

Statistical Drivers of Regional Healthcare Patterns in Spain

Ignacio Escañuela Romana

ignacioesro@gmail.com

Independent researcher <https://orcid.org/0000-0002-5376-0543>

Research Article

Keywords: Public health-care services, public financing, public health-care expenditure, public pharmaceutical expenditure, health-care resources, health-care decentralization

Posted Date: September 23rd, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10009105/v2>

License:   This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: The authors declare no competing interests.

1 Statistical Drivers of Regional Health-care Patterns in Spain

2 Escañuela Romana, Ignacio^a

3 Independent researcher, PhD in Data Science (Universidad Loyola Andalucía)

4 Email: ignacioesro@gmail.com

5 Abstract

6 **Background:** This study estimates the quantitative statistical relationships underlying the observed series of
7 data on Spain's regional public health-care services, including financing, expenditure, and human and physical
8 health-care resources. Since Spain's public health-care services are devolved to the country's regional
9 governments, this analysis is conducted at the autonomous community level. The estimated relationships refer to
10 the time-series evolution of these variables since 2000.

11 **Methods:** Dynamic fixed-effects panel estimation is employed. Driscoll–Kraay fixed-effects panel methods are
12 applied because serial correlation and cross-sectional dependence are present. When endogeneity is detected,
13 instrumental-variables panel estimations are also used as a preliminary step, employing autonomous-financing
14 series as instruments.

15 **Results:** Higher autonomous community public financing per capita is significantly associated with growth in
16 public health-care expenditure per capita. Moreover, the growth in public health-care expenditure per capita
17 maintains a relevant relationship with the availability of health-care personnel and certain physical resources
18 such as day hospital places per 1000 inhabitants. Finally, the evolution of health-care service resources is
19 associated with the growth in pharmaceutical expenditure.

20 **Conclusions:** Significant statistical relationships have been identified that interrelate the evolution of several
21 relevant variables in Spain's public health-care system. This study confirms the association between financing
22 and health-care expenditure, estimates the nexus between expanding health-care services and increased public
23 spending in the sector, and establishes the connection between increased health-care resources and public
24 pharmaceutical expenditure. The panel method employed makes it possible to distinguish the effects of the
25 independent variable from the structural differences among the autonomous communities. This indicates the
26 specific avenues of research needed to explain both types of differences.

27 **Keywords:** Public health-care services, public financing, public health-care expenditure, public pharmaceutical
28 expenditure, health-care resources, health-care decentralization

29 **JEL classification codes:** H51, H75, I10, I18.

^a I thank Editage for their professional assistance with English-language editing.

1. Background

This study evaluated several quantitative relationships that explain the evolution of Spain's health-care service metrics. Specifically, it examined the statistical relationships among public funding, public health-care expenditure, the human and physical capacities of public health-care services, and public pharmaceutical spending. The current results confirm the presence of general and significant associations among these sets of variables.

Evaluation is performed at the regional government level within Spain's autonomous communities (ACs). Spain's national health-care service (*Sistema Nacional de Salud*, SNS) is universal and public (see Articles 1 and 3 of Spain's General Health-care Act [1]) and is financed by taxation ([2], pp. 93–94).^b It is also devolved and principally falls within the remit of the country's regional governments (see Chapter 2 of Spain's General Health-care Act [1], among others). Health-care service devolution was completed in 2001 ([3], p. 2). These regional governments are the public authorities that decide on and deliver Spain's core public health-care services, health-care financing and expenditure within their respective ACs. The only exceptions are the autonomous cities of Ceuta and Melilla, where the service is managed by the national institute for health-care management (*Instituto Nacional de Gestión Sanitaria*). There is also a statutory minimum service level, financed by each regional government ([2], p. 94).

The empirical question of how public health-care services evolve—together with their financing and capacities—falls squarely within the debate regarding the effects of decentralization. Musgrave [4] analyzed the theoretical framework of federalism, namely that if preferences between fiscally autonomous regions differ, each region will provide a set of goods broadly aligned with those preferences (p. 4 *et seq.*).

Furthermore, Spain has two distinct regional financing frameworks. On the one hand, the Basque Country and Navarre have their own autonomous systems. Herrero Alcalde and Tránchez Martín [5] report that under this regional system “transferidos prácticamente todos los impuestos —que pasan a calificarse de «concertados»— [practically all taxation is devolved to AC level and classified as ‘concessionary’]” [own translation] (p. 39), after which a portion of the fiscal resources collected is transferred to the central administration (p. 39). On the other hand, the rest of Spain's ACs operate under a common regime.

For a summary of regional financing under the common regime, along with the associated sources of financing and their respective amounts for 2021, see [6] (p. 5, Chart 3). De la Fuente [7] synthesizes the revenue

^b Co-payment is restricted to outpatient pharmaceuticals ([2], p. 94): public pharmaceutical expenditure through copayments for prescriptions issued by the SNS

system of the ACs under the common regime: a smaller block of tax revenues collected directly by the ACs, a larger block of state transfers linked to the different funds, and the “tramos autonómicos de los impuestos gestionados por la Agencia Tributaria estatal” [“the regional shares of the taxes managed by the national Tax Agency”] [own translation] (p. 3). As Cabré and Ferrer [8] note, ‘más de la mitad de los ingresos autonómicos se obtienen a través de fuentes sobre las cuales las Comunidades Autónomas no tienen capacidad legislativa para poder tomar sus decisiones de política tributaria’ [“more than half of regional revenues come from sources over which the ACs have no legislative capacity to make their own tax-policy decisions”] [own translation] (p. 54). This implies that ACs’ financing is mostly exogenous. Moreover, their revenue is subject to the system of advance payments (“entregas a cuenta”)^c, or provisional revenues based on forecasts about tax performance, with final settlements two years later [7].

Concurrently, Spain’s regions differ in average income per capita and, consequently, in fiscal capacity. As Sánchez Maldonado and Gómez Sala [10] point out, this creates tension between the principles of equity and devolution (pp. 6 et seq.). A higher degree of regional fiscal responsibility could diminish equity ([11], p. 3). This debate arises when considering health-care services. Valls Martínez et al. [12] stated, “it could be said that in Spain there are 17 different (regional) health-care systems, each with its own spending policy” (p. 3). Sáenz Royo [2] concludes that the health-care financing system in Spain is confusing and opaque, making it impossible “una rendición de cuentas en el ámbito sanitario” [“accountability in the health-care sphere”] [own translation] (p. 94). Under Spain’s devolved health-care system, ACs exhibit significant differences in public health-care expenditure per capita. These differences are evident, for example, in López-Casasnovas [13] (p. 4). In addition, as González et al. [14] point out: “Hay diferencias regionales, en muchos casos notables, en la oferta pública de servicios. [“There are regional differences, in many cases significant ones, in public service provision”] [own translation]. (p. 88).

Xu and Lin [15] examined whether fiscal decentralization in China leads to improvements in public health, concluding that decentralization does indeed enhance public health outcomes^d. Arends [16] studies 32 OECD countries and argues that territorial decentralization appears to produce both higher public health-care expenditures and worse results in terms of “infant mortality and efficiency, confirming the argument that local planning, management and provision may be of poorer quality than in centralized systems” (p. 164). Hao et al.

^c The “entregas a cuenta” include, among others, the forecast of the revenue corresponding to each autonomous community from Personal Income Tax (IRPF), Value Added Tax (VAT), and Excise Duties on Manufactured Products (Cuenca [9]).

^d Local governments are better able to identify spending priorities aligned with citizens’ needs and “fiscal decentralization does promote public health by increasing public health expenditure” ([15], pp. 9-10).

[17] conclude that income disparities across Chinese regions—combined with fiscal decentralization—have negative effects on public health. Zhang et al. [18] likewise find that local government fiscal pressure in China negatively affects public health-care fiscal expenditures, and subsequently public health outcomes (among other pathways from fiscal expenditures to public health considered in their study).

Valls Martínez et al. [12] examine the relationship between health-care expenditure and several health-care service capacities with well-being and mortality rates at the regional level. Well-being is defined as ‘judging life positively and feeling good’ (p. 2), a concept that naturally encompasses health. The authors conclude that there is a positive relationship between these variables across the Spanish Autonomous Communities, with the exception of Madrid. This result highlights the existence of different situations within Spain. Referring to the financial crisis triggered in 2008, Bandrés and González [19] concluded that the ACs with the largest deficits made the deepest cuts in health-care expenditure (p. 47), suggesting a possible direct relationship between financing and health-care expenditure.

Pérez-Cantó et al. [3] considered that, in health-care services, “the heterogeneity of the autonomous communities in financing can influence the results of user opinion.” (p. 5). These authors mention that there appeared to be a gradient, with higher satisfaction in the northern half of the country and lower satisfaction in the south, “related to the decline in public spending on health-care and an increase in inequalities between autonomous communities” (p. 6).

The empirical analysis focuses on estimating statistical relationships at three levels. At the first level, the analysis examines the link between public financing and public health-care expenditure. The underlying idea is that greater availability of public funds should translate into higher public spending on health-care. This perspective, therefore, approaches the issue of rising public health-care expenditure, as described, for example, by Licchetta and Stelmach [20]: “Health spending has risen as a share of GDP in most OECD countries” (p. 35). As noted earlier in the article, several studies have shown evidence supporting the relationship between decentralization or fiscal financing and public health-care expenditure. Xu and Lin [15], for China, and Arends [16], for 32 OECD countries, found a relationship between greater territorial decentralization and higher health-care spending, whereas Zhang et al. [18] found lower health-care spending in China when local government fiscal pressures were present. This relationship is also suggested for Spain in Bandrés and González [19] and in Pérez-Cantó et al. [3].

The second level empirically studies the relationship between public health-care expenditure and the availability of human and physical health-care resources. This is a reasonable expectation: expanding health-care services requires increased public spending in the sector.

Finally, the third level estimates the relationship between increased health-care resources and public pharmaceutical expenditure. This follows the intuition that greater health-care activity is associated with higher per-capita consumption of medicines and, consequently, higher public co-payment in a public health-care system that covers a substantial share of pharmaceutical costs. The relevance of this expenditure is underscored by the fact that pharmaceutical spending represents around 20% of total public health-care expenditure in OECD countries (Belloni et al. [21], p. 4). The scientific literature often focuses on other drivers of pharmaceutical expenditure growth. Mousnad et al. [22], in a review of the literature, identify “changes in drug quantities and therapies and new drugs” (p. 143) as key explanatory factors. However, Belloni et al. [21] note that in countries that expanded “health coverage for a part of their population and/or the coverage of medicines with a consequent increase in spending” during the early 2000s, pharmaceutical expenditure rose accordingly (p. 32). This suggests that the availability of health-care services—and therefore health-care resources—may have an important relationship with pharmaceutical spending.

For reasons of scope, several questions concerning the relationship between resources and service utilization, as well as between utilization and user satisfaction—examined in a preliminary version of this research (Escañuela Romana, [23])—are left for future work. Moreover, the analysis presented here is partial, as it does not incorporate factors such as demographic trends, rising health-care service costs, or technological change—elements explored by Licchetta and Stelmach [20].

Research Hypotheses: to guide the empirical analysis, three levels are proposed. For every level, a null hypothesis (H_0) and an alternative hypothesis (H_1) are formulated.

- i. Level 1: Regional financing and public health-care expenditure. Are there significant associations between regional financing and public health-care expenditure?
 - a. H_{10} : Higher ACs’ public financing per capita does not maintain a significant association ($p > .05$) with higher public health-care expenditure per capita.
 - b. H_{11} : Higher ACs’ public financing per capita maintains a significant association ($p < .05$) with higher public health-care expenditure per capita.

- ii. Level 2: Is public health-care expenditure per capita significantly associated with the availability of human and material health-care resources? (Especially in the public sector, or in the private sector insofar as private providers operate under agreements with the public system).
 - a. H₂₀: Public health-care expenditure per capita is not positively associated ($p > .05$) with the availability of health-care personnel and health-care material resources.
 - b. H₂₁: Public health-care expenditure per capita is positively associated ($p < .05$) with the availability of health-care personnel and health-care material resources.
- iii. Level 3: Do significant relationships exist between certain human and material health-care resource variables and public pharmaceutical expenditure?
 - a. H₃₀: Public pharmaceutical expenditure is not positively associated ($p > .05$) with the availability of health-care personnel and health-care material resources.
 - b. H₃₁: Public pharmaceutical expenditure is positively associated ($p < .05$) with the availability of health-care personnel and health-care material resources.

This version substantially revises and expands the preliminary preprint (Escañuela Romana [23]).

Major methodological changes have been introduced, including the adoption of dynamic Driscoll–Kraay fixed-effects models, the treatment of serial correlation and cross-sectional dependence, and the incorporation of instrumental-variables panel estimation when endogeneity is detected.

2. Materials and methods

First, panel data estimation offers the advantage of controlling for time-invariant omitted variables ([24], p. 1). The cross-sectional units—or individuals—are Spain’s ACs. The fixed effects within groups (FEWG) model assumes a separate intercept for each AC based on the idea that, as described by [25] (pp. 16 et seq.),^e while the decisions made in each region differ, those decisions remain constant over time. Therefore, structural differences exist across regions.

The random effects (RE) model assumes that variations between ACs occur randomly ([25], p. 39). It is estimated to assess its validity prior to model selection.

The FEWG and RE models were estimated, but severe violations of assumptions (serial correlation and cross-sectional dependence) invalidate conventional inference^f.

^e I thank Dr. Oscar Torres-Reyna (Princeton University) for granting permission to cite this material.

^f The assumptions tested are: No autocorrelation (Wooldridge test, Wooldridge [26]); homoscedasticity (Breusch–Pagan test, Breusch & Pagan [27]); residual normality (Jarque–Bera test, Jarque and Bera [28]); and cross-sectional dependence (Pesaran test, Pesaran [29]).

Second, the violation of the assumptions makes the Driscoll–Kraay fixed effects model (DKFEM) the appropriate estimator, since it provides standard errors that are robust to heteroscedasticity, serial correlation, and cross-sectional dependence. This approach is based on the contributions of Driscoll and Kraay [30], who extended the nonparametric covariance matrix estimator of Newey and West [31] to panel data exhibiting autocorrelation and cross-sectional dependence. Under these conditions, lagged variables become weak instruments in dynamic GMM estimators such as Arellano–Bond and system GMM (Bun and Windmeijer [32]). Instrument proliferation further undermines identification when variables are persistent (Roodman [33]).

Third, the application of DKFEM requires two preliminary methods.

- i. Where variables reasonably considered instrumental are present, the Durbin–Wu–Hausman test (Durbin [34], Wu [35], Hausman [36]), or Hausman test, is employed, with the null hypothesis assuming no endogeneity in the panel regression^g. If endogeneity is detected and instrumental variables are available, the method used is instrumental variable regression (IV), as outlined by Angrist and Krueger [38], among others. After applying the IV method, DKFEM corrections are implemented.
- ii. To obtain robust results, a dynamic panel model (dynamic DKFEM) is estimated, where the independent variable is included as a lagged dependent variable:

$$y_{it} = \alpha y_{it-1} + \beta x_{it} + \mu_i + \epsilon_{it} \quad (1)$$

Here, i indexes the ACs, t represents time in years, μ_i captures the non-temporal structural variation across ACs not explained by the model, and ϵ_{it} represents the time-varying component within each AC not explained by the model. The inclusion of the lagged dependent variable, when significant, captures the persistence or temporal inertia of the dependent variable. Therefore, it is necessary to account for this potential dynamic component.

