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The Effect of Information-Communication Technologies (ICT) and Air Pollution on Health Expenditures

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Bilgi-İletişim Teknolojileri (BİT) ve Hava Kirliliğinin Sağlık Harcamalarına Etkisi

Abstract

This study analyses the effects of ICT and air pollution on health expenditures of 81 Turkish provinces during 2011-2018. Models were analysed through a panel data method. The results indicated that air pollution and mobile phone subscribers do not affect health expenditure. In contrast, the number of internet subscribers and index variable (devised by the authors) have a negative effect on health expenditure. This study has a unique value and contributes to the literature. It is one of the first studies scrutinizing the impact of air pollution and ICT on health expenditures in Turkey.

Keywords : Information and Communication Technologies, Health Expenditures, Air Pollution.

JEL Classification Codes : P46, Q53, Q55.

Öz

Bu çalışma Türkiye'de 2011-2018 yıllarına ait BİT ve hava kirliliğinin 81 ilin sağlık harcaması üzerine etkisini analiz etmeyi amaçlamıştır. Bu doğrultuda 4 model kurulmuş ve bu modeller panel veri yöntemiyle analiz edilmiştir. Elde edilen bulgular doğrultusunda hava kirliliği ve cep telefonu abone sayısının sağlık harcaması üzerine etkisi bulunmazken, internet abone sayısı ve endeks değişkenlerinin (yazarların kendi hesaplaması) sağlık harcaması üzerine etkisi negatiftir. Çalışma, Türkiye'de hava kirliliği ve BİT'lerin sağlık harcaması üzerine etkisini inceleyen ilk çalışmalardan olması açısından özgün bir değere sahip olmakta ve literatüre katkı sağlamaktadır.

Anahtar Sözcükler : Bilgi ve İletişim Teknolojileri, Sağlık Harcamaları, Hava kirliliği.

1. Introduction

Health indicators and health conditions are gradually changing worldwide and in Turkey. According to the World Bank 2020 data, indicators such as life expectancy or healthy life expectancy at birth significantly increase. For example, life expectancy at birth has increased globally from 52.5 in 1960 to 67.5 in 2000 and 72.7 in 2019. The same indicator increased from 45.3 in 1960 to 70 in 2000 and 77.6 in 2019 in Turkey (World Bank, 2020). Thus, significant improvements in health conditions can be observed globally and in Turkey. Even though health indicators have improved significantly, factors positively and negatively affect health status, increasing public and individual health expenditure. The increase in health expenditure, a significant proportion in both public and individual households, has led to increased studies on the determinants of health expenditure. Considerable works have been carried out on the determinants of health expenditure (Gerdtham et al., 1992; Gbesemete & Gerdtham, 1992; Murthy & Ukpolo, 1995; Hansen & King, 1996; Di Matteo & Di Matteo, 1998; Gerdtham & Lothgren, 2000; Murthy & Okunade, 2000; Herwartz & Theilen, 2003). These studies have considered several determinants of health expenditure (such as ageing, population, income, number of physicians, female participation rate, public health financing, foreign aid, and urbanization), which consist of economic and non-economic factors. However, apart from these factors, strong economic growth, especially in developing countries, has led to higher energy consumption and increasing air pollution, threatening human health (Yahaya et al., 2016). In addition, the development of technology and the increasing importance of communication have led to the use of the internet and mobile phones worldwide. The expanding use of information and communication technologies (ICT) affects health indicators and conditions.

Air pollution harms the biosphere and the natural balance of the environment as solid, liquid, and gaseous air pollutants (PM: particulate matter; CO: carbon monoxide; NO_x: nitrogen oxides; SO_2: sulfur dioxide; VOC: volatile organic compounds; ozone, methane) mount (Kılıç et al., 2014). It has been proven that these pollutants have a multifaceted effect on human health (Zeng & He, 2019). Thus, an increase in air pollution can lead to childhood asthma (Buteau et al., 2018), low birth weight in infants born near industrial areas (Gong et al., 2018), middle ear infections in early childhood (Deng et al., 2017), cancer (Fernandez-Navarro et al., 2017), infant deaths (Fotourehchi, 2016), and low life expectancy (Correia et al., 2013). Consequently, the deterioration of air quality causes many diseases and deaths, affecting both public and individual health budgets (Yahaya et al., 2016). Depending on these diseases, the demand for hospital services increases (Lagravinese et al., 2014; Fotourehchi, 2016). Accordingly, one can predict an increase in the use of health services due to severe weather impacts (Blázquez-Fernández et al., 2019). The OECD confirmed such a prediction in a 2016 study, according to which an increase in outdoor air pollution will have a global economic cost of 1% of global GDP by 2060. It will also lead to extra health expenditures in the long run (Zeng & He, 2019).

