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DETERMINANTS AND REGIONAL INTERACTIONS OF HEALTH INFLATION: EVIDENCE FROM SPATIAL PANEL DATA ANALYSIS IN TURKEY

Türkiye'de Sağlık Enflasyonunun Belirleyicileri ve Bölgesel Etkileşimleri: Mekansal Panel Veri Analizi Bulguları

Nazife Zeynep ÇAKIR DERELİ*

Keywords:
Health Inflation, Regional Interaction, Spatial Panel Data Analysis, Spatial Weight Matrix Selection.

JEL Codes:
H51, C23, R12, J11.

Abstract

Health inflation, which refers to the persistent rise in the costs of healthcare goods and services, constitutes a substantial barrier to access to medical care. By exerting pressure on the public budget, health inflation has shown an upward trend in Turkey, particularly in recent years. This study aims to examine the factors influencing health inflation in Turkey's NUTS-2 regions over the period 2011–2021 through the application of spatial panel data analysis. The study differentiates itself from previous research by addressing health inflation, which has received limited attention in the literature, and by emphasizing the selection of an appropriate spatial weight matrix in the spatial data analysis process. The analysis identified the fixed-effects spatial lag model with a queen contiguity weight matrix as the appropriate model. Among the explanatory variables included in the model, general inflation, the proportion of university graduates, and birth rates were found to increase health inflation, whereas the number of enterprises in the health sector, the number of hospital beds per 100.000 population, and the share of the young population were found to reduce it. Finally, evidence of positive spatial dependence points to regional interaction in relation to health inflation among Turkey's NUTS-2 regions.

Anahtar Kelimeler:
Sağlık Enflasyonu, Bölgesel Etkileşim, Mekansal Panel Veri Analizi, Mekansal Ağırlık Matris Seçimi.

JEL Kodları:
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Öz

Sağlık sektöründe meydana gelen mal ve hizmet fiyatlarındaki artış olarak tanımlanan sağlık enflasyonu, bireylerin sağlık hizmetlerine olan erişimini riske atmaktadır. Kamu bütçesi üzerinde baskı yaratan sağlık enflasyonu, Türkiye'de özellikle son yıllarda artış eğilimi göstermektedir. Bu doğrultuda çalışmanın temel amacı, 2011-2021 döneminde Türkiye'de Düzey-2 bölgelerindeki sağlık enflasyonunun belirleyicilerini, mekansal panel veri analizi yöntemiyle incelemektir. İlgili çalışma, literatürde yeterince ele alınmamış bir konu olan sağlık enflasyonunu araştırma konusu edinmesi ve mekansal veri analizi sürecinde uygun mekansal ağırlık matrisinin seçimine vurgu yapmasıyla diğer çalışmalardan ayrılmaktadır. Mekansal panel veri analizi neticesinde, queen komşuluk kriteri ile oluşturulan mekansal ağırlık matrisi kullanılarak tahmin edilen, sabit etkiler içeren mekansal gecikme modelinin uygun model olduğu tespit edilmiştir. Modele alınan açıklayıcı değişkenlerden genel enflasyon, üniversite mezun ve doğum oranları sağlık enflasyonunu artırmakta, sağlık alanındaki girişim sayısı, 100.000 kişi başına düşen hastane yatak sayısı ve genç nüfus oranı ise azaltmaktadır. Analizden elde edilen pozitif mekansal bağımlılık bulgusu ise sağlık enflasyonu konusunda Düzey-2 bölgelerindeki bölgesel etkileşimi vurgulamaktadır.

* Res. Assist. Dr., Çanakkale Onsekiz Mart University, Biga Faculty of Economics and Administrative Sciences, Department of Econometrics, Türkiye, zeynepcakir@comu.edu.tr

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1. Introduction

Inflation, in its broadest sense, refers to a persistent increase in the general level of prices for goods and services, which reduces purchasing power and creates adverse consequences for both individuals and societies (Movsisyan et al., 2024). In the context of healthcare, this phenomenon is described as health inflation and denotes the rise in the costs of medical goods and services. Although health inflation is closely related to health expenditures, the two are not identical. Health expenditures refer to total spending aimed at the protection and improvement of public health, whereas health inflation refers to increases in the prices of the healthcare services and products on which this spending is directed (Teimourizad et al., 2014; Çakır, 2019). Similarly, while general inflation encompasses all goods and services, health inflation is limited to price changes within the healthcare sector.

The literature indicates that health inflation and general inflation are driven by different dynamics. Health inflation is a sector-specific indicator that operates through pricing mechanisms that differ from those of general inflation. This difference has led to the two types of inflation being treated separately (Newhouse, 1992; Baumol, 1993).

At the global level, population ageing, the effects of pandemics, most notably COVID-19, and the growing demand for healthcare services have contributed to a sustained increase in health-related spending (Türkön et al., 2024). This rise in expenditure, in turn, places upward pressure on costs and prices in the healthcare sector and thereby reinforces health inflation, as shown in Figure 1.

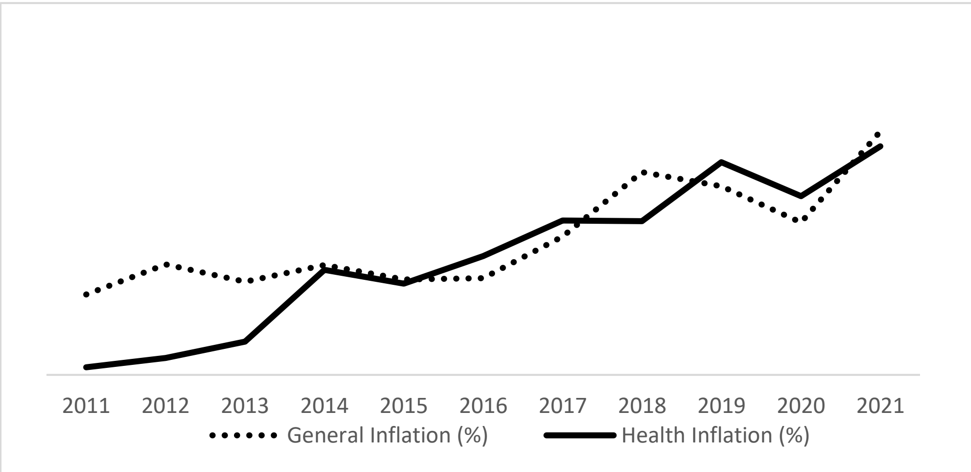

Figure 1. Turkey: General Inflation and Health Inflation (2011-2021)
Source: TurkStat.