The purpose of introducing a dynamic specification is to allow the lagged dependent variable to capture temporal persistence and to prevent the coefficient of the independent variable from absorbing inertia or trend effects. Consequently, the so-called Nickell bias (Nickell [39]), which affects the coefficient of the lagged dependent variable in dynamic fixed-effects models, is not a concern in this study. Nickell notes that bias may arise in the coefficient of the exogenous variable if that regressor is correlated with the lagged dependent variable (p. 1424). However, the bias in dynamic fixed-effects models is of order $1/T$; therefore, this bias

^g Test analyzed in papers such as that by Patrick [37].

decreases as T increases, and with T = 25, the bias is almost negligible. This is why different alternative measures of the financing variables have been used, as they cover different time spans.

Substantial methodological changes have been introduced in this study compared to the preliminary version (Escañuela Romana [23]). The earlier draft employed OLS estimation and static panel models using fixed-effects, between-groups methods. However, that approach has proven inadequate for addressing temporal inertia and autocorrelation problems already evident in the preliminary analysis. In the present version, such limitations are addressed by adopting a dynamic panel framework and estimating the model using DKFEM, which allows for the quantification of dynamic processes. Moreover, the presence of cross-dependence in the panel further justifies abandoning the previous methodological strategy in favor of a more robust dynamic specification.

Estimations are computed using the R programming language (R Core Team [40]) and the following packages: lmtree (Zeileis and Hothorn [41]), plm (Croissant and Milla [42]), tseries (Trapletti and Hornik [43]), and AER (Kleiber and Zeileis [44]). In particular, the FEWG, RE, DKFEM, and IV models are estimated using the plm package^h.

The data are drawn primarily from public institutional sources. Spain's Ministry of Health (via the Subdirectorate-General for Health Information; *Subdirección General de Información Sanitaria*, SGIS), particularly the key indicators on the Spanish national health system; the National Statistics Institute (*Instituto Nacional de Estadística*, INE); the Ministry of Finance (*Ministerio de Hacienda*); and the *Intervención General de la Administración del Estado* (IGAE).

Moreover, regional financing data were also obtained from the FEDEA Foundation for Applied Economics Studies (*Fundación de Estudios de Economía Aplicada*).ⁱ

Although the data from the cited sources are not reproduced in this study, they have been used in accordance with their respective terms and conditions of reuse, and the original sources are acknowledged in each case. The author assumes full responsibility for all calculations, results and conclusions presented.

The following tables detail the data series, the years for which data are available, the number of ACs, and the data source. The 2020 data were excluded in the preliminary version (Escañuela Romana [23]) due to the impact of the COVID 19 pandemic. In the present version, however, no year is excluded; instead, where

^h Certain R-language instructions were prepared with the assistance of Copilot.

ⁱ The author gratefully acknowledges FEDEA's authorization to use the data referenced in this article. These data are not reproduced here. All calculations, interpretations and conclusions are the sole responsibility of the author.

possible, estimates are compared using both the complete time series and a restricted sample without the 2020 and 2021 observations. This choice is also methodological: dynamic panel estimation can be problematic when an entire year is removed, as eliminating period t effectively redefines $t-2$ as $t-1$, distorting the structure of the lagged variables. Table 1 presents the financing and expenditure series, while Table 2 shows the series on health-care services. These data are used to construct panel data series.

3. Results

3.1. The relationship between the expenditure and the financing variables

The methodological decisions are as follows.

First, panel data methods yield significant results as they exploit both the structural variability across ACs and the temporal variability within each AC. Among the available panel-data approaches, the fixed-effects model (FE) performs better than the random-effects model (RE). See the notes for Table A1.

Second, the presence of very strong serial correlation in the residuals and substantial cross sectional dependence makes it necessary to rely on DKFEM. See Table A1 in the Appendix. These models provide robust inference under such conditions.

Third, instrumental variables regression is applied when an instrumental variable exists. However, at this level of the analysis, no plausible instruments are available to perform an instrumental variable regression. Moreover, the financial variables are exogenous: the ACs decide on only a minor part of their financing ability, as previously noted.

Fourth, a dynamic DKFEM specification is estimated (Table 3), and its results clearly indicate the need to apply this method due to substantial time inertia.

Fifth, an estimation for RNFEN (2014–2023) is performed using the same time period as ENTRCUE. The coefficients of the lagged endogenous variable may decrease as the time series becomes shorter, and the Nickell bias may increase when the temporal dimension of the panel is reduced. Therefore, if the coefficients of the exogenous variable remain stable across different estimations and their p values continue to be significant, the results gain additional robustness. Furthermore, an additional estimation is performed excluding the years 2020 and 2021 to minimize the impact of the COVID-19 pandemic, and the results are compared with those obtained for the full period.

The quantitative results obtained reject H_{10} and confirm the alternative H_{11} for several financing variables. The following relationships stand out because of their relevance. First, annual increases in ENTRCUEPC are associated with higher GSANPC, GSANATEPC, and GSANPRIPC. That is, when expressed

in per capita terms, an increase of 100 euros in annual advance payments to the ACs over the period 2015–2025 is related, *ceteris paribus*, to the following increases in euros: 25.36 in public health-care expenditure, 17.44 in public health-care expenditure in specialized care, and 5.29 in primary health-care spending.

The variable RNFNEPC shows a smaller impact, but it is interesting to consider because its data cover the entire period analyzed: that same per-capita increase in this variable is associated, *ceteris paribus*, with an 11.26-euro rise in GSANPC (6.91-euro rise for 2014–2023), a 6.06-euro rise in GSANATEPC (5.27 euros for 2014–2023), and a 1.71-euro rise in GSANPRIPC (2.31 euros for 2014–2023).

Second, GFARPC does not show a clear and robust relationship with either financing or IME.

Finally, the analysis decomposes public health-care expenditure per capita into the factors with which it maintains relevant relationships. Taking GSANPC / ENTRCUEPC as an example, the theoretical equation estimated is:

$$GSANPC_t = \alpha_i + 0.2536ENTRCUEPC_{it} + 0.7599GSANPC_{it-1} + u_{it} \quad (1)$$

where $i = 15$ (ACs with data), $t = 10$. The idiosyncratic error term u_{it} is assumed to have zero mean, but it is not required to be white noise.

The value of α_i reflects the structural differences between ACs, which require further investigation to determine whether they are related to factors such as aging, population dispersion, economic structure, and so on, or to long standing political decisions that persist over time.

The estimation of the relationship between regional financing and public health-care expenditure makes it possible to assess, for example, what the level of expenditure would be if financing were equal to the average observed across ACs, *ceteris paribus*. One possible objection to this calculation is that regional financing reflects the heterogeneity of competences among the different ACs. However, if public health-care expenditure maintains statistical relationships—partial but robust—with financing, then the objection shifts to other policies and requires their specific analysis.

Graphically, considering the four ACs with the largest populations in Spain (Andalusia, Catalonia, the Community of Madrid, and the Valencian Community), and based on the regression (Table 3) of GSANPC on RNFNEPC and $\text{lag}(\text{GSANPC}, 1)$:

- Figure 1 shows the observed values of GSANPC from 2002 to 2023. The widening differences among these ACs over the period are noteworthy, with the largest observed gap increasing from 96.12% to 82.17% by the end of the period. These observed differences reflect both the estimated impact of RNFNEPC and the structural heterogeneity across the ACs being compared.

- Figure 2 shows the predicted levels of GSANPC obtained by applying the estimated coefficients to the average observed level of RNFNEPC across the ACs. These theoretical values are obtained using the average growth of RNFNEPC in Spain as the baseline. They capture the structural heterogeneity among ACs. For example, the observed GSANPC difference in 2023 between Catalonia and Andalusia is 371.27 euros; if both had an RNFNEPC level equal to the average across ACs, the difference would be 272.72 euros. Thus, the amount attributable to the financing gap through RNFNEPC is 98.55 euros.

Performing the same exercise now between GSANATEPC and ENTRCUEPC (Table 3), for the following four ACs: Galicia, Castile and Leon, Castile-La Mancha, and the Region of Murcia, we obtain the following figures:

- Figure 3 shows the observed values of GSANATEPC from 2002 to 2023.
- Figure 4 shows the predicted levels of GSANATEPC obtained by applying the estimated coefficients to the average observed level of ENTRCUEPC across the ACs. These predicted values discount the observed differences in ENTRCUEPC and therefore reveal the structural differences in GSANATEPC among ACs. For example, the observed GSANATEPC difference in 2023 between Murcia and Castile-La Mancha is 164.6003 euros; if both had an ENTRCUEPC level equal to the average across ACs, the difference would be 220.1858 euros. Thus, the amount attributable to the financing gap through ENTRCUEPC is –55.5855 euros.

3.2. The relationship between health-care expenditure and health-care resources

The relationship between public health-care expenditure and health-care resources is considered here. H_{20} and H_{21} are examined in Tables 4 and 6 (IV and DKFEM models) and Tables 5 and 7 (dynamic DKFEM models). Table A2 presents the regression estimates obtained using a static DKFEM approach.

The methodology employed in this section is the same as in the previous one, a dynamic estimation is performed to account for temporal persistence, and the same DKFEM correction is applied. But in this case, instrumental variables are available, which allows for the application of the instrumental variables (IV) method. In this way, potential endogeneity in the regressors is addressed. The instruments used are ENTRCUEPC and RNFNEPC, the per-capita financing variables of the ACs, because their relevance for the expenditure variables has been demonstrated in the previous level of regressions in Table 3. The exogeneity of these variables has been established theoretically above (see [7], p. 3).

The IV estimation is again performed using the DKFEM approach to correct for strong serial autocorrelation and cross-sectional dependence.

3.2.1. The relationship with human dotation of health-care systems

The results are presented in Tables 4 (IV method) and 5 (Dynamic DKFEM method). The appendix includes Table A2, which reports the coefficients from a static DKFEM model.

The application of an IV model with robust DKFEM estimation makes it possible to quantify the association between increases in GSANPC and increases in medical and nursing staff variables. The estimated coefficients, which are significant, provide the average response for Spain. The coefficients are:

- PMEAE and PMEAEPU: 0.0006.
- PENAE and PENAEP: 0.0013;
- PMEAP: 0.00004 (and for the alternative variable MFAPPC, 0.0000001).

These coefficients seem very small, but the variables are measured per 1000 inhabitants. Therefore, using these coefficients, one can estimate, within year t , the effect of increases from year $t-1$, *ceteris paribus*. For example, taking 2022, the average values for Spain as a whole, a 10% increase in GSANPC relative to that year's figure would generate, *ceteris paribus*, the following increases:

- 0.94% in PMEAP (1.46% in the alternative variable MFAPPC).
- 5.12% in PMEAE, 5.59% in PMEAEPU.
- 6.13% in PENAE, 6.77% in PENAEP (considering a 10% increase in GSANATEPC, a 7.55% increase in PENAEP).

Table 5 reports the results of the Dynamic DKFEM model. Considering the temporal inertia exhibited by the variables analyzed, there is a statistical association between, on the one hand, the expenditure variables GSANPC and GSANATEPC, and, on the other, the human-resource variables of the health-care system: PMEAE, PMEAEPU, PNEAE, PENAEP, PMEAP, and MFAPPC. The coefficients have been computed and the statistical significance levels are robust.

- Increases in the expenditure variables affect PMEAE and PMEAEPU according to coefficients around 0.0002; PENAE and PENAEP according to coefficients between 0.0004 and 0.0007; and PMEAP according to a coefficient of 0.00002 (and 0.00000002 for the variable MFAPPC).
- When the temporal inertia of the variables is taken into account, the observed changes in the number of physicians and nurses in the health-care system are more closely related to the values

observed in the previous year than to variations in the expenditure variables—although the latter relationship remains significant.

Let us consider the relationship between PMEAEPU and GSANATEPC, based on the dynamic DKFEM estimation (Table 5).

- Figure 5 presents the observed values of PMEAEPU. The differences are relevant and continue to widen over time. The AC with the lowest value reaches 66.09% of the value of the AC with the highest level at 2023.
- Figure 6 shows the predicted levels of PMEAEPU obtained by applying the estimated coefficients to the average observed level of GSANATEPC across the ACs. The differences between these theoretical values reveal the structural heterogeneity among the four ACs, arising from factors such as population characteristics, economic activity, or persistent political preferences regarding public health-care expenditure over time. For example, the observed difference in PMEAEPU in 2023 between Madrid and Andalusia is 0.7609 specialist-care medical personnel in the SNS per 1,000 inhabitants; if both had a GSANATEPC level equal to the average across ACs, the difference would be 0.6750. Thus, the amount attributable to the difference in GSANATEPC is 0.0859.

Therefore, the differences observed in the increases in PMEAE (PMEAEPU) across ACs are explained both by variations in the growth of GSANPC (GSANATEPC) and by the structural differences in PMEAE (PMEAEPU) provision that persist over time. These differences must be addressed in future research: which structural factors, medical-care factors, or long-standing political decisions explain the divergent trends in the provision of specialist physicians within the SNS across ACs? The same questions arise from the econometric analysis of the other variables. While the econometric methods employed allow for the measurement and decomposition of statistical relationships, it is these additional investigations that must provide explanations for the underlying reasons behind them.

As an additional example, consider the relationship between PNEAEPU and GSANATEPC estimated using the IV method (Table 4), with IV RNFNEPC, for the following ACs: Aragon, Asturias, the Balearic Islands, and the Canary Islands:

- Figure 7 presents the relevant differences in observed PNEAEPU values across the ACs.

- Figure 8 again shows the predicted levels of PENAEP. The results are clear: ACs exhibit a structurally significant difference in PENAEP provision. This once more highlights the need for further research to explain the reasons behind these differences.

3.2.2. The relationship with material resources of the health-care systems

The evolution of hospital beds and day-hospital places is studied here. Table A3 reports the static DKFEM estimations. Tables 6 and 7 contain the IV model and the dynamic DKFEM estimations.

The relevant results must display significant values ($p < .05$), Hausman test outcomes supporting the IV method ($p < .05$), and consistent results for both the full time series and the series starting in 2010. Considering these criteria, the estimates obtained from the IV method and the DKFEM approach are as follows.

- No robust estimation has been achieved for CHO.
- For the variable CHOPU (SNS hospital beds per 1000 inhabitants), the estimates obtained using both instruments differ, raising doubts about the comparability of the quantified effects across periods. However, the Dynamic DKFEM method allows the proposed relationships to be quantified: a 100 euro increase in GSANPC or GSANATEPC in year t is associated, *ceteris paribus*, with an increase of 0.01 in CHOPU. For the deflated expenditure variables, the estimated increase ranges from 0.01 to 0.02.
- For the variables measuring day hospital places per 1000 inhabitants (PHOD and PHODPU), estimates have been obtained using both methods. The IV method with DKFEM estimation yields, for year t , coefficients between 0.0001 and 0.0002 for the relationship between PHOD or PHODPU and GSANPC. The coefficients for GSANATEPC range between 0.0002 and 0.0004. The Dynamic DKFEM method reduces the magnitude of this relationship by accounting for the temporal inertia of the endogenous variable: the estimated coefficient is 0.00005 for GSANPC and 0.0001 for GSANATEPC.

The coefficients obtained using the two instruments produce contradictory values, with one doubling the quantitative magnitude of the relationships. Consequently, the values estimated by the Dynamic DKFEM model are preferable because they yield results with lower variability. To understand the true meaning of these coefficients, it is useful to express the variations in percentage terms, taking, for example, the values of the variables for the Spanish average in 2022 as a whole.

