Zivot and Andrews (1992), Lee and Strazicich (2003), and Phillips and Perron (1988) tests. The Clemente et al. (1998) test is an augmented type of the Perron and Vogelsang (1992) test, which seeks for two structural breaks in the mean.

Table 1. Results of KMO and Bartlett tests for HCI and HCS indices.

KMO and Bartlett's test	HCI	HCS
Kaiser-Meyer-Olkin measure of sampling adequacy	0.800	0.630
Bartlett's test of sphericity	766.340 (0.000)	725.630 (0.000)
H0: variables are not intercorrelated	Reject	Reject

Note: Values in ( ) show the p-value.

Table 2. Descriptive statistics.

Statistics	$lnHCE_t$	lnY_t	HCI_t	HCS_t
Mean	4.7803	9.6810	-4.09E-08	2.27E-09
Median	4.9382	9.6817	0.1718	-0.0288
Maximum	7.2878	12.019	2.1657	0.5865
Minimum	2.2906	7.1995	-2.1590	-0.6567
Std. Dev.	1.3574	1.4340	1.0378	0.3809
Skewness	0.0373	0.0499	0.1813	-0.0161
Kurtosis	2.1866	1.8219	3.0225	1.6814
Jarque-Bera	1.2232	2.5626	0.2420	3.1893
(Probability)	(0.5425)	(0.2777)	(0.8860)	(0.2030)

Source: Author's calculations. The values in ( ) show the probability values.

[1] The PCA results are not reported to save space. Readers who are interested in the results may contact the authors.

[2]The KMO test compares the magnitudes of partial correlation and estimated correlation coefficients (s). It has a value between 0 and 1. The minimum value required for variable factorability is 0.600. The highest value represents the greatest correlation between the variables. Bartlett's Test of Sphericity, on the other hand, examines factorability. It converts the computed determinant value into a chi-square statistic, which is then used to determine the level of significance. The null hypothesis of variable non-collinearity can only be rejected if the probability values are less than the 5% level of significance.

Cointegration Tests

Combined cointegration test

Several cointegration tests, including those developed by Boswijk (1994), Engle and Granger (1987), Phillips and Ouliaris (1990), are available in the economic literature. The findings of these tests provide varying outcomes since none of these tests is unanimously acceptable and produces robust results (Elliott et al., 2005). In this regard, Bayer and Hanck (2013) propose a better method for detecting cointegration. Its F-Statistics integrate numerous cointegration tests to get more precise results (i.e., Boswijk, Johansen, Banerjee, Engle & Granger). Fisher's formula for performing combined cointegration tests is as follows:

$$EG - JOH = -2\left[ln(P_{EG}) + ln(P_{JOH})\right] \quad (5)$$

$$EG - JOH - BO - BMD = -2\left[ln(P_{EG}) + ln(P_{JOH}) + ln(P_{BO}) + ln(P_{BDM})\right] \quad (6)$$

Here P_{EG}, P_{JOH}, P_{BO}, and P_{BDM} are the probability value of several tests of cointegration. The general rule is that if the calculated value of the F-Statistic exceeds the critical value of the Bayer-Hanck test, the null hypothesis of no cointegration is strongly rejected, and vice versa.

Gregory Hansen cointegration test

Gregory and Hansen (1996) structural break cointegration test, which is a multivariate extension of Zivot and Andrews's univariate unit root test, is also utilized. Although the Bayer-Hanck cointegration test yields consistent results, it excludes the possibility of a structural break, which could influence the cointegration decision. Gregory and Hansen (1996) address this issue by proposing a residual-based cointegration test. To account for the structural changes in cointegration, a dummy variable is added, with $Dt(T_b) = 0$ if $t \leq T_b$ and 1 otherwise where T_b represents the time of the structural change. This test provides three different structural break formations: level shift (model C), trend shift (model C/T), and regime shift (model C/S). This study employs a regime shift model (model C/S) because other models are derived from it. In the presence of a structural break, the general long-run relationship can be specified as follows:

$$HCEt = u1 + u2Dt(Tb) + \beta 1Xt + \beta 2Dt(Tb) * Xt + \varepsilon t \quad (7)$$

In Equation (7), HCE shows public HCE (regressand), X represents the chosen determinants of HCE (regressors), and ε_t denotes the white-noise error term. Whereas μ_1 shows the intercept before the shift (break), and μ_2 shows the change in intercept at the time of shift. While β_1 shows the cointegrating slope coefficient before the structural break and β_2 represents a change in slope coefficient during the regime shift. The null hypothesis of no cointegration is tested against the alternative hypothesis of cointegration in the presence of structural breaks using the ADF statistic.