Data from the Turkish Statistical Institute (TurkStat) show that health inflation in Turkey has followed a sustained upward path. In some years, however, it has exceeded the general inflation rate. This pattern indicates that health inflation is not determined solely by movements in the overall price level, but is also shaped by demographic conditions, developments on the demand and supply sides, and structural factors.

The rise in health inflation poses a challenge to the sustainability of healthcare systems. If access to equitable, high-quality, and affordable healthcare services is not secured, health inflation may increase in an uncontrolled manner (Özer et al., 2022). For this reason, keeping health inflation under control is a matter of critical importance for countries (Reichert and Cebula, 1999).

Health inflation differs from other forms of price dynamics due to several structural characteristics of healthcare services. These include the limited and imperfect substitutability of healthcare, its non-deferrable nature, and the relatively low responsiveness of demand to price changes. When access to healthcare services becomes constrained, these characteristics can undermine household welfare and, in turn, pose risks to social stability. For this reason, health inflation, given its direct implications for social welfare, should be regarded as a central concern of public policy (Newhouse, 1992; Folland et al., 2017).

Health inflation is influenced by a range of factors, including economic conditions, demographic structure, levels of education and awareness, the institutional characteristics of the healthcare sector, and the quality of services. This range of influences indicates that health inflation has a complex and multifaceted character. Developments such as rising competition and increased entrepreneurial activity in the healthcare sector also exert an important influence on health inflation (Teimourizad et al., 2014).

Research that examines the interaction between inflation and health, and that aims to account for this relationship, remains limited. While some studies have analyzed the effects of macroeconomic variables, such as unemployment and income inequality, on health expenditures, comprehensive work that focuses specifically on the determinants of health inflation is still scarce. This gap is particularly evident in the case of Turkey, where the number of studies that address health inflation directly is very small. In the existing literature, which is itself limited in scope, attention has tended to concentrate on indicators of healthcare capacity, such as the number of hospital beds per capita, together with broader influences, including the general inflation rate and demographic factors such as the age structure of the population. By contrast, the link between educational attainment and health inflation has received little attention, even though this relationship is inherently multidimensional.

Higher levels of health literacy among more educated individuals can increase awareness of health conditions, which may lead to greater use of healthcare services and, in turn, place upward pressure on health inflation. At the same time, more educated individuals may approach healthcare in a more informed and selective way, which can reduce unnecessary use of services and slow the growth of health inflation (Getzen and Kobernick, 2022). The relationship between education and health inflation, therefore, reflects the tension between rising demand for care and preferences for its more efficient use. From a theoretical perspective, the effect of education on health inflation may thus be either inflationary or disinflationary.

In the literature, indicators related to healthcare capacity, such as the number of beds per capita and the number of businesses operating in the healthcare sector, influence price formation in healthcare services through multiple channels. An increase in beds per capita may help relieve capacity constraints in service provision, which can reduce costs and slow price growth. However, Roemer (1961) points out that a higher number of hospital beds is also linked to increased hospital utilization, potentially raising demand for healthcare services and putting upward pressure on the overall price level.

New entrants in the healthcare sector are generally expected to expand the supply of services. This expansion may improve access to healthcare and, by encouraging greater use of services, may also contribute to higher prices. In settings in which capacity constraints are binding, improved access can stimulate demand and lead to substantial increases in prices. By contrast, a rise in the number of healthcare providers may intensify competition in the market and exert downward pressure on prices (Gaynor et al., 2015). The effect of the number of enterprises in the healthcare sector on health inflation, therefore, depends on developments in supply, the level of demand, and the degree of competition.

The impact of the childbirth rate on healthcare inflation is multidimensional. Along with the rise in the childbirth rate, the need for newborn care and mother- child services is also rising. Health services are in a category that most costly relative to other health services. This circumstance results in a short-term rise in health service expenses, thus leading to increasing health inflation.

On the other hand, a higher birth rate contributes in the long run to maintaining a young and dynamic population. Since the utilization of healthcare services by younger populations is relatively lower, it reduces the overall burden on the healthcare system. In this context, price increases in healthcare services are expected to be slower in regions with a higher share of the young population. Consequently, the share of the young population is expected to play a mitigating and stabilizing role on health inflation in the long term (Cutler and Sheiner, 1998).

These assessments show that the effects of education level, healthcare capacity, entrepreneurial activities in the healthcare sector, and birth rates on health inflation are not linear or simple.

The aspects of the study that are expected to contribute to the literature are listed below.

(i) A large portion of existing studies address health inflation without considering its spatial interactions. This study, however, uses a spatial panel data framework to examine the regional dynamics and spatial interactions of health inflation in Turkey's Level-2 regions during the 2011–2021 period. In addition, instead of approaches that ignore regional differences, empirical findings are presented that will contribute to the development of region-sensitive health policies and strategies.

(ii) The analysis does not restrict the determinants of health inflation to variables that relate only to the healthcare sector. Indicators reflecting economic structure, educational attainment, and demographic characteristics are also included. In this way, the study adopts a broader and more integrated perspective on health inflation.