- A 10% increase in GSANPC is associated with a rise of 1.83% in PHOD, 2.10% in PHODPU, and 0.76% in CHOPU, *ceteris paribus*.

- A 10% increase in GSANATEPC is associated with a growth of 2.30% in PHOD, 2.64% in PHODPU, and 0.48% in CHOPU, *ceteris paribus*.

Public health-care expenditure variables partially explain the observed variation in the material resource variables considered (hospital beds in the SNS and day-hospital places). Therefore, the empirical evidence falsifies H_{20} and confirms H_{21} .

3.3. The relationship between public pharmaceutical expenditure and the availability of health-care personnel and health-care material resources

H_{30} and H_{31} are considered here. Table 8 presents the estimation of a dynamic DKFEM model, while Table A4 in the appendix reports the estimation of a static DKFEM model. In Table 8, we test different periods, with the 2013–2024 interval being particularly relevant because, as detailed above, a legislative change in pharmaceutical co payments took place in 2012. In addition, two deflated variables are examined (GFARPCD and GFARPCPID), although the former appears preferable, given that pharmaceutical prices are regulated and primarily represent public expenditure. Both the different time series and the alternative variables yield robust estimates.

GFARPC and GFARPCD are positively associated with PMEAE, PMEAEPU, PHOD, and PHODPU. However, no robust statistical relationships are found with PENAE, PNEANEPU, PMEAP, CHO, CHOPU, or IME (Table 3).

Consequently, the coefficients estimated between the dependent variable GFARPC and the independent variables are as follows: 12.7226 (PMEAE), 12.6464 (PMEAEPU), 13.8473 (PHOD), and 10.1346 (PHODPU). Moreover, based on the average values of the ACs in 2022 and the estimated coefficients, *ceteris paribus*, a 10% increase in PMEAE, PMEAEPU, PHOD, and PHODPU is associated with respective increases in GFARPC of 0.97%, 0.88%, 0.25%, and 0.16%. Therefore, the number of specialized doctors and the number of day health-care centers are the factors supporting hypothesis H_{31} and thus falsifying hypothesis H_{30} . As noted above, Belloni et al. [21] implicitly consider the relationship between the availability of health-care services and pharmaceutical spending. However, the quantified relationships are relatively small, suggesting the need to investigate other statistical associations.

4. Discussion

From a methodological standpoint, several issues have been identified that must be taken into account when estimating the relationships analyzed in this study. Panel estimation has proven significant, making it essential to account for both the structural variability across ACs and their temporal evolution. Panel estimation

challenges include endogeneity and significant violations of the assumptions of no serial autocorrelation and no cross sectional dependence. This has required the use of the instrumental variables method in cases where the instruments satisfy the theoretical conditions of exogeneity and relevance, as well as the application of the DKFEM estimator to obtain a robust covariance matrix. Dynamic panel modelling is also necessary due to the clear temporal inertia present in the variables analyzed, which justifies its use.

Based on this methodological framework, it is concluded that H_{11} , H_{21} , and H_{31} have been confirmed—albeit to varying degrees. There are relevant associations between regional financing and public health-care expenditure. Public health-care expenditure per capita is significantly associated with the availability of human and physical health-care resources. Significant relationships also exist between certain human and physical health-care resource variables and public pharmaceutical expenditure.

Moreover, the results obtained using deflated series do not differ significantly from those obtained using nominal series.

The relationship found between regional financing and public health-care expenditure is consistent with the scientific literature mentioned in the introduction: Xu and Lin [15] and Arends [16] report a relationship between greater territorial decentralization and higher health-care spending; Zhang et al. [18] identify the same relationship but through lower fiscal resources leading to lower health-care spending; and Bandrés and González [19], as well as Pérez-Cantó et al. [3], suggest a similar relationship for Spain. As noted before, health-care expenditure as a percentage of GDP has been rising in Spain [58]. Moreover, the relationship between health-care services—which are necessarily linked to health-care resources—and pharmaceutical public expenditures confirms the findings reported by Belloni et al. [21].

This resource-based perspective should be complemented by an analysis focused on care pressure: which factors drive the use of health-care services and how these factors translate into the growth of public health-care expenditure. For example, Navarro-García and Sarria-Santamera [72] examine the impact of population aging and, above all, of “the so-called need factors, which include the self-perceived state of health, the presence of chronic diseases and the presence of disability” (p. 314).

In reality, both perspectives—demand side and resource side—provide complementary views of the issues related to health-care services, expenditure, and their financing.

The findings nevertheless remain partial in several broad respects. First, this study examines quantitative relationships without addressing the effectiveness of the health-care services provided. The most relevant extension would be to investigate the relationships between, on the one hand, financing, expenditure,

and resources, and, on the other hand, measures of health-care effectiveness and population health. Moreover, the results have other limitations as well. Some of the data series do not yield significant results, and in certain cases, the observed time evolution of variables within ACs is not explained by the statistical estimations. Furthermore, the data series used are aggregated and cover a limited time span. Longer and more homogeneous series are therefore required, as is the inclusion of additional variables of interest. The phenomena analyzed involve multiple factors, meaning that the explanations necessarily remain partial. In particular, further research is required to clarify the estimated quantification of the relationships between the health-care variables examined here.

5. Conclusion

Significant, albeit partial, statistical associations have been identified that account for the observed evolution of several variables in Spain's public health-care system. This study confirms the direct relationship between financing and health-care expenditure, the expansion of health-care services and increased public spending in the sector, and the increase in health-care resources and public pharmaceutical expenditure.

The methods used to quantify these associations take advantage of the panel structure of the data, where the units are the ACs and temporal variation occurs within each of them. Concurrently, endogeneity, autocorrelation, cross sectional dependence, and temporal inertia must be addressed, as these features determine the choice of methods. The panel method employed makes it possible to distinguish the effects of the independent variable from the structural differences among the autonomous communities. This indicates the specific avenues of research needed to explain both types of differences.

List of abbreviations

AC — autonomous community
AER — Applied Econometrics with R package
CHO — operational hospital beds per 1000 inhabitants
CHOPU — operational hospital beds in the SNS per 1000 inhabitants
DKFEM — Driscoll–Kraay fixed-effects model
ENTRCUE — “Entregas a cuenta” (annual advance payments to ACs)
ENTRCUEPC — ENTRCUE per capita
FEDEA — Fundación de Estudios de Economía Aplicada
FECHHA — effective financing for homogeneous powers, adjusted per capita

489	FEWG — fixed effects within groups model
490	FCEGGN — General Government final consumption expenditure (nominal)
491	FCEGGV — General Government final consumption expenditure (volume index)
492	GFARPC — public pharmaceutical expenditure per capita
493	GFARPCD — deflated public pharmaceutical expenditure per capita
494	GFARPCPID — pharmaceutical expenditure per capita deflated by CPI (health subgroup)
495	GSANPC — public health-care expenditure per capita
496	GSANPCD — deflated public health-care expenditure per capita
497	GSANATEPC — specialist-care expenditure per capita
498	GSANCONPC — expenditure on services provided by external partners per capita
499	GSANPRIPC — primary-care expenditure per capita
500	IGAE — “Intervención General de la Administración del Estado” (General Comptroller of the State
501	Administration)
502	IME — average income per adult
503	IPCS — Consumer Price Index, health subgroup
504	IV — instrumental variables regression
505	MFAP — primary-care medical personnel per 1000 assigned individuals
506	MFAPPC — MFAP per capita
507	MFMT — occupational medicine personnel (primary care)
508	MFTO — total primary-care medical personnel
509	PENAE — specialist-care nursing staff per 1000 inhabitants
510	PENAEPU — specialist-care nursing staff in the SNS per 1000 inhabitants
511	PHOD — day-hospital places per 1000 inhabitants
512	PHODPU — day-hospital places in the SNS per 1000 inhabitants
513	PMEAE — specialist-care medical personnel per 1000 inhabitants
514	PMEAEPU — specialist-care medical personnel in the SNS per 1000 inhabitants
515	PMEAP — primary-care medical personnel per 1000 assigned individuals
516	POP — population
517	RE — random-effects model
518	RNFNE — net non-financial resources of ACs

519 RNFNEPC — RNFNE per capita

520 SNS — “Sistema Nacional de Salud” (National Health System)

521 TOTALPC — total regional financing per capita

522

523 **Declarations**

524 **Ethics approval and consent to participate**

525 Not applicable. This study uses aggregated public data from official institutional sources and does not involve
526 human participants or identifiable personal information.

527 **Consent for publication**

528 Not applicable. No individual person’s data are included in this study.

529 **Availability of data and materials**

530 The article explicitly indicates the data sources and includes references to these sources.

531 **Competing interests**

532 The author declares no competing interests.

533 **Funding**

534 The author conducted this research independently and did not receive financial support from any institution or
535 funding agency.

536 **Authors’ contributions**

537 The author solely conceived the study, collected the data, performed the analyses, and wrote the manuscript.

538 **Acknowledgements**

539 The author thanks Editage for English-language editing support and FEDEA for authorizing the use of regional
540 financing data. The author also thanks Dr. Oscar Torres-Reyna (Princeton University) for granting permission to
541 cite his material. All interpretations and conclusions are the sole responsibility of the author.

542 **Authors’ information**

543 Ignacio Escañuela Romana is an independent researcher with a PhD in Data Science from Universidad Loyola
544 Andalucía.

545 Email: ignacioesro@gmail.com

546 ORCID iD: <https://orcid.org/0000-0002-5376-0543>

547

548 **References**

- 549 1. España. Ley 14/1986, de 25 de abril, General de Sanidad. Boletín Oficial del Estado. 1986 Apr
550 29;(102). <https://www.boe.es/buscar/pdf/1986/BOE-A-1986-10499-consolidado.pdf>. Accessed 18 Aug
551 2025.
- 552 2. Sáenz Royo E. Financiación sanitaria en España y rendición de cuentas: la historia de muchos déficits.
553 Derecho Político. 2024;119:71-97. doi:10.5944/rdp.119.2024.40411.
- 554 3. Pérez-Cantó V, Maciá-Soler L, González-Chordá VM. Satisfacción de los usuarios en el sistema de
555 salud español: análisis de tendencias. Rev Saude Publica. 2019;53:1-10. doi:10.11606/S1518-
556 8787.2019053001506.
- 557 4. Musgrave RA. Economics of fiscal federalism. Neb J Econ Bus. 1971;10:3-13.
- 558 5. Herrero Alcalde A, Tránchez Martín JM. El desarrollo y evolución del sistema de financiación
559 autonómica. Presup Gasto Público. 2011;62:33-65.
- 560 6. De la Fuente A. Financiación autonómica: una breve introducción. Estudios sobre la Economía
561 Española. Madrid: FEDEA; 2023. <https://documentos.fedea.net/pubs/eee/eee2019-07.pdf>. Accessed 23
562 Nov 2025.
- 563 7. De la Fuente Á. Las finanzas autonómicas en 2025 y entre 2003 y 2025. Estudios sobre la Economía
564 Española. Madrid: Fundación de Estudios de Economía Aplicada; 2026. No. 2026/21.
- 565 8. Cabré JMD, Ferrer MV. La autonomía fiscal de las comunidades autónomas: ventajas y riesgos.
566 Informe Comunidades Autónomas. 2022:43-84.
- 567 9. Cuenca A. Las entregas a cuenta en la financiación de las comunidades autónomas: algunas opciones
568 de mejora. Madrid: Fundación de Estudios de Economía Aplicada; 2016. Fedea Policy Papers 2015/10,
569 versión revisada.
- 570 10. Sánchez Maldonado JS, Gómez Sala JG. La financiación territorial de la sanidad: especial referencia a
571 España. Estudios sobre la Economía Española. Madrid: FEDEA; 1998. No. 27.
572 <https://documentos.fedea.net/pubs/eee/eee27.pdf>. Accessed 19 Aug 2025.
- 573 11. De la Fuente Á. Financiación autonómica y local. Food for Thought: aportaciones al debate sobre
574 políticas públicas. Madrid: FEDEA; 2024. Apuntes 2024/04.
575 <https://documentos.fedea.net/pubs/ap/2024/ap2024-04.pdf>.
- 576 12. Valls Martínez MC, Grasso MS, Montero JM. Regional well-being inequalities arising from health-
577 care expenditure public policies in Spain. Front Public Health. 2022;10:953827.
578 doi:10.3389/fpubh.2022.953827.

- 579 13. López-Casasnovas GG. Qué nos dicen las cifras de gasto sobre la eficiencia de los sistemas sanitarios.
580 Health Policy Papers Collection. 2023;8. [https://repositori.upf.edu/server/api/core/bitstreams/a7300fd4-](https://repositori.upf.edu/server/api/core/bitstreams/a7300fd4-f55a-48a1-8a75-4ddffcf32354/content)
581 [f55a-48a1-8a75-4ddffcf32354/content](https://repositori.upf.edu/server/api/core/bitstreams/a7300fd4-f55a-48a1-8a75-4ddffcf32354/content). Accessed 30 Dec 2025.
- 582 14. González B, Urbanos RM, Ortega P. Oferta pública y privada de servicios sanitarios por comunidades
583 autónomas. Gac Sanit. 2004;18:82-9.
- 584 15. Xu W, Lin J. Fiscal decentralization, public health expenditure and public health: evidence from China.
585 Front Public Health. 2022;10:773728. doi:10.3389/fpubh.2022.773728.
- 586 16. Arends H. More with less? Fiscal decentralisation, public health spending and health sector
587 performance. Swiss Polit Sci Rev. 2017;23:144-74.
- 588 17. Hao Y, Liu J, Lu ZN, Shi R, Wu H. Impact of income inequality and fiscal decentralization on public
589 health: Evidence from China. Econ Model. 2021;94:934-44. doi:10.1016/j.econmod.2020.02.034.
- 590 18. Zhang X, Feng T, Wang C, Li C. Local fiscal pressure and public health: evidence from China. Int J
591 Environ Res Public Health. 2023;20:5126.
- 592 19. Bandrés E, González R. La reducción del gasto sanitario en España durante la crisis. Cuad Inf Econ.
593 2015;248:37-48.
- 594 20. Licchetta M, Stelmach M. Fiscal sustainability analytical paper: fiscal sustainability and public
595 spending on health. London: Office for Budget Responsibility; 2016. [https://obr.uk/fiscal-](https://obr.uk/fiscal-sustainability-analytical-paper-published-today/)
596 [sustainability-analytical-paper-published-today/](https://obr.uk/fiscal-sustainability-analytical-paper-published-today/).
- 597 21. Belloni A, Morgan D, Paris V. Pharmaceutical expenditure and policies: past trends and future
598 challenges. OECD Health Working Papers. Paris: OECD; 2016.
- 599 22. Mousnad MA, Shafie AA, Ibrahim MI. Systematic review of factors affecting pharmaceutical
600 expenditures. Health Policy. 2014;116:137-46.
- 601 23. Escañuela Romana I. Statistical drivers of regional health-care patterns in Spain. Research Square.
602 2026. doi:10.21203/rs.3.rs-10009105/v1.
- 603 24. Bollen KA, Brand JE. A general panel model with random and fixed effects: a structural equations
604 approach. Soc Forces. 2010;89:1-34. doi:10.1353/sof.2010.0072.
- 605 25. Torres-Reyna O. Panel data analysis: fixed and random effects using Stata. Version 4.2. Princeton
606 (NJ): Princeton University; 2007. <https://www.princeton.edu/~otorres/Panel101.pdf>. Accessed 21 May
607 2025.