Hatemi-J cointegration test

This study also employs a cointegration test based on two structural breaks suggested by Hatemi-j (2008), which is an expanded version of the cointegration test proposed by Gregory and Hansen (1996). Hatemi-j (2008) generalizes the model by incorporating two structural breaks shown in Equation (8).

$$HCE_t = u_1 + u_2D_{1t} + u_3D_{2t} + \beta_1 Xt + \beta_2(D_{1t} * X_t) + \beta_3(D_{2t} * X_t) + \varepsilon_t \quad (8)$$

In Equation (8), D1t and D2t are binary variables, which are given in Equation (8a):

$$D_{1t} = \begin{cases} 0 & if \quad t \leq T_1 \\ 1 & if \quad t > T_1 \end{cases}, \text{ and } D_{2t} = \begin{cases} 0 & if \quad t \leq T_2 \\ 1 & if \quad t > T_2 \end{cases} \quad (8a)$$

Here, T_1 represents the period preceding the first break, and T_2 denotes the period preceding the second break. $T_1 + T_2 = T$ represents the total sample size. Whereas β_1 denotes the slope coefficient before the structural break and β_2 shows the variation in slope coefficient at the time of structural break, and β_3 represents the variation in slope coefficient at the time of the second structural break.

Causality Analysis

The presence of cointegration suggests that the variables must have a causal link in at least one direction. The causality analysis clarifies and reinforces relationship between the variables.

Short-run Granger causality test

Granger (1969) suggests that if cointegration among variables exists at the first difference, then the vector error correction model (VECM) is a suitable approach for testing the causal relationship among variables. It is a restricted type of model in the unrestricted vector autoregressive (VAR) framework, in which restriction is imposed to the long-run relationship and constant. Series are used in their endogenous form in the VECM framework. In this case, the lag of the response variable, the lag of the explanatory variable(s) along with residual term, and error correction term explain the response variable. The following restricted VAR model (VECM) is estimated to evaluate the causality:

$$\Delta lnHCEt = \beta 1i \sum_{i=1}^{n} \Delta lnHCEt - i + \beta 2i \sum_{i=0}^{n} \Delta lnYt - i + \beta 3i \sum_{i=0}^{n} \Delta HCIt - i + \beta 4i \sum_{i=0}^{n} \Delta HCSt - i + \delta hECTt - 1 + \varepsilon 1t \quad (9)$$

$$\Delta lnYt = \alpha 1i \sum_{i=1}^{n} \Delta lnYt - i + \alpha 2i \sum_{i=0}^{n} \Delta lnHCEt - i + \alpha 3i \sum_{i=0}^{n} \Delta HCIt - i + \alpha 4i \sum_{i=0}^{n} \Delta HCSt - i + \delta yECTt - 1 + \varepsilon 2t \quad (10)$$

$$\Delta HCIt = \lambda 1i \sum_{i=1}^{n} \Delta HCIt - i + \lambda 2i \sum_{i=0}^{n} \Delta lnHCEt - i + \lambda 3i \sum_{i=0}^{n} \Delta lnYt - i + \lambda 4i \sum_{i=0}^{n} \Delta HCSt - i + \delta yECTt - 1 + \varepsilon 3t \quad (11)$$

$$\Delta HCSt = \gamma 1i \sum_{i=1}^{n} \Delta HCSt - i + \gamma 2i \sum_{i=0}^{n} \Delta lnHCEt - i + \gamma 3i \sum_{i=0}^{n} \Delta lnYt - i + \gamma 4i \sum_{i=0}^{n} \Delta HCIt - i + \delta yECTt - 1 + \varepsilon 4t \quad (12)$$

Where, Δ shows the difference, ECT_{t-1} expresses lag of error correction term and ε_{it} shows the residual term.

Long-run Granger causality test (Toda-Yamamoto procedure)

In addition, this study investigates the long-run causality between HCE, per capita income, HCI, and HCS in Pakistan.