Recently, another factor that increasingly affects the health of human beings has turned out to be ICT. Change and transformation in ICTs affect our lives and well-being.

The effect of ICTs can be observed in various aspects of life (education, transportation, security, banking and shopping, communication) and health care. Positive effects include multiple improvements in the provision of healthcare (e.g., electronic health records, online access to healthcare providers, e-health technologies, and online medical appointments) and easier access to medical information for patients (e.g., more information about diseases, treatments, and support via an online platform) (Benvenuto et al., 2019; Iverson et al., 2008). In addition, the development of ICT facilitates communication with friends and family, contributing to a reduction in depression and thus a decrease in health care expenditures (Bessière et al., 2010). However, excessive and unnecessary use of ICT has adverse effects on health. For instance, facilitating personal information searches can lead to self-diagnosis of diseases, which may increase health spending (e.g., redundant hospitalizations) and adversely affect the sustainability of health systems (Benvenuto et al., 2019; Iverson et al., 2008). Furthermore, the widespread use of smartphones has led to physical such as headaches, neck, back, and wrist pain and mental problems such as anxiety, depression, lack of attention, decrease in social interaction, a decline in academic success, and professional difficulties. Accordingly, increasing health problems due to ICT use is expected to increase individual and public health expenditure.

In Turkey, a developing country, increased air pollution and a rising trend in health indicators and related expenditures have been observed. For example, in the World Air Quality Report 2020 prepared by IQAir Group, Turkey ranked 46th out of 106 countries. Compared to European countries, Turkey has consistently recorded higher levels of particulate matter in the atmosphere than Europe over the past 17 years. Although atmospheric particulate matter levels in Europe have been regularly decreasing, those levels have been periodically increasing in Turkey in the same period. Thus, air pollution in Turkey, which was 5.6% higher than in Europe in 2003, grew to 31.0% in 2019 (TMMOB, 2019). Due to this air pollution, health expenditure in Turkey has also increased. For example, in 2021, the Health and Environment Alliance (hereafter HEAL) published a report highlighting the health issues and financial burdens of air pollution from thermal power plants in Turkey. There were about 5 thousand premature deaths in Turkey in 2019 due to air pollution from coal-fired power plants. On the other hand, these power plants caused many chronic and acute diseases, including 26 500 cases of bronchitis in children, 3 000 premature births, and 3230 issues of bronchitis in adults. Because of all these health problems, it has been stated that air pollution from coal-fired power plants in Turkey causes health costs of about 53.60 billion Turkish Lira (TL) every year (HEAL, 2021).

With the development of technology and the increasing importance of communication, the excessive use of the internet and mobile phones increases in Turkey and other countries. For example, according to the Household Information Technology Usage Survey (Turkish Statistical Institute) (2020), the internet usage rate among individuals between 16 and 74, 75.3% in 2019, increased to 79% in 2020. On a household basis, it increased from 88.3% in 2019 to 90.7% in 2020. Mobile phone usage increased from 93.5% to 95.3% over this period (TÜİK, 2020). It can easily be observed that air pollution and ICT use have increased in Turkey in recent years. As the effects of these elements on health intensify, the number of studies on this topic also increases. Several studies are examining the impact of air pollution on health (Karasoy & Demirtaş 2018; Tıraş & Türkmen, 2020); and some of the studies examining the effect of ICT use on health (Günal & Pekçetin, 2019); Kuyucu (2017) can be recalled readily.

While there are a limited number of studies in the literature examining the effect of air pollution on health expenditure, a recent study (Benvenuto, Sambati and Viola, 2019) directly examines the impact of ICTs on health expenditures has been found. In the case of Turkey, besides a study examining the effect of air pollution on health expenditures (Tıraş & Türkmen 2020), no study directly examining the impact of ICTs on health expenditures was found in the literature.