- 608 26. Wooldridge JM. Econometric analysis of cross section and panel data. 2nd ed. Cambridge (MA): MIT
609 Press; 2010.
- 610 27. Breusch TS, Pagan AR. A simple test for heteroscedasticity and random coefficient variation.
611 *Econometrica*. 1979;47:1287-94. doi:10.2307/1911963.
- 612 28. Jarque CM, Bera AK. Efficient tests for normality, homoscedasticity and serial independence of
613 regression residuals. *Econ Lett*. 1980;6:255-9. doi:10.1016/0165-1765(80)90024-5.
- 614 29. Pesaran MH. General diagnostic tests for cross-sectional dependence in panels. *Empir Econ*.
615 2021;60:13-50. doi:10.1007/s00181-020-01875-7.
- 616 30. Driscoll JC, Kraay AC. Consistent covariance matrix estimation with spatially dependent panel data.
617 *Rev Econ Stat*. 1998;80:549-60.
- 618 31. Newey WK, West KD. A simple, positive semi-definite, heteroskedasticity and autocorrelation
619 consistent covariance matrix. *Econometrica*. 1987;55:703-8.
- 620 32. Bun MJ, Windmeijer F. The weak instrument problem of the system GMM estimator in dynamic panel
621 data models. *Econom J*. 2010;13:95-126.
- 622 33. Roodman D. A note on the theme of too many instruments. *Oxf Bull Econ Stat*. 2009;71:135-58.
- 623 34. Durbin J. Errors in variables. *Rev Inst Int Stat*. 1954;22:23-32. doi:10.2307/1401917.
- 624 35. Wu DM. Alternative tests of independence between stochastic regressors and disturbances.
625 *Econometrica*. 1973;41:733-50. doi:10.2307/1914093.
- 626 36. Hausman JA. Specification tests in econometrics. *Econometrica*. 1978;46:1251-71.
627 doi:10.2307/1913827.
- 628 37. Patrick RH. Durbin-Wu-Hausman specification tests. In: Lee CF, Lee JC, editors. *Handbook of*
629 *financial econometrics, mathematics, statistics, and machine learning*. Hackensack (NJ): World
630 Scientific; 2021. p. 1075-108.
- 631 38. Angrist JD, Krueger AB. Instrumental variables and the search for identification: from supply and
632 demand to natural experiments. *J Econ Perspect*. 2001;15:69-85. doi:10.1257/jep.15.4.69.
- 633 39. Nickell S. Biases in dynamic models with fixed effects. *Econometrica*. 1981;49:1417-26.
- 634 40. R Core Team. *R: a language and environment for statistical computing*. Vienna: R Foundation for
635 Statistical Computing; 2024.
- 636 41. Zeileis A, Hothorn T. Diagnostic checking in regression relationships. *R News*. 2002;2:7-10.

- 637 42. Croissant Y, Millo G. Panel data econometrics in R: the plm package. J Stat Softw. 2008;27:1-43.
638 doi:10.18637/jss.v027.i02.
- 639 43. Trapletti A, Hornik K. tseries: time series analysis and computational finance. R package version 0.10-
640 58. Vienna: R Foundation for Statistical Computing; 2024. [https://CRAN.R-](https://CRAN.R-project.org/package=tseries)
641 [project.org/package=tseries](https://CRAN.R-project.org/package=tseries). Accessed 30 May 2024.
- 642 44. Kleiber C, Zeileis A. Applied econometrics with R. New York: Springer-Verlag; 2008.
- 643 45. Instituto Nacional de Estadística. Población por grupo de edad, sexo y comunidad autónoma: valores
644 absolutos, media de los cuatro trimestres del año, resultados por comunidades autónomas. Madrid:
645 Instituto Nacional de Estadística. <https://www.ine.es/jaxiT3/Datos.htm?t=66014>. Accessed 30 Dec
646 2025.
- 647 46. Subdirección General de Información Sanitaria, Ministerio de Sanidad. Ingresos medios por persona en
648 16 y más años (euros): adultos. In: Indicadores clave del Sistema Nacional de Salud.
649 <https://inclasns.sanidad.gob.es/>. Accessed 7 Jan 2026.
- 650 47. Instituto Nacional de Estadística. Índice de Precios de Consumo: tabla 50902. Madrid: Instituto
651 Nacional de Estadística. <https://www.ine.es/jaxiT3/Datos.htm?t=50902>. Accessed 19 Nov 2025.
- 652 48. Instituto Nacional de Estadística. Contabilidad Nacional Anual de España. Revisión Estadística 2024:
653 producto interior bruto a precios de mercado y sus componentes, precios corrientes, tabla 1: demanda,
654 oferta, rentas, gasto en consumo final de las AAPP. Madrid: Instituto Nacional de Estadística; 2024.
655 [https://ine.es/dyngs/INEbase/es/operacion.htm?c=Estadistica_C&cid=1254736177057&menu=resultad](https://ine.es/dyngs/INEbase/es/operacion.htm?c=Estadistica_C&cid=1254736177057&menu=resultados&idp=1254735576581)
656 [os&idp=1254735576581](https://ine.es/dyngs/INEbase/es/operacion.htm?c=Estadistica_C&cid=1254736177057&menu=resultados&idp=1254735576581). Accessed 5 Mar 2026.
- 657 49. Instituto Nacional de Estadística. Producto interior bruto a precios de mercado y sus componentes:
658 variaciones de volumen, tabla 4, índices de volumen encadenados, referencia año 2020 = 100,
659 demanda, gasto en consumo final de las AAPP. Madrid: Instituto Nacional de Estadística; 2024.
660 [https://ine.es/dyngs/INEbase/es/operacion.htm?c=Estadistica_C&cid=1254736177057&menu=resultad](https://ine.es/dyngs/INEbase/es/operacion.htm?c=Estadistica_C&cid=1254736177057&menu=resultados&idp=1254735576581)
661 [os&idp=1254735576581](https://ine.es/dyngs/INEbase/es/operacion.htm?c=Estadistica_C&cid=1254736177057&menu=resultados&idp=1254735576581). Accessed 5 Mar 2026.
- 662 50. Ministerio de Hacienda. Informes sobre la financiación provisional de las comunidades autónomas a
663 través del sistema de financiación. Madrid: Ministerio de Hacienda. [https://www.hacienda.gob.es/es-](https://www.hacienda.gob.es/es-es/cdi/paginas/sistemasfinanciaciondeuda/informacionccaas/informes%20financiacion%20comunidadess%20autonomas1.aspx)
664 [es/cdi/paginas/sistemasfinanciaciondeuda/informacionccaas/informes%20financiacion%20comunidade](https://www.hacienda.gob.es/es-es/cdi/paginas/sistemasfinanciaciondeuda/informacionccaas/informes%20financiacion%20comunidadess%20autonomas1.aspx)
665 [s%20autonomas1.aspx](https://www.hacienda.gob.es/es-es/cdi/paginas/sistemasfinanciaciondeuda/informacionccaas/informes%20financiacion%20comunidadess%20autonomas1.aspx). Accessed 5 Sep 2025.

- 666 51. Ministerio de Hacienda. Informes sobre la financiación definitiva de las comunidades autónomas a
667 través del sistema de financiación. Madrid: Ministerio de Hacienda. [https://www.hacienda.gob.es/es-](https://www.hacienda.gob.es/es-ES/CDI/Paginas/SistemasFinanciacionDeuda/InformacionCCAAAs/Informes%20financiacion%20comunidades%20autonomas2.aspx)
668 [ES/CDI/Paginas/SistemasFinanciacionDeuda/InformacionCCAAAs/Informes%20financiacion%20comu-](https://www.hacienda.gob.es/es-ES/CDI/Paginas/SistemasFinanciacionDeuda/InformacionCCAAAs/Informes%20financiacion%20comunidades%20autonomas2.aspx)
669 [nidades%20autonomas2.aspx](https://www.hacienda.gob.es/es-ES/CDI/Paginas/SistemasFinanciacionDeuda/InformacionCCAAAs/Informes%20financiacion%20comunidades%20autonomas2.aspx). Accessed 5 Sep 2025.
- 670 52. Fundación de Estudios de Economía Aplicada. Financiación efectiva a comp. homog. por hab.
671 ajustado, a precios corrientes (euros por persona). In: La evolución de la financiación de las
672 comunidades autónomas de régimen común, 2002–2023. Madrid: Fundación de Estudios de Economía
673 Aplicada; 2025. <https://fedea.net/datos/>. Accessed 16 Jul 2026.
- 674 53. Intervención General de la Administración del Estado IGAE. Non-financial operations of the regional
675 government subsector and breakdown by autonomous communities. Madrid: Ministerio de Hacienda y
676 Administraciones Públicas; 2017. [https://www.igae.pap.hacienda.gob.es/sitios/igae/es-](https://www.igae.pap.hacienda.gob.es/sitios/igae/es-ES/Contabilidad/ContabilidadNacional/Publicaciones/Paginas/ianofinancierasCA.aspx)
677 [ES/Contabilidad/ContabilidadNacional/Publicaciones/Paginas/ianofinancierasCA.aspx](https://www.igae.pap.hacienda.gob.es/sitios/igae/es-ES/Contabilidad/ContabilidadNacional/Publicaciones/Paginas/ianofinancierasCA.aspx). Accessed 10
678 Jul 2026.
- 679 54. Subdirección General de Información Sanitaria, Ministerio de Sanidad. Gasto farmacéutico por
680 habitante y año a través de recetas médicas SNS en oficinas de farmacia, en las comunidades
681 autónomas. In: Indicadores clave del Sistema Nacional de Salud. Madrid: Ministerio de Sanidad; 2025.
682 <https://inclasns.sanidad.gob.es/>. Accessed 9 Jul 2026.
- 683 55. Subdirección General de Información Sanitaria, Ministerio de Sanidad. Porcentaje del gasto de los
684 servicios de atención especializada por las comunidades autónomas. In: Indicadores clave del Sistema
685 Nacional de Salud. Madrid: Ministerio de Sanidad; 2025. <https://inclasns.sanidad.gob.es/>. Accessed 27
686 Aug 2025.
- 687 56. Subdirección General de Información Sanitaria, Ministerio de Sanidad. Porcentaje del gasto dedicado a
688 conciertos por las comunidades autónomas. In: Indicadores clave del Sistema Nacional de Salud.
689 Madrid: Ministerio de Sanidad; 2025. <https://inclasns.sanidad.gob.es/>. Accessed 27 Aug 2025.
- 690 57. Subdirección General de Información Sanitaria, Ministerio de Sanidad. Gasto sanitario público
691 gestionado por las comunidades autónomas, por habitante protegido. In: Indicadores clave del Sistema
692 Nacional de Salud. Madrid: Ministerio de Sanidad; 2025. <https://inclasns.sanidad.gob.es/>. Accessed 9
693 Jul 2026.
- 694 58. Bernal-Delgado E, Angulo-Pueyo E, Ridao-López M, Urbanos Garrido RM, Oliva-Moreno J, García-
695 Abiétar D, et al. Spain: health system review. Health Syst Transit. 2024;26.

- 696 59. Subdirección General de Información Sanitaria, Ministerio de Sanidad. Porcentaje del gasto sanitario
697 en atención primaria por las comunidades autónomas. In: Indicadores clave del Sistema Nacional de
698 Salud. Madrid: Ministerio de Sanidad; 2025. <https://inclasns.sanidad.gob.es/>. Accessed 11 Jul 2026.
- 699 60. Subdirección General de Información Sanitaria, Ministerio de Sanidad. Camas hospitalarias en
700 funcionamiento por 1000 hab. In: Indicadores clave del Sistema Nacional de Salud. Madrid: Ministerio
701 de Sanidad; 2025. <https://inclasns.sanidad.gob.es/>. Accessed 14 Jul 2026.
- 702 61. Subdirección General de Información Sanitaria, Ministerio de Sanidad. Camas hospitalarias en
703 funcionamiento (% SNS). In: Indicadores clave del Sistema Nacional de Salud. Madrid: Ministerio de
704 Sanidad; 2025. <https://inclasns.sanidad.gob.es/>. Accessed 14 Jul 2026.
- 705 62. Ministerio de Sanidad. Medicina de familia AP: recursos de medicina de familia y ratios. In: Sistema
706 de Información de Atención Primaria. Información estadística: recursos y población protegida. Madrid:
707 Ministerio de Sanidad; 2025.
708 <https://consultasiap.sanidad.gob.es/siapAppConsulta/inicio.do?metodo=cargarPaginaInicio>. Accessed 7
709 Sep 2025.
- 710 63. Ministerio de Sanidad. Medicina de familia MT: recursos de medicina de familia y ratios. In: Sistema
711 de Información de Atención Primaria. Información estadística: recursos y población protegida. Madrid:
712 Ministerio de Sanidad; 2025.
713 <https://consultasiap.sanidad.gob.es/siapAppConsulta/inicio.do?metodo=cargarPaginaInicio>. Accessed 7
714 Sep 2025.
- 715 64. Subdirección General de Información Sanitaria, Ministerio de Sanidad. Personal de enfermería en
716 atención especializada por 1000 hab. In: Indicadores clave del Sistema Nacional de Salud. Madrid:
717 Ministerio de Sanidad; 2025. <https://inclasns.sanidad.gob.es/>. Accessed 9 Jul 2026.
- 718 65. Subdirección General de Información Sanitaria, Ministerio de Sanidad. Personal de enfermería en
719 atención especializada por 1000 hab. (% SNS). In: Indicadores clave del Sistema Nacional de Salud.
720 Madrid: Ministerio de Sanidad; 2025. <https://inclasns.sanidad.gob.es/>. Accessed 9 Jul 2026.
- 721 66. Subdirección General de Información Sanitaria, Ministerio de Sanidad. Personal médico en atención
722 primaria por 1000 personas asignadas. In: Indicadores clave del Sistema Nacional de Salud. Madrid:
723 Ministerio de Sanidad; 2025. <https://inclasns.sanidad.gob.es/>. Accessed 12 Jul 2026.

67. Subdirección General de Información Sanitaria, Ministerio de Sanidad. Personal médico en atención especializada por 1000 hab. In: Indicadores clave del Sistema Nacional de Salud. Madrid: Ministerio de Sanidad; 2025. <https://inclasns.sanidad.gob.es/>. Accessed 9 Jul 2026.
68. Subdirección General de Información Sanitaria, Ministerio de Sanidad. Personal médico en atención especializada por 1000 hab. (% SNS). In: Indicadores clave del Sistema Nacional de Salud. Madrid: Ministerio de Sanidad; 2025. <https://inclasns.sanidad.gob.es/>. Accessed 9 Jul 2026.
69. Subdirección General de Información Sanitaria, Ministerio de Sanidad. Puestos en hospitales de día por 1000 hab. In: Indicadores clave del Sistema Nacional de Salud. Madrid: Ministerio de Sanidad; 2025. <https://inclasns.sanidad.gob.es/>. Accessed 31 Dec 2025.
70. Subdirección General de Información Sanitaria, Ministerio de Sanidad. Puestos en hospitales de día por 1000 hab., porcentaje de los puestos en SNS. In: Indicadores clave del Sistema Nacional de Salud. Madrid: Ministerio de Sanidad; 2025. <https://inclasns.sanidad.gob.es/>. Accessed 31 Dec 2025.
71. Simó Miñana J. La causa de la causa del ocaso de la atención primaria española. Rev Clin Med Fam. 2021;14:129-30. doi:10.55783/rcmf.140302.
72. Navarro-García C, Sarría-Santamera A. The effect of older population on public health spending: evidence from Spain. Health Care Sci. 2023;2:306-16.