(iii) In estimating the spatial panel data models, spatial weight matrices based on different neighborhood criteria are employed in order to evaluate the sensitivity of the results to the choice of matrix.

2. Literature Review

In studies that examine the effects of economic variables on the healthcare sector, primary attention has generally been given to health expenditures, while health inflation has received comparatively little consideration. The present study contributes to this literature by examining possible determinants of health inflation. A small number of studies that address this issue are reviewed below.

Using data from 92 hospitals in the United States for 1971, Huddleston (1976) analyzed the relationship between healthcare costs and changes in hospital capacity, staffing levels, and the range of services offered. In that study, increases in hospital beds and staff, as well as the expansion of services into new areas, were found to be associated with higher healthcare costs, which the author described in terms of health inflation. At the same time, the magnitude of these effects differed across hospitals, which suggests that expansion of hospital resources alone does not fully account for observed differences in health inflation.

Kim and Chun (1989), drawing on South Korea's health insurance data for the period 1983–1987, investigated inflation in healthcare costs by estimating both stochastic and deterministic models. Their set of explanatory variables included the share of the elderly population, the degree of urbanization, the number of physicians and hospital beds per capita, and the rate of healthcare utilization. Their results showed that utilization was the primary factor associated with rising healthcare costs. In addition, greater physician and bed availability per capita, higher levels of urbanization, and a larger elderly population were also linked to higher costs and stronger inflationary pressures.

Using data from the United States for the period 1960–1994, Reichert and Cebula (1999) found that a higher proportion of the population aged 65 and over was associated with increases in health inflation, whereas a higher physician-to-population ratio was associated with a moderating effect.

Cutler and Lleras-Muney (2006) examined the link between educational attainment and health outcomes and found a strong relationship between the two, much of which they argue is causal in nature. Their findings further indicate that individuals with higher levels of education tend to utilize healthcare services more frequently, thereby increasing overall demand for care.

Erasmus and Fourie (2014) examined the drivers of health inflation in South Africa covering the 2008-2013 period. They reasoned that medical materials and medication services, demographic makeup, and level of salaries paid to medical professionals are key predictors of medical inflation. This finding suggests the importance of structural, demographic, and economic drivers of healthcare inflation.

Bayati et al. (2014), using Iranian Central Bank reports in their study, focused on the period 1985–2013. Their study found a statistically significant relationship between health inflation and general inflation rates. Additionally, they determined that the increase in the number of physician visits and the increased demand for pharmaceutical products contributed to the rise in health inflation.

Teimourizad et al. (2014) examined the factors impacting health inflation in Iran. With this aim, the overall inflation rate, ratio of physicians per capita, mean duration of education, and the bed capacity are incorporated to the model as descriptive variables. It is established that overall inflation contributes to health inflation, whereas physicians to population ratio per capita and the beds capacity constrain health inflation. Furthermore, the results of the study reveal that there is statistically insignificant correlation between the average duration of education and health inflation.

Using data from TurkStat and the Central Bank of the Republic of Turkey, Ankara and Zeybek (2021) studied the contribution of medical product prices and expenditures on outpatient and inpatient treatment services to health inflation in Turkey over the period 2005–2017, which followed the implementation of the Health Transformation Program. Their findings indicated that rising costs of medical products and outpatient services accounted for a substantial part of the increase in health inflation.

Poongavanam et al. (2023) explored the components of medical inflation in India covering the years 2016-2022. It is concluded that the rise in the aging population, resulting increasing number in chronic diseases, and the inadequate number of physicians have a significant role in medical inflation. It is also concluded that domestic factors have an important impact on medical inflation.

3. Econometric Methodology

Spatial effects were first assessed using cross-sectional spatial regression models. Nevertheless, since panel data provide more extensive modeling possibilities than other data structures, spatial panel data models have gained prominence for analyzing spatial effects (Baltagi, 2005).

In spatial panel data models, spatial weight matrices, representing spatial interaction and neighborhood relations across units, are of dimension NTxNT (LeSage and Pace, 2009). In Equation (1), I_T denotes the T-dimensional identity matrix, while W_N refers to the N-dimensional weight matrix employed in spatial regression models.

$$W_{NT} = I_T \otimes W_N \tag{1}$$

Using Equation (1), the representation of the spatially lagged dependent variable, explanatory variables, and the error term can be expressed as in Equation (2) (Anselin et al., 2008).

$$\begin{aligned} W_y &= W_{NT}y = (I_T \otimes W_N)\, y \\ W_X &= W_{NT}X = (I_T \otimes W_N)\, X \\ W_u &= W_{NT}u = (I_T \otimes W_N)\, u \end{aligned} \tag{2}$$

When spatial interaction effects – either spatial lag dependence or spatial error dependence – are incorporated into the classical panel data model, the resulting spatial panel data models can be expressed as in Equations (3) and (4).

Spatial Autoregressive Panel Data Model (SAR)

$$\begin{gathered} y = \rho(I_T \otimes W_N)y + X\beta + \varepsilon \\ \varepsilon \sim N(0, \sigma^2 I_n) \end{gathered} \tag{3}$$

Spatial Error Panel Data Model (SEM)

$$\begin{gathered} y = X\beta + u \\ u = \lambda(I_T \otimes W_N)u + \varepsilon \\ \varepsilon \sim N(0, \sigma^2 I_n) \end{gathered} \tag{4}$$

In the equations, ρ and λ represent the spatial relationship coefficients. Furthermore, W_N refers to the spatial weight matrix, X to the vector of explanatory variables, and β to the vector of coefficients (Anselin et al., 2008).

These models, which incorporate unobserved effects, are classified into fixed-effects and random-effects spatial panel data models. When the unobserved effects are captured in the intercept term of the model, the specification is defined as a fixed-effects spatial panel data model; when they are contained in the error term, the specification is defined as a random-effects spatial panel data model (Yılgör, 2019).