The current study is essential since it is the first study to examine the effects of air pollution and ICTs on health expenditures on a regional basis in Turkey. Additionally, to measure the use of ICTs more comprehensively, the ICT index variable covering the number of fixed telephone line subscribers, the number of mobile telephone line subscribers, and the number of internet subscribers was created using the Principal Component Analysis technique. Therefore, the study differs from other studies examining the effect of ICTs on health expenditure and creating an index that measures ICTs more comprehensively, thus contributing to the literature. This study investigates whether air pollution and ICT use affect health expenditure and, if so, to what extent.

This study consists of four parts. In the second section, studies conducted in Turkey and foreign literature on the topic of the study are reported. In the third part, the data set and the methodology are explained, and, in the last section, the study results and the conclusions are presented.

2. Background Literature

Studies focusing on the determinants of health expenditures have classified these determinants as income and non-income. While per capita income is usually used as an income determinant, they have identified components such as demographic structure, people's lifestyle, health care delivery model, technological development, or environmental factors as non-income determinants (Zeng & He, 2019; Blázquez-Fernández et al., 2019; Apergis et al., 2020; Yahaya et al., 2016).

The most referred determinant can be recognized as income. In studies dealing with the determinants of health expenditure, extensive literature on income exists. Many researchers (Newhouse, 1977; Hitiris & Posnett, 1992; Samadi & Homaie, 2013; Chaabouni & Abednnadher, 2014; Yahaya et al., 2016; Boachie & Ramu, 2016; Taşkaya & Demirkıran, 2016; Karasoy & Demirtaş, 2018; Zeng & He, 2019; Blázquez-Fernández et al., 2019; Öztürk & Küsmez, 2019; Apergis et al., 2020) acknowledge income as the primary explanatory variable. Most of these studies have found a positive relationship between health expenditure and income. However, the income elasticity of health expenditure differs according to the explanatory variables used, the estimation method, and the country sample analyzed.

The demographic structure comes as the second significant determinant. Population structure has an impact on health expenditures. Therefore, previous studies have indicated that being over 60 and under 5 or 15 means increasing health expenditures. It has been stressed that primarily the elderly population causes higher health expenditures and requires more health services. There is a correlation between the ageing population and health expenditures for upper-middle and high-income countries where the elderly population is rapidly expanding (Kea et al., 2011). Consequently, the impact of the ageing population on health and welfare systems is the focus of political agendas in developed countries (Apergis et al., 2020). In low-income countries, it is not expected to cause an increase in health expenditures since the elderly population is not substantial (Kea et al., 2011). Works by Di Matteo and Di Matteo (1998), Murthy and Okunade (2009), Chaabouni and Abednnadher (2014), Novignon et al. (2015), Bloom et al. (2015), Ergün and Polat (2018), and Apergis et al. (2020) can be referred as the studies examining the effect of demographic structure on health expenditures.

Environmental impact comes as the third determinant. In recent years, the effects of weather conditions and environmental factors on health have increased, primarily in developing countries, depending on economic performance. Accordingly, more than 5.5 million people die at an early age every year due to health problems caused by air pollution. Consequently, deterioration of air quality causes various diseases affecting both public and individual health budgets (Yahaya et al., 2016). This condition has increased the number of studies examining the effects of air and environmental quality indicators on health expenditures.

Studies examining the effects of air and environmental quality indicators on health expenditures have been classified according to the countries’level of development, analysing a sample of developed countries and finding a negative effect on health expenditure (Apergis et al., 2018; Janke et al., 2009; Narayan & Narayan, 2008; Jerrett et al., 2003; Brunekreef & Holgate, 2002). Such studies also found a negative effect in a sample of developing countries (Shen et al., 2021; Yahaya et al., 2016; Qureshi et al., 2015; Khoshnevis-Yazdi et al., 2014). Some studies have examined mixed samples of both developed and developing countries, have similarly found a negative impact on health expenditure (Blázquez-Fernández et al., 2019; Khoshnevis-Yazdi & Khanalizadeh, 2017). Examples of developed, developing, and underdeveloped countries were examined (Apergis et al., 2020). However, air pollution on health expenditure is more dominant in developed countries. A study conducted in Turkey (Tıraş & Türkmen, 2020) found that air pollution does not affect health expenditure.