Table 1. Economic data series

Variable	Years	ACs	Name	Data source
Population by age group, sex and autonomous community. Absolute values. Average of the four quarters of the year.	2006–2024	19	POP	INE [45]
Average income per person aged 16 and over (euro) (adults)	2008–2024	19	IME	SGIS [46]
Consumer Price Index, subgroup 06: Health.	2002–2024	Spain	IPCS	INE [47]
Gross domestic product at market prices and its components. Current prices. Table 1: Demand, Supply, Income. Final consumption expenditure of General Government ^a	1995–2024	Spain	FCEGGN	INE [48]
Gross domestic product at market prices and its	1995–2024	Spain	FCEGGV	INE [49]

components. Volume changes. Table 4:

Chain-linked volume indices, reference year 2020

= 100. Demand. Final consumption expenditure of

General Government ^a

Total payments. Million euro. ^b	2014–2024	17	ENTRCUE	Hacienda [50]
Final autonomous community financing via the financing system. Thousand euro. ^b	2012–2023	17	LIQUDEF	Hacienda [51]
“Financiación efectiva a comp. homog. por hab. ajustado, a precios corrientes” [Effective financing for homogeneous powers, adjusted per capita, at current prices, own translation]. ^{bc}	2009–2023	15	FECHHA	FEDEA [52]
Net non-financial resources, including net transfers from other public authorities. Million euro at current prices. ^{bd}	2000–2024	17	RNFNE	IGEA (from FEDEA) [53]
Pharmaceutical expenditure per capita/year as per SNS prescriptions collected at pharmacies. Euro per capita at current prices. ^{efg}	2010–2024	19	GFARPC	SGIS [54]
Percentage of expenditure on specialist care services. ^c	2002–2022	17	GSANATE	SGIS [55]
Percentage of expenditure on services provided by external partners. ^{he}	2002–2022	17	GSANCON	SGIS [56]
Public health-care expenditure by ACs, per capita covered. Euro per capita at current prices. ^{ei}	2002–2023	17	GSANPC	SGIS [57]
Percentage of health-care expenditure on primary care. ^j	2002–2023	17	GSANPRI	SGIS [59]

^a 2023: provisional; 2024: advance estimate.

^b ENTRCUE (“entregas a cuenta”) is the total annual financing received by the ACs prior to the settlement adjustment (LIQUDEF), which is applied two years later. ENTRCUE (year n) plus LIQUDEF (year n–2) equals TOTAL (year n). Dividing ENTRCUE by POP yields ENTRCUEPC, and dividing LIQUDEF by POP yields LIQUDEFPC. Dividing TOTAL by POP yields TOTALPC (year n). ENTRCUE represents the largest component of annual regional financing and includes the revenue forecasts already discussed above (Cuenca [9]). ENTRCUE provides no data for the Basque Country and Navarre, whereas RNFEN provides no data for Ceuta and Melilla. FECHHA lacks data for the Basque Country, Navarre, Ceuta, and Melilla.

^c Only data from 2009 to 2022 are used because of a lack of homogeneity with the data prior to 2009 following the change in the financing system, “el modelo actualmente vigente se regula en la Ley 22/2009 de 18 de

diciembre (BOE, 2009)” [the model currently in force is regulated by Law 22/2009 of 18 December (BOE, 2009)] [own translation] (De la Fuente [6], p. 1).

^d The data for 2023 and 2024 are provisional (forecast and advance estimate). Unlike the other financing variables used, RNFNE does include data for the Basque Country and Navarre, the two Autonomous Communities with their own financing arrangements, in which the normative capacity to decide their revenues is much greater than that of the other ACs.

^e The public health-care expenditure series is deflated using the implicit deflator of General Government final consumption. This deflator is obtained by dividing FCEGGN by FCEGGV. For example, applying this deflator to the GSANPC series yields GSANPCD. The aim is to empirically assess whether significant differences arise when deflates series are employed. Per capita pharmaceutical expenditure series is also deflated by the underlying CPI: GFARPCPID.

^f Public pharmaceutical expenditure: SNS spending on prescribed medicines dispensed through pharmacies. It does not include the cost of pharmaceutical products that may be supplied directly within health-care institutions (SGIS [45]).

^g Sáenz Royo [2] notes the reform of the co-payment system for medical prescriptions, or outpatient pharmaceutical provision, introduced through Royal Decree-Law 16/2012 of 20 April. This makes it necessary to verify whether the regressions referring to GFARPC are identical for the full data period or whether they yield different results when the series is re-estimated starting in 2013.

^h “Las Administraciones Públicas Sanitarias, en el ámbito de sus respectivas competencias, podrán establecer conciertos para la prestación de servicios sanitarios con medios ajenos a ellas [Public health-care authorities may, within the scope of their respective powers, enter into agreements with external partners for the provision of health-care services]” (Art. 90.1, Spain [1]) [own translation].

ⁱ As noted by Bernal-Delgado et al. [58], health-care expenditure as a percentage of GDP has been rising in Spain, from 6.8% in 2000 to 9.3% in 2019 and 10.8% in 2021, while the share of health-care public spending remained around 71.7% in 2021 (Table 3.1, p. 41).

^j Multiplying the GSANPC series by GSANPRI (divided by 100) yields values in euro per capita: GSANPRIPC. The same applies to GSANATE: GSANATEPC, and to GSANCON: GSANCONPC. Thus, for example, GSANATEPC represents expenditure on specialist services in euro per capita covered.

Table 2. Health-care service data series for Spain’s ACs

Variable	Years	Name	Data source
Operational hospital beds per 1000 inhabitants. ^{ab}	1996–2024	CHO	SGIS [60]
Operational hospital beds per 1000 inhabitants. (% SNS).	1996–2024	CHOSNS	SGIS [61]
^{ab}			
Family medicine – primary care. ^{cd}	2004–2024	MFAP	MinSan [62]
Family medicine – occupational medicine. ^c	2004–2024	MFMT	MinSan [63]
Specialist care nursing staff per 1000 inhabitants.	1996–2024	PENAE	SGIS [64]
Specialist care nursing staff per 1000 inhabitants. (% SNS). ^b	1996–2024	PENAESNS	SGIS [65]
Primary care medical personnel per 1000 assigned individuals. ^c	2004–2024	PMEAP	SGIS [66]
Specialist care medical personnel per 1000 inhabitants.	1996–2024	PMEAE	SGIS [67]
Specialist care medical personnel per 1000 inhabitants. (% SNS). ^b	1996–2024	PMEAESNS	SGIS [68]

Day hospital places per 1000 inhabitants. ^f	1996–2024	PHOD	SGIS [69]
Day hospital places in the SNS per 1000 inhabitants. ^{bf}	1996–2024	PHODSNS	SGIS [70]

^a It is based on the annual average number of beds that were in service (SGIS [60]). “Hasta el año 2009 sólo se contabilizaban los centros de Red de Utilización Pública con finalidades de Hospitales Generales y Especializados (Hospitales de Agudos). A partir del 2010 se contabilizan todos los hospitales de Red de Utilización Pública independientemente de su finalidad. [Until 2009, only Public Use Network centers classified as ‘General and Specialized Hospitals’ (Acute Care Hospitals) were counted. From 2010 onwards, all Public Use Network hospitals are included, regardless of their purpose.]” [own translation] (SGIS [61]).

^b Certain series combine public and private health-care services. For instance, Specialist care nursing staff per 1000 inhabitants (PENAE) includes both sectors. The SNS-specific admission rate (PENAEPUS) can be calculated: $PENAEPUS = PENAE \times PENAESNS / 100$. This method is used to derive public sector series where initial data aggregate both service types. The same approach applies to operational hospital beds in the SNS per 1000 inhabitants (CHOPUS), specialist medical personnel in the SNS per 1000 inhabitants (PMEAEPUS), day hospital places in the SNS per 1000 inhabitants (PHODPUS).

^c “A partir del año 2020, ruptura de serie por revisión de los datos de recursos humanos de Cataluña. Año 2023 provisionales: los datos de profesionales del Principado de Asturias corresponden a los últimos disponibles” [“From 2020 onwards, the series is broken due to a revision of human-resources data for Catalonia. The figures for 2023 are provisional: the data on health-care professionals in the Principality of Asturias correspond to the latest available] [own translation] (SGIS [66]). However, a correction in a single decentralized unit does not seem sufficient to alter the overall results. An additional estimation is therefore performed excluding that unit. Moreover, MFTO represents the total, obtained by summing MFAP and MFMT. Dividing this by POP yields MFAPPC and MFMTPC.

^d “Entre 2004 y 2018, el número de médicas y médicos y de personal de enfermería aumentó casi el doble en los hospitales que en los centros de Atención Primaria [Between 2004 and 2018, the number of doctors and nurses in hospitals increased at almost twice the rate of those in primary care centers]” (Simó Miñana, [71]) [own translation].

^f “Hasta el año 2009 sólo se contabilizaban los centros de Red de Utilización Pública con finalidades de Hospitales Generales y Especializados (Hospitales de Agudos). A partir del 2010 se contabilizan todos los hospitales de Red de Utilización Pública independientemente de su finalidad. [Until 2009, only Public Use Network centers classified as ‘General and Specialized Hospitals’ (Acute Care Hospitals) were counted. From 2010 onwards, all Public Use Network hospitals are included, regardless of their purpose.]” [own translation] (SGIS [70]).

Table 3. Regression results for expenditure and financing variables (Dynamic DKFEM)

Variables, Dynamic DKFEM.				
Observations used in estimation (n = ACs, T = years, N = observations)	Coefficient	Standard error	p-value	Adjusted intra-R ²
GSANPC (dependent variable)/RNFNEPC (independent variable). n = 17, T = 22, N = 357 ^{ab}				
RNFNEPC	0.1126	0.0183	< .0001 ^c	0.9245
Lag (GSANPC, 1)	0.7537	0.0478	< .0001	
GSANPC/ RNFNEPC. n = 17, T = 10, N = 153 (2014–2023)				
RNFNEPC	0.0691	0.0111	< .0001	0.9563

Lag (GSANPC, 1)	0.8870	0.0563	< .0001	
GSANPC / TOTALPC. n = 15, T = 10, N = 135				
TOTALPC	0.1538	0.0361	< .0001	0.9619
Lag (GSANPC, 1)	0.8916	0.0600	< .0001	
GSANPC / ENTRCUEPC. n = 15, T = 10, N = 135 ^b				
ENTRCUEPC	0.2536	0.0318	< .0001	0.9637
Lag (GSANPC, 1)	0.7599	0.0570	< .0001	
GSANPC / FECHHA. n = 15, T = 15, N = 210				
FECHHA	0.1660	0.0755	.0289	0.8482
Lag (GSANPC, 1)	0.7545	0.1712	< .0001	
GSANPC/IME. n = 17, T = 15, N = 238				
IME	0.0895	0.0199	< .0001	0.8671
Lag (GSANPC, 1)	0.5877	0.1217	< .0001	
GSANATEPC/RNFNEPC. n = 17, T = 22, N = 357				
RNFNEPC	0.0606	0.0150	< .0001	0.9186
Lag (GSANATEPC, 1)	0.8026	0.0600	< .0001	
GSANATEPC/RNFNEPC. n = 17, T = 10, N = 153 (2014–2023)				
RNFNEPC	0.0527	0.0107	< .0001	0.9242
Lag (GSANATEPC, 1)	0.7746	0.0648	< .0001	
GSANATEPC/TOTALPC. n = 15, T = 10, N = 135				
TOTALPC	0.1037	0.0319	.0015	0.9295
Lag (GSANATEPC, 1)	0.8002	0.0746	< .0001	
GSANATEPC/ENTRCUEPC. n = 15, T = 10, N = 135				

ENTRCUEPC	0.1744	0.0278	< .0001	0.9352
lag(GSANATEPC, 1)	0.6617	0.0616	< .0001	
GSANATEPC/FECHHA. n = 15, T = 15,				
N = 210				
FECHHA	0.1330	0.0718	.0652	0.7899
lag(GSANATEPC, 1)	0.5964	0.2561	.0208	
GSANATEPC/IME. n = 17, T = 16, N =				
255				
IME	0.0486	0.0167	.0040	0.8257
Lag (GSANATEPC, 1)	0.6447	0.1401	< .0001	
GFARPC/RNFNEPC. n = 17, T = 15, N =				
238 ^d				
RNFNEPC	0.0159	0.0025	< .0001	0.8852
Lag (GFARPC, 1)	0.6911	0.0545	< .0001	
GFARPC/RNFNEPC. n = 17, T = 10, N =				
153 (2014–2023) ^d				
RNFNEPC	0.0031	0.0016	0.0531	0.9706
Lag (GFARPC, 1)	0.9749	0.0347	< .0001	
GFARPC/TOTALPC. n = 17, T = 10, N =				
153 ^d				
TOTALPC			.907	
Lag (GFARPC, 1)			< .0001	
GFARPC/ENTRCUEPC. n = 17, T = 10,				
N = 153 ^d				
ENTRCUEPC			.1759	
Lag (GFARPC, 1)			< .0001	
GFARPC/ FECHHA. n = 15, T = 15, N =				
210				
FECHHA ^d	0.0349	0.0049	< .0001	0.9132
Lag (GFARPC, 1)	0.5339	0.0522	< .0001	

n = 15, T = 11, N = 150 (2013-2024)				
FECHHA ^d	0.0097	0.0012	< .0001	0.9728
Lag (GFARPC, 1)	0.8905	0.0316	< .0001	
GFARPC/IME. n = 19, T = 15, N = 266				
IME	0.0088	0.0022	< .0001	0.8484
Lag (GFARPC, 1)	0.5976	0.1020	< .0001	
n = 19, T = 11, N = 190 (2013-2024)				
IME	0.0008	0.0006	0.169	0.9713
Lag (GFARPC, 1)	1.0030	0.0372	< .0001	
GSANPRIPC/RNFNEPC. n = 17, T = 22, N = 357				
RNFNEPC	0.0171	0.0022	< .0001	0.8801
Lag (GSANPRIPC, 1)	0.7545	0.0397	< .0001	
GSANPRIPC/RNFNEPC. n = 17, T = 10, N = 153 (2014–2024)				
RNFNEPC	0.0231	0.0029	< .0001	0.8579
Lag (GSANPRIPC, 1)	0.6523	0.0560	< .0001	
GSANPRIPC / TOTALPC. n = 15, T = 10, N = 135				
TOTALPC	0.0368	0.0070	< .0001	0.8323
Lag (GSANPRIPC, 1)	0.7461	0.0760	< .0001	
GSANPRIPC / ENTRCUEPC n = 15, T = 10, N = 135				
ENTRCUEPC	0.0529	0.0054	< .0001	0.8416
Lag (GSANPRIPC, 1)	0.6213	0.0398	< .0001	
GSANPRIPC / FECHHA. n = 15, T = 10, N = 135				
FECHHA	0.0288	0.0083	.0007	0.7502
Lag (GFARPC, 1)	0.6680	0.1026	< .0001	
GSANPRIPC/IME. n = 17, T = 16, N =				

255				
IME	0.0122	0.0025	< .0001	0.7630
Lag (GFARPC, 1)	0.6027	0.0945	< .0001	
ENTRCUEPC/IME. n = 17, T = 10, N =				
153				
IME	0.0413	0.0151	.0069	0.9516
Lag (ENTRCUEPC, 1)	0.9240	0.1104	< .0001	
GSANPC / ENTRCUEPC, IME. n = 15, T				
= 10, N = 135				
ENTRCUEPC	0.2041	0.0262	< .0001	0.9652
IME	0.0206	0.0075	.0072	
Lag (GSANPC, 1)	0.7122	0.0647	< .0001	

^a Table A1, note c: the empirical data implying the falsation of the hypotheses of the FE panel regression. Table A1, note b: panel regressions exhibit strong serial correlation and cross-sectional dependence. Moreover, related to the FE dynamic panel without Driscoll–Kraay: GSANPC / RNFNEPC + lag(GSANPC, 1), the diagnostic tests reveal multiple violations of classical assumptions. To reflect the magnitude of the assumption violations, extremely small p-values are reported in full. Normality is rejected by the Jarque–Bera test ($\chi^2 = 1105.7$, $df = 2$, $p < 2.2 \times 10^{-16}$). Homoskedasticity is rejected by the Breusch–Pagan test (BP = 36.844, $df = 2$, $p = 9.99 \times 10^{-9}$). Serial correlation is present according to the Breusch–Godfrey/Wooldridge test for panel models ($\chi^2 = 49.754$, $df = 21$, $p = .0004$). Cross-sectional dependence is strongly indicated by the Pesaran CD test ($z = 13.039$, $p < 2.2 \times 10^{-16}$). Taken together, these violations justify the use of Driscoll–Kraay standard errors.