Spatial Autoregressive Panel Data Model - Fixed Effects (SAR-FE)

$$y_{it} = \mu + \rho \sum_{i \neq j} W_{ij} y_{jt} + X_{it}\beta + \alpha_i + \varepsilon_{it} \qquad \varepsilon_{it} \sim N(0, \sigma^2 I_n) \tag{5}$$

In Equation (5), μ denotes the constant parameter, while α_i represents the individual effect. In the SAR-FE model, it is assumed that individual effects are related to the explanatory variable. (E(x_{it}, α_i) ≠0).

Spatial Error Panel Data Model - Fixed Effects (SEM-FE)

$$y_{it} = \mu + X_{it}\beta + \alpha_i + u_{it} \qquad u_{it} = \lambda \textstyle\sum_{i \neq j} W_{ij} u_{jt} + \varepsilon_{it} \qquad \varepsilon_{it} \sim N(0, \sigma^2 I_n) \tag{6}$$

In SEM-FE models, spatial dependence arises from the correlation among the error terms.

Spatial Autoregressive Panel Data Model - Random Effects (SAR – RE)

$$y_{it} = \mu + \rho \textstyle\sum_{i \neq j} W_{ij} y_{jt} + X_{it}\beta + u_{it} \qquad u_{it} = \alpha_i + \varepsilon_{it} \qquad \varepsilon_{it} \sim N(0, \sigma^2 I_n) \tag{7}$$

In the SAR-RE model, it is assumed that there is no relationship between individual effects and explanatory variables (E(x_{it}, α_i) = 0). In these models, the individual effect (α_i) is treated as a component of the error term, thereby forming a new composite error structure (Hsiao, 2003; Salima et al., 2018).

Spatial Error Panel Data Model - Random Effects (SEM – RE)

$$y_{it} = \mu + X_{it}\beta + u_{it} \qquad u_{it} = \alpha_i + \lambda \textstyle\sum_{i \neq j} W_{ij} u_{jt} + v_{it} \qquad v_{it} \sim N(0, \sigma^2 I_n) \tag{8}$$

In random-effects panel data models, since the individual effect constitutes a component of the error term, two different specifications have been proposed for SEM-RE models. In the first specification, presented in Equation (8), spatial dependence is assumed only for the idiosyncratic error term, but not for the individual effects.

$$y_{it} = \mu + X_{it}\beta + u_{it} \qquad u_{it} = \lambda \textstyle\sum_{i \neq j} W_{ij} u_{jt} + v_{it} \qquad v_{it} = \alpha_i + \varepsilon_{it} \quad \varepsilon_{it} \sim N(0, \sigma^2 I_n) \tag{9}$$

In the second specification proposed by Kapoor et al. (2007) (Equation 9), spatial dependence is assumed to hold for both the individual effects and the idiosyncratic error term components. Although the two specifications of the SEM-FE model appear similar, the differences in their variance–covariance matrix structures imply distinct spatial spillover patterns (Millo, 2014).

The estimation of panel data models incorporating spatially lagged dependent variables or spatially correlated error terms is based on principles comparable to those applied in cross-sectional model estimation. In the literature, the most frequently recommended estimation methods are Maximum Likelihood (ML) and Generalized Method of Moments (GMM) (Anselin et al., 2008). Among these methods, the ML approach has been shown to produce more efficient estimates than the GMM approach under appropriate conditions in spatial panel data models (Elhorst, 2014).

In the context of spatial panel data models, an essential step in the analysis is to identify the presence and form of spatial dependence and to ensure that the model is specified appropriately.

3.1. Spatial Dependence Tests for Classical Spatial Panel Data Models and Fixed-Effects Spatial Panel Data Models

In cross-sectional data, the LM tests ($LM_{error(\lambda)}$ve $LM_{lag(\rho)}$) are commonly employed to detect spatial dependence. These tests were extended for application in panel data models, as shown below (Anselin et al., 2008; Elhorst, 2014).

$$LM_{\rho} = \frac{\left[e'(I_T \otimes \mathrm{W})\mathrm{Y}/\hat{\sigma}^2\right]^2}{J} \sim X^2_{(1)}$$
$$LM_{\lambda} = \frac{\left[e'(I_T \otimes \mathrm{W})e\,/\hat{\sigma}^2\right]^2}{TxT_W} \sim X^2_{(1)} \tag{10}$$

In the LM test statistics presented in Equation (10), $\otimes$ represents the Kronecker product, I_T represents the identity matrix, and e refers to the residuals of the model. J and T_W are defined as follows:

$$J = \frac{1}{\hat{\sigma}^2}\left[((I_T \otimes \mathrm{W})\mathrm{X}\widehat{\beta})'(I_{NT} - X(X'X)^{-1}X')(I_T \otimes \mathrm{W})\mathrm{X}\widehat{\beta} + TT_W\hat{\sigma}^2\right]$$
$$T_W = tr(WW + W'W) \tag{11}$$

In Equation (11), tr denotes the trace of the matrix.

In the one-directional LM tests, the null hypothesis corresponds to the classical model, while the alternative hypothesis of the LM_{ρ} test indicates spatial lag dependence, and the alternative hypothesis of the LM_{λ} test indicates spatial error dependence. When both one-directional LM tests are statistically significant, robust LM tests (LM^*) are employed to determine the appropriate model specification.