When the abovementioned studies’findings are broadly assessed, increasing air pollution increases health expenditures. However, this effect differs in developed countries and Turkey. While the result was more dominant in developed countries, Turkey was not observed.

The fourth determinant is technology development, mainly the development of ICTs. The result of information and communication technologies contributes globally to improving health systems. Technology can improve healthcare and other health indicators in many ways. Information and communication technologies enhance access to healthcare in geographically isolated communities, support healthcare workers, and increase data sharing. The result of ICTs improves access to healthcare in geographically insulated communities, provides support for healthcare workers, and improves data sharing.

Similarly, online health information generates positive health outcomes through various mechanisms, some of which are as follows: Firstly, web health information can empower patients and increase their sense of control over the disease by increasing the knowledge and self-awareness needed to make informed decisions that improve their quality of life (Broom, 2005). Secondly, web health information contributes to the effective and efficient use of clinical time. Some healthcare professionals have reported that empowering patients helps them diagnose diseases early and helps them seek healthcare (Laing et al., 2004). Thirdly, health information on the web improves patients'knowledge of their health problems and their relationships with their doctors (Ferguson, 2000). Due to health information on the internet, less time is needed to decide on the treatment to be applied due to learning basic information about the disease (Gerber & Eiser, 2001). Some studies examining the effects of air pollution and ICTs on health are included in the literature review. Studies examining the impact of air pollution on health expenditures will be included primarily, and then reflections on ICT and health will be covered.

Studies examining the effects of ICTs on health have been classified according to the development level of countries. Studies focusing on developed countries (Iverson et al., 2008; Bessière et al., 2010; Liu et al., 2011; Kim & Kim, 2015; Benvenuto et al., 2019; Alsalameh et al., 2019; Baabdullah et al., 2020) have found a positive effect (Benvenuto et al., 2019), adverse effects (Liu et al., 2011; Kim & Kim, 2015; Alsalameh et al., 2019; Baabdullah et al., 2020) and both positive and negative effects (Iverson et al., 2008; Bessière et al., 2010). Some of the studies focused on a sample of developing countries (Blaya et al., 2010; Déglise et al., 2011; Zhang et al., 2019; Hanphitakphong et al., 2021; Yuan, 2021). Accordingly, some studies state that it has a positive effect (Blaya et al., 2010; Déglise et al., 2012; Zhang et al. 2019), some studies that say a negative impact (Hanphitakphong et al., 2021), and some report both positive and negative effects (Yuan, 2021). Mixed samples of developed and developing countries (Cole-Lewis & Kershaw, 2010) have identified a positive impact.

Studies conducted in Turkey (Günal & Pekçetin, 2019; İnal & Arslan, 2021; Mustafaoglu et al., 2021) find that ICTs on health has a negative effect.

Analysing the study findings broadly in developed and developing countries, it can be understood that the effect of ICTs on health vary in developed countries, the negative impact is more dominant; in contrast, in developing countries, the positive results are more prevalent; in Turkey, which is included in the sample of developing countries, the negative impact is more prevalent.

A study by Benvenuto, Sambati, and Viola (2019) directly examined the effect of ICTs on health expenditures, but no such research in Turkey exists. Although other studies reviewed in the literature have examined the impact of ICT on health in various aspects, this has been discussed as it will indirectly affect health expenditures. In this respect, the present study is critical since it is the first to examine the effects of air pollution and ICTs on health expenditure on a regional basis in Turkey.

3. Model, Data, and Methodology

In this part of the study, the effects of ICT and air pollution variables for 2011-2018 on the health expenditures of 81 provinces in Turkey are analysed. Based on the theoretical framework and empirical literature, econometric models applied to assess the determinants of health expenditure have been expanded to cover air pollution and ICTs and analyse them on a regional basis for Turkey. The prediction models of the research are defined in the following equations:

$$\text{lnhealth} = \beta_{0it} + \beta_{1it}\ln income + \beta_{2it}\ln \text{population} + \varepsilon_{\text{it}} \qquad \textbf{\textit{(Model I)}}$$

$$\text{lnhealth} = \beta_{0it} + \beta_{1it}\ln income + \beta_{2it}\ln \text{population} + \beta_{3it}\ln air + \varepsilon_{\text{it}} \qquad \textbf{\textit{(Model II)}}$$

$$\text{lnhealth} = \beta_{0it} + \beta_{1it}\ln income + \beta_{2it}\ln \text{population} + \beta_{3it}\ln ICT + \varepsilon_{\text{it}} \qquad \textbf{\textit{(Model III)}}$$

$$\text{lnhealth} = \beta_{0it} + \beta_{1it}\ln income + \beta_{2it}\ln \text{population} + \beta_{3it}\ln index + \varepsilon_{\text{it}} \qquad \textbf{\textit{(Model IV)}}$$