^b The difference between the full data period and the period excluding the years 2020 and 2021 due to the impact of the COVID-19 pandemic is minimal:

GSANPC / RNFNEPC: coefficient = 0.1158, SE = 0.0178, $p < .0001$.

GSANPC / lag(GSANPC, 1): coefficient = 0.7366, SE = 0.0496, $p < .0001$.

^c For reference, some diagnostic tests produced extremely small p-values (e.g., $p = 2.178 \times 10^{-9}$).

^d Ceuta and Melilla do not have responsibilities for pharmaceutical expenditure.

Table 4. Relationship between health-care expenditure and sanitary personnel (IV panel methods, with DKFEM estimation of covariances)

Variables. Periods.	Coefficien t	Standard error	p-value	Hausman Test (p- value)	Adjusted R ² (intra)
PMEAE (dep.var.) ~ GSANPC (indep. var.) ENTRCUEPC (instrument) ^a					
n = 15, T = 10, N = 150	0.0006	< .0001	< .0001	< .0001	0.7924

PMEA ~ GSANPC					
RNFNEPC					
n = 17, T = 22, N = 374	0.0007	< .0001	< .0001	.0135	0.7657
PMEA ~ GSANPC					
ENTRCUEPC					
n = 15, T = 10, N = 150	0.0006	< .0001	< .0001	< .0001	0.7744
PMEA ~ GSANPC					
RNFNEPC					
n = 17, T = 22, N = 374	0.0007	< .0001	< .0001	.0622	0.7630
PENAE ~ GSANPC					
ENTRCUEPC					
n = 15, T = 10, N = 150	0.0013	0.0001	< .0001	< .0001	0.7369
PENAE ~ GSANPC					
RNFNEPC					
n = 17, T = 22, N = 374	0.0017	0.0002	< .0001	< .0001	0.6809
PENAE ~ GSANPC					
ENTRCUEPC					
n = 15, T = 10, N = 150	0.0013	0.0001	< .0001	< .0001	0.7099
PENAE ~ GSANPC					
RNFNEPC					
n = 17, T = 22, N = 374	0.0017	0.0002	< .0001	< .0001	0.64551
PMEA ~ GSANATEPC					
ENTRCUEPC					
n = 15, T = 10, N = 150	0.0010	< .0001	< .0001	.3158	0.8010
PMEA ~ GSANATEPC					
RNFNEPC					
n = 17, T = 22, N = 374	0.0010	< .0001	< .0001	.0061	0.8012
PMEA ~ GSANATEPC					
ENTRCUEPC					
n = 15, T = 10, N = 150	0.0009	< .0001	< .0001	.5739	0.7906

PMEAEP ~ GSANATEPC					
RNFNEPC					
n = 17, T = 22, N = 374	0.0010	< .0001	< .0001	.0648	0.8084
PENAE ~ GSANATEPC					
ENTRCUEPC					
n = 15, T = 10, N = 150	0.0022	0.0002	< .0001	.2646	0.7479
PENAE ~ GSANATEPC					
RNFNEPC					
n = 17, T = 22, N = 374	0.0024	0.0002	< .0001	< .0001	0.71667
PENAEP ~ GSANATEPC					
ENTRCUEPC					
n = 15, T = 10, N = 150	0.0021	0.0002	< .0001	.7590	0.7221
PENAEP ~ GSANATEPC					
RNFNEPC					
n = 17, T = 22, N = 374	0.0023	0.0002	< .0001	< .0001	0.6850
PMEAP ~ GSANPC					
ENTRCUEPC					
n = 15, T = 10, N = 150	0.00004	< .0001	< .0001	< .0001	0.1158
PMEAP ~ GSANPC					
RNFNEPC					
n = 17, T = 22, N = 374	0.0001	< .0001	< .0001	.0433	0.3298
MFAPPC ~ GSANPC					
ENTRCUEPC					
(n = 15, T = 10, N = 150	5.1006e-				
	08	< .0001	< .0001	< .0001	0.3138
MFAPPC ~ GSANPC					
RNFNEPC					
n = 17, T = 20, N = 340	9.3552e-				
	08	< .0001	< .0001	.0883	0.4529

^a The difference between the full data period and the period excluding the years 2020 and 2021 due to the impact of the COVID-19 pandemic is minimal: coefficient = 0.0006, St. error < .0001, $p < .0001$, Adjusted $R^2 = 0.8392$.

^b Comparison of the estimations with and without Catalonia (Table 2, note c), coefficients expressed in scientific notation to make comparison easier:

PMEAP ~ GSANPC | ENTRCUEPC, coefficient = 3.4842e-05, $p = 3.079e-10$, Hausman Test (p-value) < 2.2e-16. (without Catalonia)

PMEAP ~ GSANPC | RNFNEPC, coefficient = 7.3777e-05, $p = 1.484e-05$, Hausman Test (p-value) 0.0577. (without Catalonia)

PMEAP ~ GSANPC | ENTRCUEPC, coefficient = 3.6414e-05, $p = 2.19e-10$, Hausman Test (p-value) < 2.2e-16. (with Catalonia)

PMEAP ~ GSANPC | RNFNEPC, coefficient = 7.4511e-05, $p = 2.547e-05$, Hausman Test (p-value) 0.04331. (with Catalonia)

Table 5. Regression results for expenditure and financing variables (Dynamic DKFEM)

Variables. Observations used in estimation (n = ACs, T = years, N = observations)	Coefficient	Standard error	p-value	Adjusted intra-R ²
PMEAE (dependent variable)/GSANPC				
(independent variable). n = 17, T = 21, N = 340 ^{ab}				
GSANPC	0.0002	< 0.0001	.0001	0.9194
Lag (PMEAE, 1)	0.7950	0.0488	< .0001	
PMEAE/GSANPCD. n = 17, T = 21, N = 340 ^a				
GSANPCD	0.0002	< .0001	< .0001	0.9174
Lag (PMEAE, 1)	0.8447	0.0372	< .0001	
PMEAE/GSANATEPC. n = 17, T = 21, N = 340				
GSANATEPC	0.0002	0.0001	.0002	0.9186
Lag (PMEAE, 1)	0.7772	0.0538	< .0001	
PMEAE/GSANATEPCD. n = 17, T = 21, N = 340				
GSANATEPCD	0.0003	0.0001	.0003	0.9157
Lag (PMEAE, 1)	0.8265	0.0418	< .0001	
PMEAEPU / GSANPC. n = 17, T = 21, N = 340				
GSANPC	0.0001	< .0001	< .0001	0.9313
Lag (PMEAEPU, 1)	0.8048	0.0420	< .0001	
PMEAEPU / GSANPCD. n = 17, T = 21, N = 340				

GSANPCD	0.0002	< .0001	< .0001	0.9301
Lag (PMEAEP, 1)	0.8457	0.0335	< .0001	
PMEAEP / GSANATEPC. n = 17, T = 21, N =				
340				
GSANATEPC	0.0002	< .0001	< .0001	0.9304
Lag (PMEAEP, 1)	0.7837	0.0451	< .0001	
PMEAEP / GSANATEPCD. n = 17, T = 21, N				
= 340				
GSANATEPCD	0.0002	0.0001	< .0001	0.9282
Lag (PMEAEP, 1)	0.8245	0.0352	< .0001	
PENAE / GSANPC. n = 17, T = 21, N = 340				
GSANPC	0.0004	0.0002	.0037	0.8468
Lag (PENAE, 1)	0.7385	0.0768	< .0001	
PENAE / GSANPCD. n = 17, T = 21, N = 340				
GSANPCD	0.0007	0.0003	.0114	0.8453
Lag (PENAE, 1)	0.7831	0.0735	< .0001	
PENAE / GSANATEPC. n = 17, T = 21, N = 340				
GSANPC	0.0007	0.0002	.0038	0.8514
Lag (PENAE, 1)	0.6997	0.0860	< .0001	
PENAE / GSANATEPCD. n = 17, T = 21, N =				
340				
GSANPC	0.0010	0.0004	.0105	0.8508
Lag (PENAE, 1)	0.7339	0.0832	< .0001	
PENAEP / GSANPC. n = 17, T = 21, N = 340				
GSANPC	0.0004	0.0001	.0017	0.8474
Lag (PENAEP, 1)	0.7607	0.0697	< .0001	
PENAEP / GSANPCD. n = 17, T = 21, N = 340				
GSANPCD	0.0006	0.0002	.0046	0.8472
Lag (PENAE, 1)	0.7919	0.0688	< .0001	
PENAEP / GSANATEPC. n = 17, T = 21, N =				

340				
GSANATEPC	0.0006	0.0002	.0022	0.8512
Lag (PENAE, 1)	0.7268	0.0771	< .0001	
PENAEP / GSANATEPCD. n = 17, T = 21, N =				
340				
GSANATEPCD	0.0009	0.0003	.0059	0.8517
Lag (PENAE, 1)	0.7479	0.0757	< .0001	
PMEAP / GSANPC. n = 17, T = 18, N = 306 ^c				
GSANPC	0.00002	< .0001	< .0001	0.6878
Lag (PMEAP, 1)	0.6988	0.0391	< .0001	
PMEAP / GSANPCD. n = 17, T = 18, N = 306 ^c				
GSANPCD	0.00003	< .0001	.0003	0.6831
Lag (PMEAP, 1)	0.7193	0.0415	< .0001	
MFAPPC / GSANPC. n = 17, T = 18, N = 306				
GSANPC	1.8799e-08	< .0001	.0002	0.8410
Lag (MFAPPC, 1)	0.7702	0.0239	< .0001	
MFAPPC / GSANPCD. n = 17, T = 18, N =				
306				
GSANPCD	2.4098e-08	< .0001	.0138	0.8367
Lag (MFAPPC, 1)	0.7952	0.0221	< .0001	

^a The static DKFEM results are In Table A2. The difference between the static and dynamic coefficients, together with the significance of the lagged dependent variable, shows that the static specification attributes to the independent variable an effect that is, in reality, driven by temporal inertia.

^b The difference between the full data period and the period excluding the years 2020 and 2021 due to the impact of the COVID-19 pandemic is minimal:

GSANPC: coefficient = 1.4553e-04, St.error = 3.5726e-05, p .0001

lag(PMEAE, 1) 0.7867, St.error = 0.0550, p < 2.2e-16.

However, the temporal structure has changed, t-3 is now for 2022 t-1.

^c Comparison of the estimations with and without Catalonia (Table 2, note c), coefficients expressed in scientific notation to make comparison easier:

PMEAP ~ GSANPC + lag(PMEAP,1), coefficient (GSANPC) = 2.3290e-05, p 4.013e-05. (without Catalonia)

PMEAP ~ GSANPCD + lag(PMEAP,1), coefficient (GSANPCD) = 3.4732e-05, p = .0002662. (without Catalonia)

PMEAP ~ GSANPC + lag(PMEAP,1), coefficient (GSANPC) = 2.3039e-05, p 3.837e-05. (with Catalonia)

PMEAP ~ GSANPCD + lag(PMEAP,1), coefficient (GSANPCD) = 3.3753e-05, p = .000347. (with Catalonia)

Table 6. Relationship between health-care expenditure and health-care recourses (IV panel methods, with DKFEM estimation of covariances)

Variables. Periods.	Coefficient	Standard error	<i>p</i> -value	Hausman Test (p-value)	Adjusted R ² (intra)
CHO (dependent variable) ~					
GSANPC (independent variable)					
ENTRCUEPC (instrument)					
n = 15, T = 10, N = 150	-0.0001	4.0108e-05	.1028	< .0001	-0.0774
CHO ~ GSANPC RNFNEPC					
n = 17, T = 22, N = 374	-0.0005	0.0001	< .0001	.4403	0.3601
Without data from 2000 to 2009. n =					
17, T = 14, N = 238 ^a	-0.0002	0.0001	.015	< .0001	-0.0166
CHO ~ GSANATEPC					
ENTRCUEPC					
n = 15, T = 10, N = 150	-0.0001	0.0001	.1204	< .0001	-0.0839
CHO ~ GSANATEPC RNFNEPC					
n = 17, T = 22, N = 374	-0.0006	0.0001	< .0001	.0322	0.4287
Without data from 2000 to 2009. n =					
17, T = 14, N = 238 ^a	-0.0003	0.0001	.0071	.0025	0.0193
CHOPU ~ GSANPC					
ENTRCUEPC					
n = 15, T = 10, N = 150	0.0002	2.4896e-05	< .0001	< .0001	0.0642
CHOPU ~ GSANPC RNFNEPC					
n = 17, T = 22, N = 374	9.8444e-06	0.0001	.8813	.1156	-0.0485
Without data from 2000 to 2009. n =					
17, T = 14, N = 238 ^a	0.0001	3.8906e-05	.0045	.0501	0.0155
CHOPU ~ GSANATEPC					
ENTRCUEPC					
n = 15, T = 10, N = 150.	0.0003	4.0266e-05	< .0001	< .0001	0.05105
CHOPU ~ GSANATEPC					
RNFNEPC					
n = 17, T = 22, N = 374	2.1881e-05	0.0001	.8025	.1118	-0.0468

Without data from 2000 to 2009. n =					
17, T = 14, N = 238 ^a	0.0002	0.0001	.01306	.7265	-0.0194
PHOD ~ GSANPC ENTRCUEPC					
n = 15, T = 10, N = 150	0.0001	1.1021e-05	< .0001	< .0001	0.2591
PHOD ~ GSANPC RNFNEPC					
n = 17, T = 22, N = 374	0.0003	3.4803e-05	< .0001	.7662	0.5150
Without data from 2000 to 2009. n =					
17, T = 14, N = 238 ^a	0.0002	0.0001	.0001	< .0001	0.2358
PHOD ~ GSANATEPC					
ENTRCUEPC					
n = 15, T = 10, N = 150	0.0002	< .0001	< .0001	< .0001	0.2579
PHOD ~ GSANATEPC RNFNEPC					
n = 17, T = 22, N = 374	0.0004	< .0001	< .0001	.0080	0.6278
Without data from 2000 to 2009. n =					
17, T = 14, N = 238 ^a	0.0003	0.0001	< .0001	.0114	0.3129
PHODPU ~ GSANPC					
ENTRCUEPC					
n = 15, T = 10, N = 150	0.0001	< .0001	< .0001	< .0001	0.2049
PHODPU ~ GSANPC RNFNEPC					
n = 17, T = 22, N = 374	0.0003	< .0001	< .0001	.4950	0.4837
Without data from 2000 to 2009. n =					
17, T = 14, N = 238 ^a	0.0002	< .0001	.0001	< .0001	0.21905
PHODPU ~ GSANATEPC					
ENTRCUEPC					
n = 15, T = 10, N = 150	0.0002	< .0001	< .0001	< .0001	0.18856
PHODPU ~ GSANATEPC					
RNFNEPC					
n = 17, T = 22, N = 374	0.0004	< .0001	< .0001	.0024	0.5959
Without data from 2000 to 2009. n =					
17, T = 14, N = 238 ^a	0.0003	0.0001	< .0001	.0034	0.2740

^a See notes a and f of Table 2. Owing to the possible heterogeneity of the data series, the estimation is also performed for the period starting in 2010 and compared with the estimation based on the full series.