The robust LM test statistics developed for panel data are presented in Equation (12) (Elhorst, 2014).

$$LM^*_{\rho} = \frac{[e'(I_T \otimes \mathrm{W})\mathrm{Y}/\hat{\sigma}^2 - e'(I_T \otimes \mathrm{W})e/\hat{\sigma}^2]^2}{J - TT_W}$$
$$LM^*_{\lambda} = \frac{[e'(I_T \otimes \mathrm{W})e/\hat{\sigma}^2 - TT_W/Jxe'(I_T \otimes \mathrm{W})Y/\hat{\sigma}^2]^2}{TT_W[1 - TT_W/J]} \tag{12}$$

3.2. Spatial Dependence Tests for Random-Effects Spatial Panel Data Models

Baltagi et al. (2003) proposed a set of tests for random-effects spatial panel data models that account for both individual effects and spatial dependence in the error structure. These tests were designed to jointly evaluate the significance of spatial error dependence and individual effects within panel data models. Conditional LM tests assess individual effects while controlling for spatial error dependence and, conversely, evaluate spatial error dependence in the presence of individual effects. By contrast, one-directional LM tests either omit spatial error dependence when testing for individual effects or disregard individual effects when examining spatial error dependence. The literature emphasizes that joint and conditional LM tests, which simultaneously address both sources of variation, yield more robust results in the face of potential specification error (Baltagi et al., 2003).

The hypotheses of these LM-based tests are presented in Table 1 (Baltagi et al., 2003; Salima et al., 2018). In the presence of unobserved effects, the Hausman test is employed to choose among estimators in spatial panel data models.

Table 1. Spatial Dependence Tests in Random-Effects Spatial Panel Data Models

Test	Null Hypothesis	Alternative Hypothesis
Joint LM Test	$H_0^a: \lambda = \sigma_\alpha^2 = 0$ (No individual effect and no spatial dependence)	$H_1^a: \lambda \neq 0 \; or \; \sigma_\alpha^2 \neq 0$
Marginal LM Test–1	$H_0^b: \sigma_\alpha^2 = 0$, assuming $\lambda = 0$ (No individual effect under no spatial dependence)	$H_1^b: \sigma_\alpha^2 \neq 0$, assuming $\lambda = 0$
Marginal LM Test–2	$H_0^c: \lambda = 0$, assuming $\sigma_\alpha^2 = 0$ (No spatial dependence under no individual effect)	$H_1^c: \lambda \neq 0$, assuming $\sigma_\alpha^2 = 0$
Conditional LM Test–1	$H_0^d: \lambda = 0$, assuming $\sigma_\alpha^2 \geq 0$ (No spatial dependence under nonnegative individual effects)	$H_1^d: \lambda \neq 0$, assuming $\sigma_\alpha^2 \geq 0$
Conditional LM Testi-2	$H_0^e: \sigma_\alpha^2 = 0$, assuming $\lambda \geq 0$ (No individual effect under nonnegative spatial dependence)	$H_1^e: \sigma_\alpha^2 \neq 0$, assuming $\lambda \geq 0$

Source: Salima et al., 2018

3.3. Hausman Test

The Hausman test, which follows a X^2 distribution, was originally developed to detect specification errors. In this context, the random-effects model is tested against the fixed-effects model using Hausman's specification test. The test statistic and the corresponding hypotheses are presented in Equation (13) (Hausman, 1978; Baltagi, 2005).

$$H_0: h = 0 : (E(x_{it}, \alpha_i) = 0) : \Rightarrow \text{FE consistent, RE consistent and efficient}$$

$$H_1: h \neq 0 : (E(x_{it}, \alpha_i) \neq 0) : \Rightarrow \text{FE consistent, RE inconsistent} \tag{13}$$

$$h = d'[var(d)]^{-1}d$$

$$d = \hat{\beta}_{FE} - \hat{\beta}_{RE}$$

$$Var(d) = \hat{\sigma}_{RE}^2 (X^{\circ'} X^{\circ})^{-1} - \hat{\sigma}_{FE}^2 (X^{*'} X^{*})^{-1} \tag{14}$$

In Equation (13), which specifies the Hausman test statistic (h), FE represents the fixed-effects estimator, while RE corresponds to the random-effects estimator. Hausman's specification test is extendable to spatial regression frameworks in the presence of either spatial lag or spatial error dependence (Elhorst, 2014). Since the spatial lag panel data model includes an additional explanatory variable (the spatially lagged dependent variable), the "d" expression required to obtain a test statistic with a X^2 distribution of, k+1 degrees of freedom is given in Equation (15).

$$d = \left[\hat{\beta}'\hat{\rho}\right]'_{FE} - \left[\hat{\beta}'\hat{\rho}\right]'_{RE} \tag{15}$$

The computed test statistic is evaluated against the X^2 critical value in order to identify the appropriate estimator. When the null hypothesis is not rejected, the random-effects estimator is considered preferable due to its efficiency. If the null hypothesis is rejected, the random-effects estimator becomes inconsistent, and the fixed-effects estimator is selected (Elhorst, 2014).

4. Data Set and Variables

This study analyses the determinants of health inflation in Turkey using data for NUTS-2 regions over the period 2011–2021. The choice of this period is dictated by the availability of consistent data for all variables included in the analysis. All data used in the analysis were obtained from the TurkStat. The NUTS-2 regions and the variables used in the model are presented in Tables 2 and 3, respectively.