In the equations, i = 1, 2, 3,…,N denotes cross-section units, t = 1, 2, 3,…,T denotes time dimension and Ɛ denotes panel error term. The abbreviations, explanations, and sources of the variables used in this study are listed in Table 1.

Table: 1
Variables Used and Their Descriptions

Abbreviations	Variables	Description	Source
health*	Health expenditure per capita	Real gross domestic product per capita* Share of health expenditure in total household consumption expenditure	TUIK
income	Income per capita	Real gross domestic product per capita	TUIK
population	Population	Total population	TUIK
air	Air pollution	PM10 value is taken as the unit measuring air quality.	Republic of Turkey Ministry of Environment and Urbanization
phone**	Information Communication Technologies	Number of mobile phone subscribers per 100 people	BTK
internet**	Information Communication Technologies	Number of internet subscribers per 100 people	BTK
index**	Information Communication Technologies	Number of internets, mobile, and fixed telephone subscribers per 100 people	Devised by the authors

Note: [a] The logarithms of the variables are taken.

[b] *The health expenditure values prepared by TUIK in the 2nd Level of the Classification of Statistical Regional Units were distributed to the provinces in the same group and converted to province level. The province-level health expenditure variable multiplied the provinces'real per capita gross domestic product values.*

[c] *Three different variables were adopted in this study as indicators of ICT. These variables consist of the number of mobile phone subscribers (phone), the number of internet subscribers (internet), and the index variable (index) developed by the authors through making use of the Principal Component Analysis technique. The dataset for these variables was created as per 100 inhabitants due to the differences in the population numbers of the provinces.*

Table: 2
Descriptive Statistics

Variables	Mean	Min.	Max.	S.D	Obs.	Num. of Provic.
lnhealth	2.575593	2.065714	3.289212	.2224079	648	81
lnincome	4.309268	3.786112	4.899021	.1880421	648	81
lnpopulation	5.744387	4.878637	7.178048	.4107834	648	81
lnair	1.735978	1.079181	2.095588	.174874	572	81
lnphone	1.906529	1.683544	2.16317	.0660638	648	81
lninternet	1.61727	.721809	2.104183	.2835915	648	81
lnindex	1.937692	1.599505	2.239606	.0935416	648	81

Before estimating the models, it is essential to test the multicollinearity assumption, which shows no exact relationship between the independent variables. The multicollinearity problem causes issues such as the R^2 value being higher than it should be, the coefficient variances being significant, and the variables being meaningless (Gujarati, 1999). Variance Inflation Factor (VIF) values were estimated to detect this problem. A VIF value less than 10 indicates no multicollinearity problem between the variables (Hair et al., 1998) to see this problem.

Table: 3
Variance Inflation Factor (VIF) Values

Variables	VIF Value	Variance Coefficient
lnincome	3.34	0.299190
lnpopulation	1.29	0.774479
lnair	1.23	0.812433
lnphone	1.73	0.579496
lninternet	2.65	0.376651

When the obtained VIF values were considered, it was determined that the explanatory variables used in the study took values between 1.23 and 3.34. In line with these findings, it can be assumed that there is no multicollinearity problem between the explanatory variables.

It is essential to decide which fixed effects, random-effects, and classical models will be used for estimation to determine whether air pollution and ICT use affect health expenditures. Thus, F test, Breusch-Pagan LM and Hausman tests were adopted. The analysis results of these tests are presented in Table 4.