Most research studies utilize significance and a sign of error correction term (ECT) to determine causality in the long run (Ang, 2010; Chaabouni & Abednnadher, 2014; Tang, 2011; Wang et al., 2019), however, this does not provide a clear picture. The significant ECT only indicates long-run causality, which runs from explanatory variables to the response variable, but it does not tell which variable causes the response variable in the long run. To solve this problem, Toda and Yamamoto (1995) suggest a modified Granger causality test, which is used in this study:

$$lnHCE_t = \alpha_0 + \alpha_{1i}\sum_{i=1}^{n+dmax} lnHCE_t + \alpha_{2i}\sum_{i=1}^{n+dmax} lnY_t + \alpha_{3i}\sum_{i=1}^{n+dmax} HCI_t + \alpha_{4i}\sum_{i=1}^{n+dmax} HCs_t + \varepsilon_{1t} \quad (13)$$

$$lnY_t = \beta_0 + \beta_{1i}\sum_{i=1}^{n+dmax} lnY_t + \beta_{2i}\sum_{i=1}^{n+dmax} lnHCE_t + \beta_{3i}\sum_{i=1}^{n+dmax} HCI_t + \beta_{4i}\sum_{i=1}^{n+dmax} HCs_t + \varepsilon_{1t} \quad (14)$$

$$lnHCI_t = \delta_0 + \delta_{1i}\sum_{i=1}^{n+dmax} HCI_t + \delta_{2i}\sum_{i=1}^{n+dmax} lnHCE_t + \delta_{3i}\sum_{i=1}^{n+dmax} lnY_t + \delta_{4i}\sum_{i=1}^{n+dmax} HCS_t + \varepsilon_{3t} \quad (15)$$

$$HCS_t = \gamma_0 + \gamma_{1i}\sum_{i=1}^{n+dmax} HCS_t + \gamma_{2i}\sum_{i=1}^{n+dmax} lnHCE_t + \gamma_{3i}\sum_{i=1}^{n+dmax} lnY_t + \gamma_{4i}\sum_{i=1}^{n+dmax} HCS_t + \varepsilon_{1t} \quad (16)$$

In Equations (13-16), ‘n' represents the length of the lag, whereas d_{max} represents the highest possible integration order of the variables used in the models. The intercept is included in the model because this test is used in an unconstrained VAR framework.

RESULTS AND DISCUSSION

Unit root tests without and with structural breaks

The results of traditional (ADF & PP) unit root tests are shown in Table 3, confirming the stationarity at first difference. We also use structural break unit root tests to examine the stationarity of variables (i.e., Lee-Strazicich and Clemente-Montanes-Reyes). As seen in Table 4, the results show that all of the series are stationary at integrated of order one. Table 5 describes information on lag order selection, Lutkepohl (2006) states that the Akaike information criterion (AIC) provides suitable and consistent results owing to its better characteristics when compared to alternative lag length criteria. Therefore, the optimal lag length is determined using AIC, which is 2.

Cointegration Tests

We use conventional and structural break cointegration tests to determine the long-run relationship among variables. Table 6 shows the results of the Bayer-Hanck cointegration test. The findings demonstrate that the computed F-Statistic values for the EG-JOH and EG-JOH-BO-BDM tests exceed critical values at a 10% level of significance, indicating the presence of cointegration among the variables. Although the combined cointegration tests yield satisfactory results, they fail to account for structural breaks when examining the long-run relationship. To resolve the issue, we perform threshold cointegration tests in the presence of structural breaks, and the results are presented in Table 6. The modified ADF test rejects the null hypothesis of no cointegration at 10% and 1% significance levels for Gregory and Hansen (1996) single structural break and Hatemi-j (2008) two structural break cointegration tests, respectively. Despite significant evidence of a long-run cointegrating relationship between HCE, per capita income, HCI, and HCS, this evidence is insufficient to draw judgments regarding the direction of causality between variables. The existence of a long-run association is necessary but not sufficient for confirming the direction of causality (Morley, 2006). There must be a causal relationship if there is a cointegrating relationship.

Table 3. ADF and PP unit root tests results.

Variables	ADF		PP	
	Level	1st Diff.	Level	1st Diff.
$lnHCE_t$	-2.3237	-6.4957***	-2.7421	-10.201***
lnY_t	-2.4613	-3.8717**	-2.7522	-6.3461***
HCI_t	-1.8223	-5.9783***	-1.8223	-5.9688***
HCS_t	-0.6459	-3.5262**	0.9838	-3.4657**

Note: *** and ** shows 1% and 5 % level of significance, respectively. Critical values are derived from (MacKinnon, 1996) for ADF and PP unit root tests.

Table 4. Structural break unit root tests results.