Table 2. NUTS-2 Regional Classification in Turkey

TR10	İstanbul	TR71	Kırıkkale, Aksaray, Niğde, Nevşehir, Kırşehir
TR21	Tekirdağ, Edirne, Kırklareli	TR72	Kayseri, Sivas, Yozgat
TR22	Balıkesir, Çanakkale	TR81	Zonguldak, Karabük, Bartın
TR31	İzmir	TR82	Kastamonu, Çankırı, Sinop
TR32	Aydın, Denizli, Muğla	TR83	Samsun, Tokat, Çorum, Amasya
TR33	Manisa, Afyon, Kütahya, Uşak	TR90	Trabzon, Ordu, Giresun, Rize, Artvin, Gümüşhane
TR41	Bursa, Eskişehir, Bilecik	TRA1	Erzurum, Erzincan, Bayburt
TR42	Kocaeli, Sakarya, Düzce, Bolu, Yalova	TRA2	Ağrı, Kars, Iğdır, Ardahan
TR51	Ankara	TRB1	Malatya, Elâzığ, Bingöl, Tunceli
TR52	Konya, Karaman	TRB2	Van, Muş, Bitlis, Hakkâri
TR61	Antalya, Isparta, Burdur	TRC1	Gaziantep, Adıyaman, Kilis
TR62	Adana, Mersin	TRC2	Şanlıurfa, Diyarbakır
TR63	Hatay, Kahramanmaraş, Osmaniye	TRC3	Mardin, Batman, Şırnak, Siirt

Source: TurkStat

Table 3. Variables Used in the Model

Variable	Abbreviation	Definition
Healthcare Inflation	HINF	Consumer Price Index (CPI) annual percentage change – Health sector
Inflation	INF	Consumer Price Index (CPI) annual percentage change – General
University Graduate	UG	Proportion of university graduates (%)
Number of Interventions	NI	Share of interventions related to human health (%)
Number of Hospital Beds	NHB	Total number of hospital beds per 100.000 population
Young Population	YP	Proportion of young population (ages 15–24) (%)
Number of Births	NB	Birth rate (%)

Source: TurkStat

In order to assess the risk of multicollinearity among the relationships between the variables included in the model, a correlation matrix was constructed, and the Variance Inflation Factor (VIF) was calculated. An examination of Table 4 shows that the correlation matrix reveals a strong relationship between HINF, the dependent variable, and INF, the explanatory variable. From a theoretical standpoint, the fact that the cost of healthcare services is directly influenced by the general price level lends support to this finding. The possible implications of this relationship for the estimation results, particularly with respect to the risk of endogeneity, are discussed in the empirical findings section.

Table 4. Correlation Matrix and VIF Values

Variables	HINF	INF	UG	NI	NHB	YP	NB	VIF
HINF	1.0000							
INF	0.7754	1.0000						6.97
UG	0.5794	0.4736	1.0000					6.33
NI	0.1201	0.1639	0.5952	1.0000				4.21
NHB	0.2423	0.1930	0.4399	0.0609	1.0000			2.6
YP	-0.1863	-0.1685	-0.5935	-0.4047	-0.3494	1.0000		1.99
NB	-0.2713	-0.2292	-0.5766	-0.2327	-0.5753	0.7896	1.0000	1.44

Another notable result from the correlation matrix is the strong association between YP and NB. This relationship reflects the fact that both variables are demographic in nature and are closely related in substantive terms. The table also reports the VIF values calculated to detect potential multicollinearity, both between these variables and among the other explanatory variables in the model. While the average VIF value is 3.923, all individual VIF values are observed to be below 10. It indicates that there is no serious multicollinearity problem among the variables included in the model that would distort parameter estimates, and it supports the stability of the coefficient estimates (Gujarati and Porter, 2009).

In spatial data analysis, researchers often rely on quantile maps to reveal the spatial distributions of variables. Through quantile maps, it is possible to identify spatial clusters associated with the variable under consideration. In this context, the quantile map of the annual healthcare inflation rate across NUTS-2 regions in Turkey is presented in Figure 2.

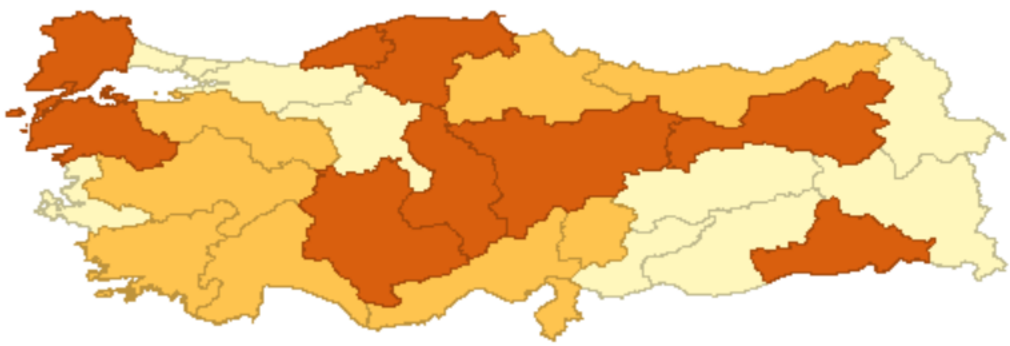

Figure 2. Healthcare Inflation Rates in NUTS-2 Regions, 2021
Source: Prepared by the author.

In Figure 2, the regions shaded in darker colors represent those with the highest healthcare inflation rates in 2021, whereas the lighter-colored regions indicate comparatively lower healthcare inflation rates. From dark to light shading, healthcare inflation rates gradually decrease. The quantile map constructed for health inflation indicates that relatively high health inflation rates are particularly concentrated in certain subregions of Central Anatolia, Eastern Anatolia, and Southeastern Anatolia, as well as in the interior parts of the Marmara region and the inland and central subregions of the Black Sea region.

5. Empirical Findings

Before estimating the spatial panel data model, it is necessary to assess whether spatial effects are present, since this has direct implications for the reliability of the results. This step requires the specification of spatial weight matrices. The literature, however, does not offer a consensus on which type of matrix should be preferred or which yields the most accurate results. The choice of spatial weight matrix is therefore of particular importance, as the estimation results are highly sensitive to this specification. For this reason, Table 5 reports the results of Moran's (1948) I and LM tests, together with Geary's (1954) C coefficient, computed under alternative spatial weight matrices.