Table: 4
Results of F test, LM, and Hausman Test

Tests	Type	Statis.	Effective Estimator							
			Model I		Model II		Model III		Model IV	
F-Test	Pooled	F-sta.	9.08	FE	8.33	FE	7.28	FE	8.56	FE
	FE	Prob	0.00		0.00		0.00		0.00	
LM Test	Pooled	χ^2 sta.	401.1	RE	368.5	RE	417.6	RE	367.2	RE
	RE	Prob> χ^2	0.00		0.00		0.00		0.00	
Hausman Test	FE	χ^2 sta.	72.51	FE	32.52	FE	14.25	FE	39.66	FE
	RE	Prob	0.00		0.00		0.006		0.00	

FE, Fixed Effect; RE, Random Effect.

In the first stage, the F-Test was applied to determine whether to use the fixed effects model or the classical model. It was concluded that the fixed effects model is more effective than the classical model. In the next step, the LM test was applied to choose between the random effect model and the classical model in the solution of the model. According to the results, the random effect model is a more efficient estimator than the classical model. In the last stage, the Hausman test was applied to choose between the random effect model and the fixed effect model in the solution of the model. The findings show that the fixed-effects model is a more efficient estimator than the random-effects model.

Before proceeding to the solution of the model, it should be concluded whether there is autocorrelation, heteroscedasticity, and cross-section dependence (CD) in the error terms of the model. Modified Wald Test for heteroscedasticity, detection of autocorrelation with Durbin-Watson and Baltagi-Wu LBI test, and CD with Pesaran test. Details of the tests are presented in Table 5.

Table: 5
Heteroscedasticity, Autocorrelation, and CD Test Results

		Model I		Model II		Model III		Model IV	
	Tests	Test sta.	Result	Test sta.	Result	Test sta.	Result	Test sta.	Result
HC	MWald Test	2506.4	✓	1.7e+28	✓	3770.5	✓	2815.7	✓
		0.000		0.000		0.000		0.000	
AC	D-W and Baltagi-Wu LBI	.73410	✓	.77905	✓	.7467	✓	.7419	✓
		1.1389		1.2784		1.143		1.143	
CD	Pesaran	4.220	✓	3.210	✓	1.039	X	1.360	X
		0.000		0.000		0.298		0.173	

AC, Autocorrelation; HC, Heteroscedasticity; ✓, Available; X, None.

Tests for detecting heteroscedasticity, autocorrelation, and CD in the error terms of the model show heteroscedasticity, autocorrelation, and CD (except Model III and IV) in the error terms of the model. In the presence of these problems, the standard errors should be corrected with resistant standard errors without touching the parameter estimates (Hoechle, 2007). Various resistant estimators have been developed to make predictions in the presence of these problems. One of them is the estimator of Arellano, Froot, and Rogers. Arellano, Froot, and Rogers produced resistant standard errors in the presence of heteroscedasticity and autocorrelation. Although the Arellano, Froot, and Rogers estimators are resistant to the problems of heteroscedasticity and autocorrelation, it does not consider CD (Driscoll & Kraay, 1998; Hoechle, 2007). Some estimators consider account heteroscedasticity, autocorrelation, and CD. One of them is the Driscoll Kraay. The Driscoll Kraay estimator can produce robust standard error estimations in cases of heteroscedasticity, autocorrelation, and CD regardless of the cross-section size N (Driscoll & Kraay, 1998; Hoechle, 2007). Therefore, the Arellano, Froot, and Rogers estimator was used in Models I and II since heteroscedasticity and autocorrelation were problems. The Driscoll Kraay estimator was used in Models III and IV, as there was heteroscedasticity, autocorrelation, and CD. Table 6 presents the estimation results.

Table: 6
Estimation Results

Dependent Variable (health expenditure)	Model I	Model II	Model III	Model IV
C	-5.125** (1.02)	-4.570** (1.37)	-5.869** (1.54)	-3.620** (2.30)
lnincome	.838* (.041)	.877* (.057)	1.021* (.057)	1.011* (.087)
lnpopulation	.712** (.205)	.567*** (.287)	.694 (.287)	.436 (.432)
lnair		.054 (.033)		
lninternet			-.095* (.033)	
lnphone			.110 (.208)	
lnindex				-.341** (.146)
R^2	.784	.785	.790	.789
Prob	0.000	0.000	0.000	0.000

*Note: *, **, *** indicate the significance level of 0.01, 0.05, 0.10, respectively.*

According to the findings, income and population statistically affect individual health expenditure in Model 1. Accordingly, for a 1% change in income, health expenditure increases by 8%, and for a 1% change in population, health expenditure increases by 7%.