Variables	Lee Strazicich				Clemente-Montanes-Reyes					
	Level		1st Diff.		Level			1st Diff.		
	Break date	t-statistic	Break date	t-statistic	TB1	TB2	t-statistic	TB1	TB2	t-statistic
$lnHCE_t$	2009	-2.1985	2012	-5.6892***	1978	2010	-2.6780	1988	2009	-9.6990**
lnY_t	2010	-2.9610	1977	-4.5652***	1989	2003	-3.5980	2007	2010	-7.4590**
HCI_t	2013	-2.3858	1994	-4.1790***	1986	2010	-4.8890	1992	2011	-10.7270**
HCS_t	2010	-1.6963	2012	-5.1103***	1982	2011	-0.5540	1995	2010	-5.8990**

Note: *** and ** denote a level of significance of 1% and 5%, respectively. The 1% critical value is -4.0840, while the 5% critical value is -3.4870. These critical values are derived from (Lee & Strazicich, 2003). The critical values for the Clemente structural break unit root test are taken from (Clemente et al., 1998). In the Clemente structural break unit root test, the break dates are TB_1 and TB_2.

Table 5. Lag length criterion.

Lag	SC	LR	LogL	HQ	FPE	AIC
0	6.8767	NA	-136.9357	6.7719	0.0097	6.7112
1	-5.2999	503.2185	148.6748	-5.8241	2.58e-08	-6.1274
2	-5.3940*	50.0927*	180.5519	-6.3375*	1.24e-08*	-6.8834*

Note: * indicates the lag order chosen by the criteria, and each test is significant at the 5% level of significance. SC: Schwarz information criterion, LR: sequential modified LR test statistic, HQ: Hannan-Quinn information criterion FPE: Final prediction error, AIC: Akaike information criterion.

Table 6. Cointegration tests results.

Estimated Model	Combined cointegration		Gregory Hansen cointegration		Hatemi-J cointegration	
	EG-JOH	EG-JOH-BO-BDM	ADF-test	Break date	ADF-test	Break dates
lnHCEt = f (lnYt, HCIt, HCSt)	16.9813*	30.0721*	-6.24*	1990	-11.28***	1987 and 2000

Note: ***and * shows 1%and 10% level of significance respectively. Critical values at 10% level are provided by Bayer and Hanck (2013) that are 16.097, for (EG-JOH-BO-BDM) and 8.363 for (EG-JOH), respectively. Lag length is based on the minimum value of AIC whereas 2 lags are used in the combined co-integration test. The critical values for Gregory Hansen and Hatemi-J tests are taken from Gregory and Hansen (1996) and Hatemi-j (2008).

Causality analysis

Short-run causality test results

The Granger causality under VECM framework provides a better way to investigate the direction of the causal relationship between HCE and its determinants because the variables are integrated of order one and cointegrated, the results are provided in Table 7.

The findings indicate that there is a short-run unidirectional causal relationship that runs from per capita income to HCE , which is statistically significant at a 5% level of significance. These results support the growth-led HCE hypothesis, which postulates that as the economy grows, people and the government will have more financial means to spend in HCI and HCS. The results support Wagner's law. The findings suggest that an increase in government income will raise government expenditures. These results are consistent with many empirical studies (Akram et al., 2008; Apergis et al., 2018; Kiymaz et al., 2006; Zaidi & Saidi, 2018) while contradicting a few studies (Chen et al., 2014; Imran et al., 2012; Shamsi & Waqas, 2016; Wang et al., 2019). There is also bidirectional causality between per capita income and HCI. This demonstrates that as per capita income rises, more HCI is made available, and vice versa. These results are consistent with (Taskaya & Demirkiran, 2016) and contradict the findings of (Akram et al., 2008; Raza et al., 2013).

From Table 7, we found unidirectional causality that runs from HCE to HCI and HCS. These results are significant at 5% and 1% levels of significance respectively. These results are in direct opposition to those of (Akram et al., 2008; Chaabouni & Abednnadher, 2014; Raza et al., 2013). The results confirmed the supply-induced demand hypothesis for Pakistan. This hypothesis states that providing more HCI and HCS leads to increased public use of medical services and, as a result, increased spending on HCI and HCS. The causality inferences also show bidirectional causality between HCI and HCS in the short run. This explains that HCI and HCS are mutually dependent. It means that the establishment of new HCI needs the hiring of specialized medical staff, who, in turn, require adequate infrastructure to function properly. These results contradict from those of Taskaya and Demirkiran (2016), who found no causal relationship between HCI and HCS.