Table 5. Detection of Spatial Dependence

Tests	W_{Queen} Test Statistics	$W_{k\text{-Nearest Neighbors}}$ Test Statistics	$W_{Threshold\ Value}$ Test Statistics
Moran's I	0.2061^{***}	0.1778^{***}	0.2028^{***}
Geary's c	0.7896^{***}	0.8633^{***}	0.8085^{***}
LM_{λ}	23.5898^{***}	19.4069^{***}	13.0522^{***}
LM_{λ}^{*}	3.4857	1.6995	0.6402
LM_{ρ}	28.9946^{***}	30.7741^{***}	18.7827^{***}
LM_{ρ}^{*}	8.8905^{***}	13.0667^{***}	6.3707^{**}

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Test results indicate the presence of spatial effects in the model. LM tests provide researchers with information about spatial dependence specifications as well as their detection. Therefore, a robust LM test (LM^{*}) result suggests that the SAR model is more preferable for the estimation process.

Assuming the absence of individual effects in panel data models is quite restrictive and can lead to biased or unreliable estimates. For this purpose, the Breusch–Pagan LM test, together with the Sosa-Escudero–Yoon LM and ALM tests, was applied (Table 6). The ALM tests are adjusted versions of the original tests and were designed to offer greater robustness in the presence of autocorrelation.

Table 6. Detection of Individual Effects

Tests	Test Statistics
Breusch-Pagan LM Testi	23.9234^{***}
Breusch-Pagan ALM Testi	17.7874^{***}
Sosa-Escudero-Yoon LM Testi	4.8912^{**}
Sosa-Escudero-Yoon ALM Testi	4.2175^{**}

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Given the evidence of individual effects in the model, the Hausman test is employed to guide the choice between alternative estimators (Table 7).

Table 7. Hausman Test

Test	W_{Queen} Test Statistics	$W_{k\text{-Nearest Neighbors}}$ Test Statistics	$W_{Threshold\ Value}$ Test Statistics
Hausman	24.0279***	26.0226***	38.1287***

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

A fixed effects specification is adopted for the model, and the SAR-FE estimates are reported in Table 8. The results of the Hausman test indicate that the fixed-effects estimator is appropriate for the model, as it controls for the effects of unobserved, time-invariant regional factors that cannot be directly incorporated into the specification. The prevailing view in the literature is that the fixed-effects estimator restricts the potential correlation arising from unobserved heterogeneity between the explanatory variables and the error term. In this context, the use of the fixed-effects estimator in the estimation of spatial panel data models contributes to reducing the risk of endogeneity (Baltagi, 2005; Elhorst, 2014).

Table 8. SAR-FE Model

Variables	W_{Queen} Coefficients	$W_{k\text{-Nearest Neighbors}}$ Coefficients	$W_{Threshold\ Value}$ Coefficients
INF	0.2302* (0.1305)	0.1759 (0.1272)	0.2607** (0.1296)
UG	2.8535*** (0.5619)	2.2001*** (0.5569)	3.4746*** (0.4795)
NI	-1.0266*** (0.3056)	-0.7859** (0.3026)	-1.1104*** (0.3020)
NHB	-0.9547* (0.5712)	-0.6592 (0.5592)	-1.2086** (0.5654)
YP	-2.2912* (1.3791)	-2.2736* (1.3380)	-2.5354* (1.3831)
NB	0.9639* (0.5736)	0.9425* (0.5510)	1.2663** (0.5632)
Intercept	8.8764* (5.1762)	8.6469* (5.0225)	10.7867** (5.1916)
ρ	0.4881*** (0.0813)	0.6121*** (0.0833)	0.3918*** (0.0664)
R^2	0.9714	0.9731	0.9713
Log- Likelihood	-132.2103	-123.5721	-132.7875
AIC	0.1594	0.1500	0.1600
SC	0.1835	0.1727	0.1842
HQ	0.1686	0.1587	0.1693

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

In this study, the determinants of health inflation are investigated using a single-equation framework rather than simultaneous equation systems based on mutual interaction, as in Lu (2023). In this context, the effects of the general inflation rate, which is expected to be highly correlated with health inflation, are examined together with the other explanatory variables. To support this approach, the one-period lag of the general inflation rate (INF(-1)) was added to an alternative specification as an explanatory variable, and the estimation results indicate that this variable is statistically insignificant. The fact that the spatial dependence coefficient (ρ) is found to be statistically significant in the estimated model suggests that dependence in health inflation is driven to a considerable extent by spatial factors. Moreover, the consistency of the results across models estimated using spatial weight matrices constructed under different neighborhood criteria contributes to the robustness of the findings.

The study period includes the COVID-19 pandemic. All NUTS-2 regions were simultaneously affected by the time-specific shocks caused by the COVID-19 pandemic. For this reason, time effects are controlled for in the analysis. In this way, common time effects affecting the entire country, including those related to the COVID-19 pandemic, are accounted for, allowing the analysis to focus on the regional determinants of health inflation.

In this study, the SAR-FE model, identified as the most appropriate specification for the research question, was estimated separately using spatial weight matrices constructed under the queen, k-nearest neighbors, and threshold contiguity criteria. According to the estimation results, all explanatory variables in the models based on the queen and threshold contiguity criteria were found to have statistically significant effects on health inflation. By contrast, the model estimated with the k-nearest neighbors weight matrix contained statistically insignificant variables, indicating that this specification is not preferable. Therefore, the choice must be made between the other two models. To determine empirical adequacy, goodness-of-fit measures were considered. Since the R^2 statistic is not reliable in spatial panel data models, model comparison was based on log-likelihood values and the information criteria AIC, SC, and HQ (LeSage and Pace, 2009; Elhorst, 2014; Bac, 2025). The results in Table 8 indicate that the model estimated with the queen contiguity weight matrix is more appropriate, as it yields a higher log-likelihood value and lower information criteria.

The estimation results also reveal that the spatial lag coefficient (ρ) is statistically significant and positively signed, demonstrating the presence of spatial dependence in health inflation across NUTS-2 regions in Turkey during the period 2011–2021. In other words, the health inflation rate in one region is influenced by that of its neighboring regions.