In Model 2, the air pollution variable was added to Model 1 (income and population). As in Model 1, income and population have a statistically significant effect on individual health expenditure, while the impact of air pollution on health expenditure is statistically insignificant, although it is positive.

In Model 3, besides the variables in Model 1 (income and population), internet usage and mobile phone subscribers were added as ICT variables. While income and internet usage have a statistically significant effect on individual health expenditure, the impact of population and mobile phone subscribers on health expenditure is statistically insignificant, even though it is positive. A 1% change in internet usage, which is statistically significant, reduces individual health expenditure by approximately 1%.

Finally, in Model 4, in addition to the variables in Model 1 (income and population), the index variable obtained by the Principal Components Analysis technique from internet usage, mobile, and fixed telephone subscribers was added as an ICT variable. While income and internet use have a statistically significant effect on individual health expenditure, the impact of the population variable on health expenditure is statistically insignificant, although positive. A 1% change in the statistically significant index variable reduces the individual health expenditure by 3%.

In line with the findings, air pollution, which constitutes the aim of the study, has a positive effect on health expenditure, as it can be seen by the ICT variables (excluding the number of mobile phone subscribers), internet use, and index variables. Therefore, the increase in internet usage and ICT technologies reduces expenditures on health.

4. Conclusion

This study aimed to analyse the effects of ICT and air pollution on the health expenditures of 81 provinces in Turkey during 2011-2018. In this context, four models are fashioned. Tests for detecting heteroscedasticity, autocorrelation, and CD in the error terms of the models show that there is heteroscedasticity, autocorrelation, and CD (except Model III and IV) in the error terms of the model. Due to these problems, the standard errors were corrected with resistant ones without touching the parameter estimates. Thus, Models I and II used the Arellano, Froot, and Rogers estimators because of heteroscedasticity and autocorrelation difficulties. The Driscoll Kraay estimator was used in Models III and IV since heteroscedasticity, autocorrelation, and CD existed.

Model 1 analyses the impact of income and population on health care spending. Both revenue and population have a significant and positive influence on health expenditure. Although the effects of income and population on health expenditure are substantial, it should be recalled that the study's key target was the impact of air pollution and ICTs on health expenditure. Accordingly, in addition to income and population, air pollution was included in Model 2. In this step, it was detected that the effect of the air pollution variable on health expenditure was not statistically significant, although it was positive. Thus, air pollution hardly affected health expenditures at the provincial level. Three different variables were used to measure the impact of ICT on health expenditure. Therefore, Model 3 appraised the impact of the variables the number of mobile phone subscribers and the number of internet subscribers. The findings indicated that mobile phone subscribers were positive but not statistically significant.

In contrast, the number of internet subscribers on health expenditure was statistically significant and negative. In model 4, the effect of the index variable formulated by the authors on health expenditure was analysed using the Principal Component Analysis technique. The impact of the index variable, the third variable used as an ICT indicator on health expenditure, was statistically significant and negative. As a result, air pollution and mobile phone subscribers cannot affect health expenditure. In contrast, the number of internet subscribers and index variable on health expenditure is negative. Thus, the increase in internet use can be recognized as a factor in decreasing health expenditure in Turkey.

This study has a unique value as it contributes to the literature on the impact of air pollution and ICT on health expenditure in Turkey. Henceforward, some suggestions are offered to researchers and policymakers.

As a suggestion for researchers, it is considered that the topic can be further developed given different aspects by classifying provinces differently (e.g., development level, geographical location), by making comparisons through differentiating econometric methods, and by extending the study period in case of accessing to more extended time series.

As for recommendations for policymakers, in fixed broadband internet penetration rate, Turkey ranks among the last among OECD countries. Considering this situation, it can be expected that increasing internet access in Turkey will reduce health expenditures. It can also help reduce existing inequalities in access to health services, with increased access to the internet. In addition to increasing existing internet access, it is also beneficial to increase applicable health-related online content. Thus, since helpful information about the health problem will be obtained online, it can reduce unnecessary health expenditures. Although it is beneficial to facilitate access to health-related information, the practical situation can become harmful due to information pollution on the internet. In this context, it is essential to carry out the necessary inspection. Otherwise, it is expected to increase health expenditures as unnecessary demand for health services increases.

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