Long-run causality test results

In a VAR framework, the Toda-Yamamoto causality test is also used to explore the direction of the long-run causal relationship between the variables. The AIC criterion is used to determine the appropriate lag length, which is 2 (See results in Table 5), while the maximum order of integration according to different unit root tests whether the conventional or structural break is one (i.e., d_{max}=1). As a result, the Toda-Yamamoto causality test has a maximum lag length of three. Table 8 displays the long-run causality results. These results suggest that there is sufficient evidence for long run two-way causality between HCS and HCE. This means that an increase in HCE causes an increase in HCS, while an increase in HCS causes a rise in HCE. The government may increase HCE in order to improve HCS in Pakistan. Resultantly, healthcare services require more healthcare expenditures. Both HCE and HCS are required for the improvement of the health of the people, who are a critical element in the production process of emerging nations such as Pakistan. Further, the causality results show long-run unidirectional causality from per capita income to HCE, which is significant at a 5% level of significance. These findings emphasize the significance of per capita income in making people more health-conscious and willing to spend more money on health in order to stay active members of society. Aside from that, the causality inferences indicate long-run unidirectional causality from HCE, per capita income, and HCS to HCI, which is significant at the 10%, 5%, and 1% levels of significance, respectively. These findings support the relevance of HCE, per capita income, and HCS in improving HCI.

Table 7. Short-run causality results.

Dependent variable	Source of causation			
	$\Delta lnHCE_t$	ΔlnY_t	ΔHCI_t	ΔHCS_t
$\Delta lnHCE_t$	-	6.1130**	2.1416	3.1996
ΔlnY_t	2.8170	-	7.4691**	4.0442
ΔHCI_t	6.7758**	8.7483***	-	10.823***
ΔHCS_t	11.023***	1.4572	5.1699*	-

Note: ***, ** and * shows 1%, 5% and 10% level of significance, respectively.

Table 8. Long-run causality results.

Dependent variable	Source of causation			
	$lnHCE_t$	lnY_t	HCI_t	HCS_t
$lnHCE_t$	-	6.3806**	1.8392	5.1014*
lnY_t	2.0258	-	0.0341	3.0263
HCI_t	5.1457*	7.5336**	-	9.5277***
HCS_t	8.1927***	1.4959	0.1076	-

Note: ***, ** and * shows 1%, 5% and 10% level of significance, respectively.

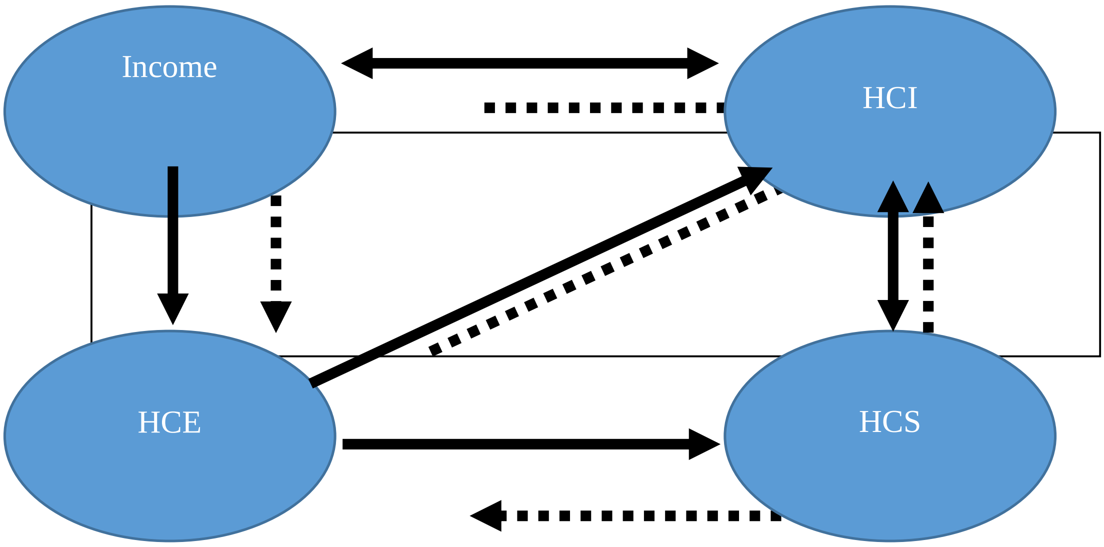

Figure 3. Short-run and long-run Granger causalities.
Note: continuous line shows short-run Granger causality while the discontinuous line shows long-run causality.