In order to report the effects of the explanatory variables included in the model on health inflation in detail, the approach proposed by LeSage and Pace (2009) was employed. In this context, the direct and indirect marginal effects of the variables were computed using the spatial multiplier approach, as presented in Table 9 (LeSage and Pace, 2009).

Table 9. Direct – Indirect – Total Spatial Effects

Variables	Direct Effects	Indirect Effects	Total Effects
INF	0.2471	0.2027	0.4499
UG	3.0633	2.5121	5.5755
NI	-1.1021	-0.9038	-2.0059
NHB	-1.0249	-0.8405	-1.8655
YP	-2.4597	-2.0171	-4.4768
NB	1.0348	0.8486	1.8834

In spatial models, the concept of a direct effect in the interpretation of coefficients refers to a change in the dependent variable in a given unit resulting from a change in an explanatory variable in that same unit. Another effect, the indirect effect, is characterized by changes in the dependent variable that provide information about spatial distributions (Elhorst, 2012). The sum of these two components constitutes the total effect.

When the total effects obtained from the SAR-FE model are examined, it is observed that, ceteris paribus, a one-unit increase in INF, UG, and NB raises health inflation by 0.4499, 5.5755, and 1.8834 units, respectively. By contrast, a one-unit increase in NI, NHB, and YP reduces health inflation by 2.0059, 1.8655, and 4.4786 units, respectively, holding other variables constant.

The fact that the estimated indirect effects are close in size to the direct effects points to the importance of spatial interaction in health inflation. The estimates show that, for a given region, a one-unit increase in INF, UG, and NB raises the level of health inflation in neighboring regions by 0.2027, 2.5121, and 0.8486 units, respectively. By contrast, a one-unit increase in NI, NHB, and YP reduces health inflation in neighboring regions by 0.9038, 0.8405, and 2.0171 units, respectively.

The results also indicate that the contribution of general inflation to health inflation is smaller than that of the other variables included in the model. This can be linked to the fact that price increases in Turkey are largely determined at the national level and tend to display a relatively uniform pattern across regions. As general inflation varies little across regions, its ability to account for regional differences in health inflation is limited. The positive and statistically significant association between health inflation and general inflation is consistent with the findings of Bayati et al. (2014). That study likewise reports a modest quantitative relationship between the two variables and a relatively low coefficient of determination.

The estimates further show that, over the period 2011–2021, educational attainment in Turkey is associated with higher health inflation. Both the direct and indirect effects indicate that the influence of education on health inflation is stronger than that of the other variables. This result is in line with the arguments of Cutler and Lleras-Muney (2006), who note that higher levels of education are associated with greater demand for healthcare, specifically preventive services, and with Feinstein et al. (2006), who argue that this tendency contributes to higher healthcare prices.

An increase in the birth rate is likewise associated with higher demand for healthcare services. By contrast, a rise in the number of hospital beds per 100,000 population and in the number of enterprises in the healthcare sector is associated with stronger competition and, in turn, with lower health inflation. The results also suggest that a larger share of the young population, which is linked to a more dynamic demographic structure, is associated with lower health inflation.

Several of these findings are consistent with earlier work, including the studies of Reichert and Cebula (1999), Cutler and Lleras-Muney (2006), Bayati et al. (2014), Teimourizad et al. (2014), and Poongavanam et al. (2023).

6. Conclusion

The sustainable nature of health care systems is directly linked to the rate of health inflation. For this purpose, health inflation is strategically important for countries. Economic and structural differentials among countries also contribute to variability in the drivers determining health inflation.

The fact that there is a limited amount of domestic and international studies on health inflation in the existing literature is an essential factor in defining the scope of this study. In this regard, the drivers of healthcare inflation in NUTS-2 regions in Turkey are analyzed using the spatial panel data method for the period 2011–2021. SAR-FE models predicted by spatial weight matrices generated using various neighborhood criteria are compared based on goodness-of-fit criteria. The finalized model, identified with goodness-of-fit criteria, shows a strong and statistically meaningful spatial dependency. This result demonstrates that trends in health inflation in an area are associated with developments in neighboring areas.

The results show that health inflation cannot be attributed to a single cause. The findings indicate that health inflation is affected in different ways by economic conditions, individuals' education levels, demographic factors, and specific elements of the health system, each influencing price dynamics. This result highlights the importance of considering both supply- and demand-side conditions in analyses of health inflation.

The empirical evidence also suggests that macroeconomic stability, education policy, and healthcare planning need to be considered together if health inflation is to be kept at manageable levels. In addition, regional characteristics, including demographic structure and patterns of access to healthcare services, deserve close attention. Among the variables included in the analysis, educational attainment emerges as the strongest factor associated with higher health inflation. This result points to the importance of managing the link between education and healthcare use more carefully, particularly by limiting unnecessary use of services and by strengthening preventive healthcare.

The presence of spatial dependence indicates that health inflation cannot be understood solely in terms of conditions within individual regions. Price developments in healthcare are also connected across neighboring regions. This suggests that policies aimed at containing health inflation would benefit from a degree of interregional coordination. Future analyses of health inflation should take account of its multidimensional character, regional differences, and spatial interaction. In this respect, the present study contributes a new perspective to the existing literature.

Declaration of Research and Publication Ethics
This study which does not require ethics committee approval and/or legal/specific permission complies with the research and publication ethics.

Researcher's Contribution Rate Statement
I am a single author of this paper. My contribution is 100%.

Declaration of Researcher's Conflict of Interest
There is no potential conflicts of interest in this study.

Declaration of Artificial Intelligence Usage
During the preparation of this study, the author used ChatGPT / OpenAI for Language Editing. After using this tool/service, the content was reviewed and edited as necessary, and the author is solely responsible for the content of the published article.

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