Table 7. Regression results for expenditure and financing variables (Dynamic DKFEM)

Variables. Observations used in estimation (n = ACs, T = years, N = observations)	Coefficient	Standard error	p-value	Adjusted intra-R ²
CHO (dependent variable) ~ GSANPC (independent variable). n = 17, T = 22, N = 357 ^a				
GSANPC			.0553	
Lag (CHO, 1)			< .0001	
CHO ~ GSANPC. n = 17, T = 14, N = 221 (2010– 2024)				
GSANPC			.4752	
Lag (CHO, 1)			< .0001	
CHO ~ GSANPCD. n = 17, T = 22, N = 357.				
GSANPCD			.1457	
Lag (CHO, 1)			< .0001	
CHO ~ GSANPCD. n = 17, T = 14, N = 221 (2010– 2024)				
GSANPCD			.707	
Lag (CHO, 1)			< .0001	
CHO ~ GSANATEPC. n = 17, T = 22, N = 357 ^a				
GSANATEPC			.0869	
Lag (CHO, 1)			< .0001	
CHO ~ GSANATEPC. n = 17, T = 14, N = 221 (2010–2024)				
GSANATEPC			.6539	
Lag (CHO, 1)			< .0001	
CHO ~ GSANATEPCD. n = 17, T = 22, N = 357.				
GSANATEPCD			.1993	
Lag (CHO, 1)			< .0001	

CHO ~ GSANATEPCD. n = 17, T = 14, N = 221				
(2010–2024)				
GSANATEPCD			.9429	
Lag (CHO, 1)			< .0001	
CHOPU ~ GSANPC. n = 17, T = 22, N = 357.				
GSANPC	0.00005	< .0001	.0002	0.6202
Lag (CHOPU, 1)	0.7782	0.0865	< .0001	
CHOPU ~ GSANPC. n = 17, T = 14, N = 221				
(2010–2024)				
GSANPC	0.0001	< .0001	.0001	0.3498
Lag (CHOPU, 1)	0.5785	0.0276	< .0001	
CHOPU ~ GSANPCD. n = 17, T = 22, N = 357. ^b				
GSANPCD	0.0001	< .0001	< .0001	0.6200
Lag (CHOPU, 1)	0.7765	0.0857	< .0001	
CHOPU ~ GSANPCD. n = 17, T = 14, N = 221				
(2010–2024)				
GSANPCD	0.0002	< .0001	< .0001	0.3499
Lag (CHOPU, 1)	0.5828	0.0287	< .0001	
CHOPU ~ GSANATEPC. n = 17, T = 22, N = 357.				
GSANATEPC	0.0001	< .0001	.0004	0.6201
Lag (CHOPU, 1)	0.7783	0.0872	< .0001	
CHOPU ~ GSANATEPC. n = 17, T = 14, N = 221				
(2010–2024)				
GSANATEPC	0.0001	< .0001	.0004	0.3424
Lag (CHOPU, 1)	0.5923	0.0276	< .0001	
CHOPU ~ GSANATEPCD. n = 17, T = 22, N = 357. ^b				
GSANATEPCD	0.0001	< .0001	.0004	0.6200
Lag (CHOPU, 1)	0.7779	0.0871	< .0001	
CHOPU ~ GSANATEPCD. n = 17, T = 14, N =				

221 (2010–2024)				
GSANATEPCD	0.0002	0.0001	.0009	0.3375
Lag (CHOPU, 1)	0.0006	0.0278	< .0001	
PHOD ~ GSANPC. n = 17, T = 22, N = 357				
GSANPC	0.00004	< .0001	.0024	0.8917
Lag (PHOD, 1)	0.8471	0.0410	< .0001	
PHOD ~ GSANPC. n = 17, T = 14, N = 221 (2010–2024)				
GSANPC	0.0001	< .0001	.0016	0.6088
Lag (PHOD, 1)	0.6252	0.0807	< .0001	
PHOD ~ GSANPCD. n = 17, T = 22, N = 357				
GSANPCD	0.0001	< .0001	.0097	0.8905
Lag (PHOD, 1)	0.8665	0.0385	< .0001	
PHOD ~ GSANPCD. n = 17, T = 14, N = 221 (2010–2024)				
GSANPCD	0.0001	< .0001	.0091	0.5996
Lag (PHOD, 1)	0.6557	0.0745	< .0001	
PHOD ~ GSANATEPC. n = 17, T = 22, N = 357				
GSANATEPC	0.0001	< .0001	.0001	0.8939
Lag (PHOD, 1)	0.8119	0.0412	< .0001	
PHOD ~ GSANATEPC. n = 17, T = 14, N = 221 (2010–2024)				
GSANATEPC	0.0001	< .0001	.0004	0.6108
Lag (PHOD, 1)	0.6112	0.0786	< .0001	
PHOD ~ GSANATEPCD. n = 17, T = 22, N = 357				
GSANATEPCD	0.0001	< .0001	< .0001	0.8938
Lag (PHOD, 1)	0.8154	0.0382	< .0001	
PHOD ~ GSANATEPCD. n = 17, T = 14, N = 221 (2010–2024)				

GSANATEPCD	0.0001	< .0001	.0031	0.5998
Lag (PHOD, 1)	0.6469	0.0698	< .0001	
PHODPU ~ GSANPC. n = 17, T = 22, N = 357				
GSANPC	< .0001	< .0001	.0030	0.8801
Lag (PHODPU, 1)	0.8653	0.0534	< .0001	
PHODPU ~ GSANPC. n = 17, T = 14, N = 221				
(2010–2024)				
GSANPC	0.0001	< .0001	.0001	0.5164
Lag (PHODPU, 1)	0.6041	0.0745	< .0001	
PHODPU ~ GSANPCD. n = 17, T = 22, N = 357				
GSANPC	0.0001	2.6401e-05	.0211	0.8777
Lag (PHODPU, 1)	0.8909	0.0510	< .0001	
PHODPU ~ GSANPCD. n = 17, T = 14, N = 221				
(2010–2024)				
GSANPC	0.0001	< .0001	.0098	0.5002
Lag (PHODPU, 1)	0.6450	0.0705	< .0001	
PHODPU ~ GSANATEPC. n = 17, T = 22, N = 357 °				
GSANATEPC	0.0001	< .0001	.0011	0.8812
Lag (PHODPU, 1)	0.8361	0.0570	< .0001	
PHODPU ~ GSANATEPC. n = 17, T = 14, N = 221 (2010–2024)				
GSANATEPC	0.0001	< .0001	.0002	0.5126
Lag (PHODPU, 1)	0.5985	0.0701	< .0001	
PHODPU ~ GSANATEPCD. n = 17, T = 22, N = 357				
GSANATEPC	0.0001	< .0001	.0033	0.8795
Lag (PHODPU, 1)	0.8487	0.0560	< .0001	
PHODPU ~ GSANATEPCD. n = 17, T = 14, N = 221 (2010–2024)				

GSANATEPC	0.0001	< .0001	.0106	0.4935
Lag (PHODPU, 1)	0.6473	0.0658	< .0001	

^a The difference between the static and dynamic coefficients, together with the significance of the lagged dependent variable, shows that the static specification attributes to the independent variable an effect that is driven by temporal inertia.

^b CHOPU ~ GSANCONPC + lag(CHOPU, 1); GSANCONPC: $p = .6778$.

^c Without 2020–2021 ($n = 17$, $T = 19$, $N = 323$): PHODPU ~ GSANATEPC + lag(PHODPU,1).

GSANATEPC: coefficient = 0.0001, SE = < .0001, $p = .0011$.

lag(PHODPU,1): coefficient = 0.8317, SE = 0.0592, $p < .0001$.

Adj. $R^2 = 0.8801$.

Table 8. Regression results for expenditure and financing variables (Dynamic DKFEM)

Variables. Observations used in estimation (n = ACs, T = years, N = observations)	Coefficient	Standard error	p-value	Adjusted intra- R^2
GFARPC (dependent variable)/PMEAE (independent variable). $n = 19$, $T = 15$, $N = 266$ ^a				
PMEAE	77.2581	14.7810	< .0001	0.8823
Lag (GFARPC, 1)	0.6625	0.0747	< .0001	
$n = 19$, $T = 12$, $N = 211$ (2013–2023) ^b				
PMEAE	12.7226	4.0478	0.0019	0.9725
Lag (GFARPC, 1)	0.9817	0.0173	< .0001	
GFARPCD/PMEAE. $n = 19$, $T = 15$, $N = 266$				
PMEAE	34.9291	8.9628	.0001	0.7338
Lag (GFARPCD, 1)	0.5801	0.0500	< .0001	
$n = 19$, $T = 12$, $N = 211$ (2013–2023)				
PMEAE	8.7293	4.2525	0.0415	0.8540
Lag (GFARPCD, 1)	0.7776	0.0503	< .0001	
GFARPCCPID/PMEAE. $n = 19$, $T = 12$, $N = 211$ (2013–2023)				
PMEAE	9.7141	3.5622	0.0072	0.9658
Lag (GFARPCCPID, 1)	0.8953	0.0205	< .0001	
GFARPC/PMEAEPU. $n = 19$, $T = 15$, $N = 266$				

PMEAPU	78.5015	15.8201	< .0001	0.8736
Lag (GFARPC, 1)	0.6777	0.0770	< .0001	
n = 19, T = 12, N = 211 (2013-2023)				
PMEAEPU	12.6464	4.2109	0.0030	0.9724
Lag (GFARPC, 1)	0.9858	0.0183	< .0001	
GFARPCD/PMEAEPU. n = 19, T = 15, N =				
266				
PMEAPU	35.7563	9.4306	.0002	0.7234
Lag (GFARPCD, 1)	0.5834	0.0507	< .0001	
n = 19, T = 12, N = 211 (2013-2023)				
PMEAEPU	9.0361	4.3162	0.0377	0.8540
Lag (GFARPCD, 1)	0.7795	0.0508	< .0001	
GFARPCCPID/PMEAEPU. n = 19, T = 12,				
N = 211 (2013-2023)				
PMEAEPU	10.0427	3.6396	0.0065	0.9659
Lag (GFARPCCPID, 1)	0.8971	0.022506	< .0001	
GFARPC/PENAE. n = 19, T = 15, N = 266				
PENAE	23.1185	7.3061	.0018	0.8496
Lag (GFARPC, 1)	0.7398	0.1063	< .0001	
n = 19, T = 12, N = 211 (2013-2023)				
PENAE	1.7753	1.7075	0.2998	0.9713
Lag (GFARPC, 1)	1.0238	0.0173	< .0001	
GFARPCD/PENAE. n = 19, T = 15, N = 266				
PENAE	11.1520	3.5347	.0018	0.6979
Lag (GFARPCD, 1)	0.5934	0.0494	< .0001	
n = 19, T = 12, N = 211 (2013-2023)				
PENAE	1.1679	1.2612	0.3556	0.8476
Lag (GFARPCD, 1)	0.8274	0.0480	< .0001	
GFARPC/PENAEPU. n = 19, T = 15, N =				
266				

PENAEPU	22.2544	7.2707	.0025	0.8410
Lag (GFARPC, 1)	0.7549	0.1085	< .0001	
n = 19, T = 12, N = 211 (2013-2023)				
PENAEPU	1.7634	1.6311	0.281	0.9713
Lag (GFARPC, 1)	1.0246	0.0166	< .0001	
GFARPCD/PENAEPU. n = 19, T = 15, N =				
266				
PENAEPU	10.8933	3.5162	.0022	0.6890
Lag (GFARPCD, 1)	0.5962	0.0506	< .0001	
n = 19, T = 12, N = 211 (2013-2023)				
PENAEPU	1.2287	1.2137	0.3126	0.8478
Lag (GFARPCD, 1)	0.8270	0.0483	< .0001	
GFARPC/PMEAP. n = 19, T = 15, N = 266				
c				
PMEAP	159.7036	73.4623	.0307	0.7451
Lag (GFARPC, 1)	0.9148	0.1292	< .0001	
n = 19, T = 12, N = 211 (2013-2023) ^b				
PMEAP	-23.7089	10.6629	0.0274	0.9711
Lag (GFARPC, 1)	1.0535	0.0175	< .0001	
GFARPCD/PMEAP. n = 19, T = 15, N =				
266				
PMEAP	78.2301	33.1698	.0191	0.5670
Lag (GFARPCD, 1)	0.6240	0.0862	< .0001	
n = 19, T = 12, N = 211 (2013-2023)				
PMEAP	-6.8197	14.0618	0.6283	0.8464
Lag (GFARPCD, 1)	0.8570	0.0475	< .0001	
GFARPC/PHOD. n = 19, T = 15, N = 266				
PHOD	119.3757	29.1133	.0001	0.8107
Lag (GFARPC, 1)	0.8605	0.0906	< .0001	
n = 19, T = 12, N = 211 (2013-2023)				

PHOD	13.8473	3.5804	0.0002	0.9714
Lag (GFARPC, 1)	1.0292	0.0188	< .0001	
GFARPCD/PHOD. n = 19, T = 15, N = 266				
PHOD	62.5739	17.3100	.0004	0.6475
Lag (GFARPCD, 1)	0.6363	0.0539	< .0001	
n = 19, T = 12, N = 211 (2013-2023)				
PHOD	12.6031	4.6551	0.0074	0.8492
Lag (GFARPCD, 1)	0.8256	0.0457	< .0001	
GFARPCCPID/PHOD. n = 19, T = 12, N = 211 (2013-2023)				
PHOD	17.1700	3.1782	< .0001	0.9660
Lag (GFARPCCPID, 1)	0.9276	0.0227	< .0001	
GFARPC/PHODPU. n = 19, T = 15, N = 266				
PHODPU	108.5482	31.0600	.0006	0.8014
Lag (GFARPC, 1)	0.8521	0.0991	< .0001	
n = 19, T = 12, N = 211 (2013-2023)				
PHODPU	10.1346	3.3736	0.0030	0.9712
Lag (GFARPC, 1)	1.0321	0.0207	< .0001	
GFARPCD/PHODPU. n = 19, T = 15, N = 266				
PHODPU	58.8085	16.0019	.0003	0.6445
Lag (GFARPCD, 1)	0.6240	0.0546	< .0001	
n = 19, T = 12, N = 211 (2013-2023)				
PHODPU	13.8254	3.9529	0.0006	0.8506
Lag (GFARPCD, 1)	0.8196	0.0472	< .0001	
GFARPCCPID/PHODPU. n = 19, T = 12, N = 211 (2013-2023)				
PHODPU	12.8444	3.8724	0.0011	0.9653
Lag (GFARPCCPID, 1)	0.9314	0.0250	< .0001	

GFARPC/CHO. n = 19, T = 15, N = 266				
CHO	-41.2794	17.5130	.0192	0.7586
Lag (GFARPC, 1)	0.9358	0.1119	< .0001	
n = 19, T = 12, N = 211 (2013-2023)				
CHO	0.4833	3.0570	0.8745	0.9708
Lag (GFARPC, 1)	1.0462	0.0196	< .0001	
GFARPCD/CHO. n = 19, T = 15, N = 266				
CHO	-17.3986	6.1879	.0053	0.5724
Lag (GFARPCD, 1)	0.6446	0.0862	< .0001	
n = 19, T = 12, N = 211 (2013-2023)				
CHO	-3.7160	2.8671	0.1965	0.8471
Lag (GFARPCD, 1)	0.8477	0.0516	< .0001	
GFARPC/CHOPU. n = 19, T = 15, N = 266				
CHOPU	15.1378	8.3196	.0701	0.7365
Lag (GFARPC, 1)	0.9219	0.1386	< .0001	
n = 19, T = 12, N = 211 (2013-2023)				
CHOPU	1.1942	2.7333	0.6627	0.9709
Lag (GFARPC, 1)	1.0437	0.0197	< .0001	
GFARPCD/CHOPU. n = 19, T = 15, N = 266				
CHOPU	24.2487	7.8188	.0022	0.5892
Lag (GFARPCD, 1)	0.5803	0.0847	< .0001	
n = 19, T = 12, N = 211 (2013-2023)				
CHOPU	6.8091	1.6863	.0001	0.8495
Lag (GFARPCD, 1)	0.8297	0.0522	< .0001	
GFARPCCPID/CHOPU. n = 19, T = 12, N = 211 (2013-2023)				
CHOPU	2.2469	2.5426	0.3783	0.9643
Lag (GFARPCCPID, 1)	0.9483	0.0244	< .0001	

879 ^a The difference between the static and dynamic coefficients, together with the significance of the lagged
880 dependent variable, shows that the static specification attributes to the independent variable an effect that is
881 driven by temporal inertia.
882 ^b Table 1, note g.
883 ^c Regressions estimated omitting Catalonia (Table 2, note c):
884 GFARPC ~ PMEAP + lag(GFARPC,1), coefficient (GFARPC) = 156.6086, p = .0351.
885 GFARPC ~ PMEAP + lag(GFARPC,1), 2013-2023, coefficient (GFARPC) = -20.8512, p = .1096.