CONCLUSIONS, POLICY IMPLICATIONS, AND FUTURE DIRECTION

A healthy population and human capital are important determinants of a country's growth and long-term development. It is necessary to understand the factors that determine public HCE in order to provide a platform for evaluating and controlling government expenditures. In this response, the main objective of this study is to empirically examine the cointegration and short-and-long run causal association between per capita income, HCI, HCS, and Public HCE in Pakistan from 1974 to 2017. We used the PCA technique to construct indices that captured several dimensions of HCI and HCS. Both conventional and structural break unit root tests are applied to check the integration order of the variables. A question that arises is whether HCE, per capita income, HCI, and HCS are cointegrated and have a causal relationship, and if so, what is the directional causality. The results of cointegration tests confirmed the long-run cointegrating relationship amid the variables under consideration. The study also provides causal directions for both the short and long run. In the short run, the findings show unidirectional causalities from HCE to HCI and HCS, as well as unidirectional causality from income to HCE, whereas bidirectional causality is observed between HCI and per capita income and between HCI and HCS. Correspondingly, long-run causality results indicate unidirectional causality from per capita income to HCE, from HCE, per capita income, and HCS to HCI, and bidirectional causality between HCS and HCE.

The findings of this study have some interesting policy implications for policymakers and practitioners. First, the results indicate that income has a major effect on the growth of HCE. The government may introduce income-enhancing projects to raise inhabitants' per capita income. In this regard, the government may establish industrial units as well as mechanize the agricultural sector to increase per capita income in these sectors. Furthermore, the government may establish schools and colleges in rural areas to provide inhabitants with better education and skills. The per capita income will rise as a result of these initiatives, and the general population will have more money to spend on health care. Second, people and the government will have more financial resources to invest in the HCI and HCS if the economy is performing well. This shows that HCI and HCS demand the bulk of funds from the government of

Pakistan. More government funding for the general public is unavoidable due to rising population pressures and a rise in illness prevalence among society's inhabitants. Thus, this study suggests policymakers to design sound HCI and to implement cost-cutting policies for health expenditures. If the government avoids the fungibility of government spending, it can invest effectively in HCI and HCS. The role of bureaucracy in controlling the fungibility of government spending is critical. Therefore, the government may improve the quality of institutions, as institutional quality and good governance are crucial in the functioning of institutions. Third, this study reports unidirectional causality from HCE to HCI in the both short and long run. Therefore, the government may allocate more healthcare budget to provide sufficient HCI and HCS to the general public especially to the people residing in the remote and far-flung areas where insufficient, meager, and limited medical facilities are available. By providing these services, the majority of population living in rural areas will be able to reap the benefits of HCI and HCS. In this way, this segment of society may play an active role and assist the economy by directing their efforts toward real GDP growth. Further, the government may adopt good governance to check the corrupt practices prevalent in the health sector. Besides, the government ensures to allocate funds adequately on healthcare facilities so that HCI may be developed quantitatively and qualitatively which in turn helps to promote health status and GDP growth in Pakistan. Fourth, a short-run feedback effect is found between HCI and HCS. It means that both HCI and HCS are dependent on each other and hence both are complementary to each other. Therefore, there should be a balance between the establishment of medical care centers and the deployment of medical professionals in rural and urban areas. The shortage of any one of these factors will lead to misutilization for the other. Finally, this study demonstrates the significance of healthcare in the economic growth process. Since healthcare plays a major role in human capital formation, better healthcare ensures a healthy and energetic labor force. In that way, the employed labor force becomes productive and may contribute to economic growth. Since the labor force is supplied by both rural and urban areas, the government may ensure that HCS and HCI are readily available in both rural and urban areas. It should be noted that unequal distribution of healthcare facilities may be seriously harmful to a developing country like Pakistan, thus the government should avoid any discrimination in providing healthcare resources to its citizens. The government should not only focus on the establishment of healthcare facilities, but also on ensuring their equitable regional distribution.

In terms of future research in the healthcare sector, we have noticed that time-series data contains asymmetries and shocks (positive or negative). The impact of these shocks can be considered when investigating casual relationships. Therefore, future empirical studies should look into this aspect in order to investigate the causal relationship using the asymmetric causality technique developed by (Hacker & Hatemi-J, 2006).

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