Figures

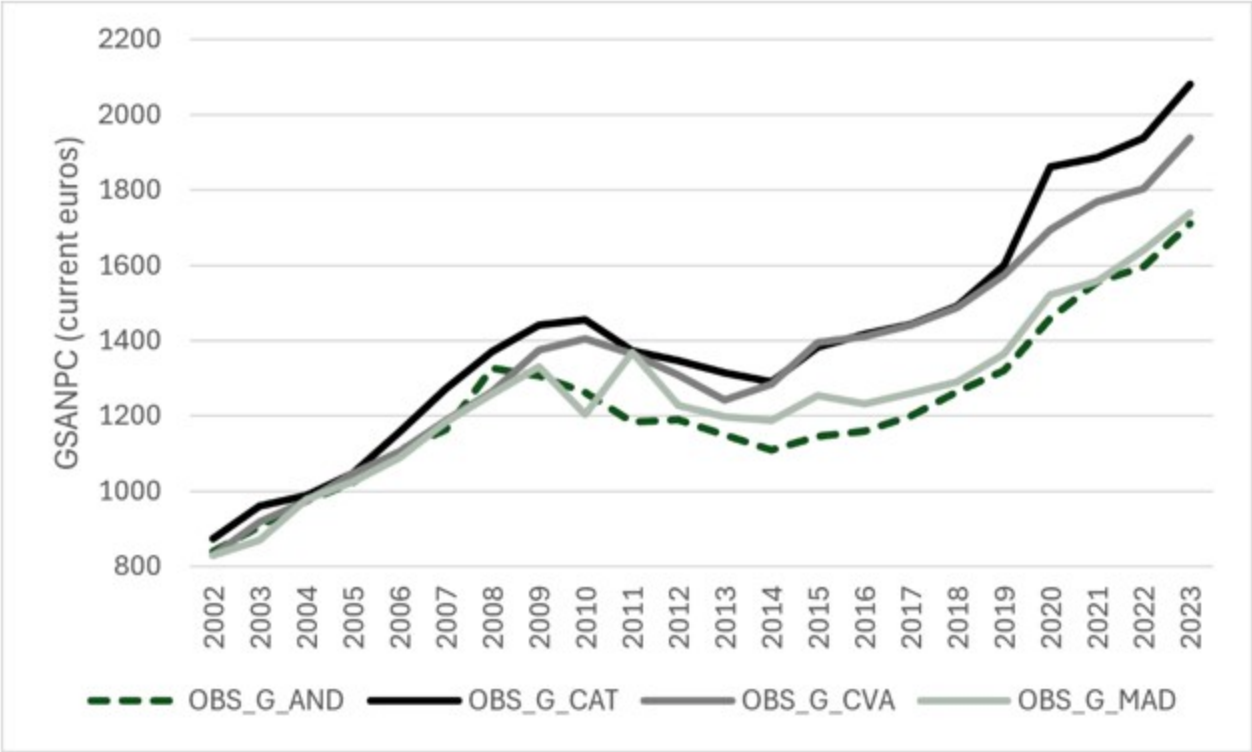


Figure 1

Observed GSANPC. Andalusia: OBS_G_AND, Catalonia: OBS_G_CAT. Madrid (Community): OBS_G_MAD. Valencian Community: OBS_G_CVA[1].

[1] GSANPC: Public healthcare expenditure by ACs, per capita covered. Euro per capita at current prices (Table 1).

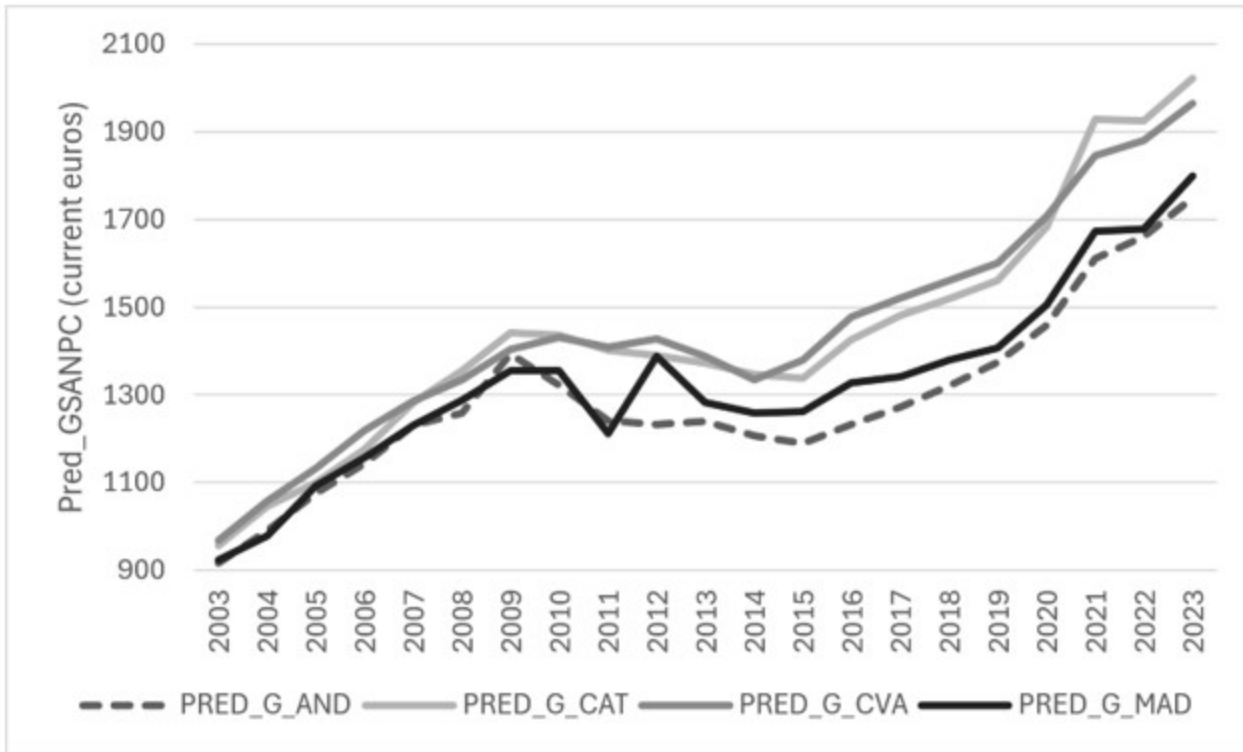


Figure 2

Predicted values of GSANPC based on average RNFNEPC of ACs and estimated coefficients (Table 3). Andalusia: PRED_G_AND, Catalonia: PRED_G_CAT. Madrid (Community): PRED_G_CVA. Valencian Community: PRED_G_MAD[1].

[1] RNFNEPC: Net non-financial resources, including net transfers from other public authorities. Million euro at current prices (per capita) (Table 1).

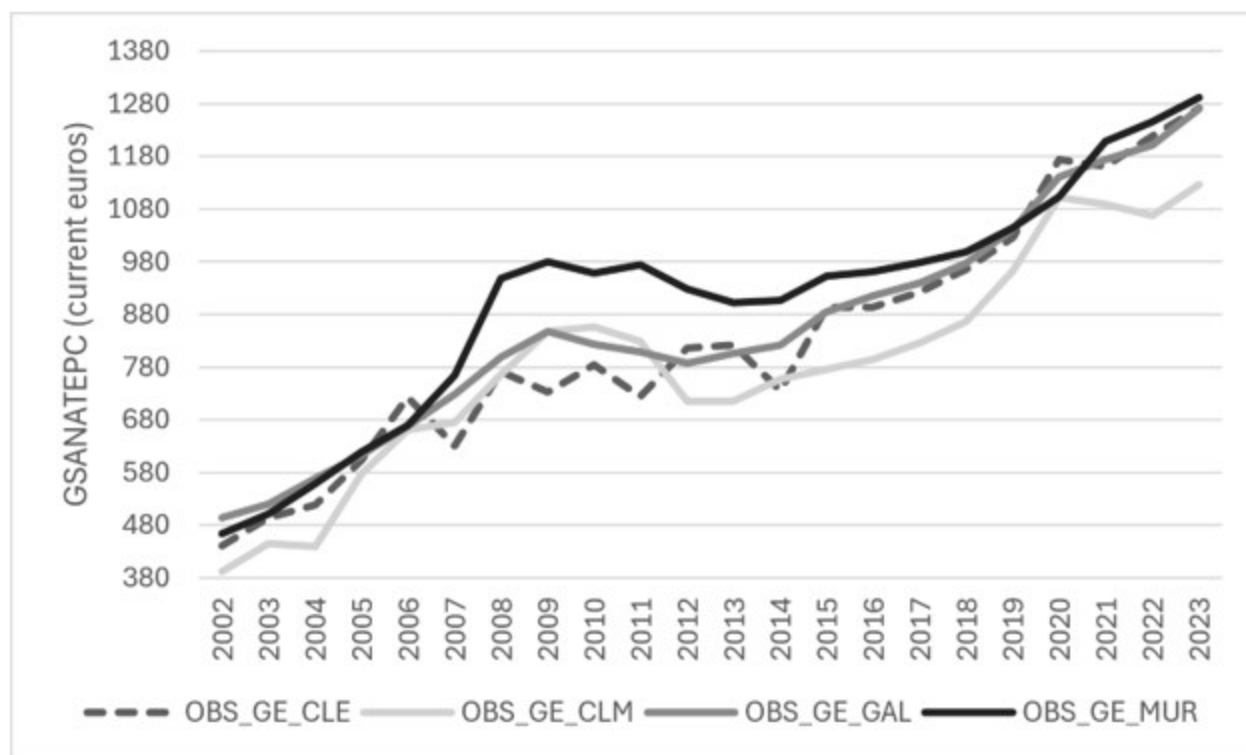


Figure 3

Observed GSANATEPC. Galicia: OBS_GE_GAL, Castile and Leon: OBS_GE_CLE, Castile-La Mancha: OBS_GE_CLM, Region of Murcia: OBS_GE_MUR.[1]

[1] GSANATEPC: expenditure on specialist care services (per capita) (Table 1).

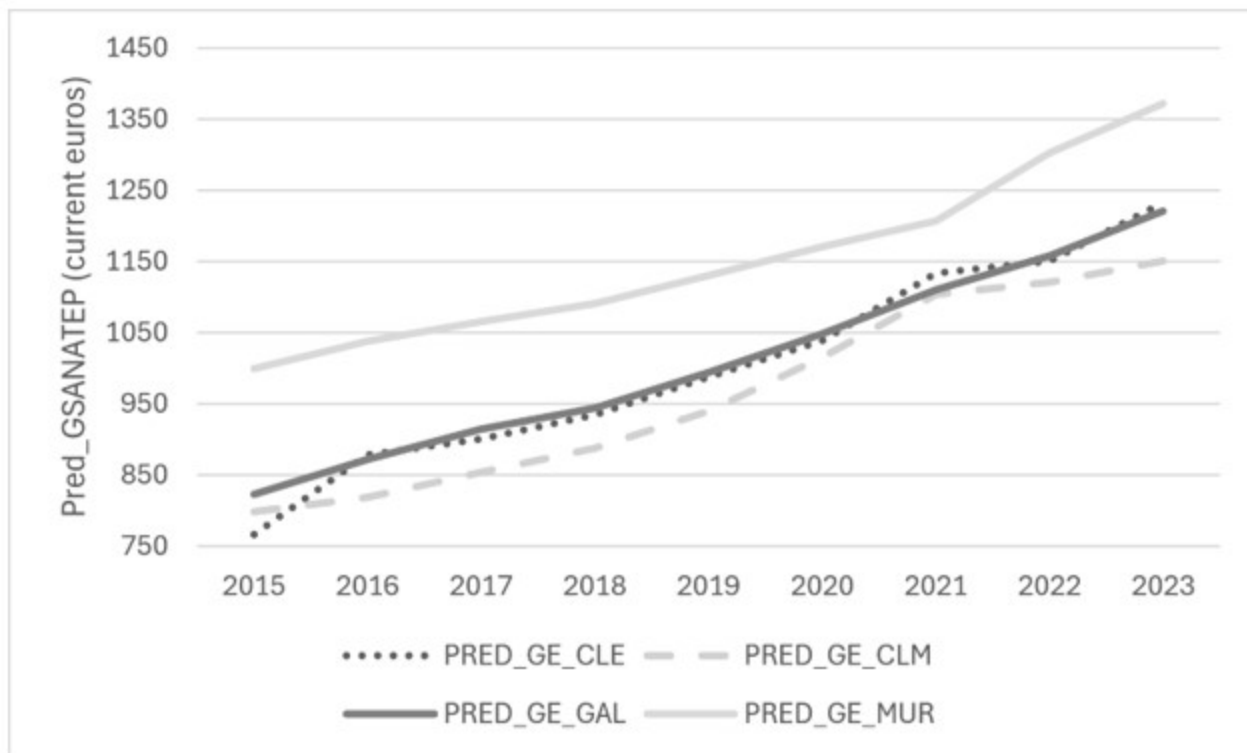


Figure 4

Predicted values of GSANATEPC based on average ENTRCUEPC of ACs and estimated coefficients (Table 3). Galicia: PRED_GE_GAL. Castile and Leon: PRED_GE_CLE. Castile-La Mancha: PRED_GE_CLM. Region of Murcia: PRED_GE_MUR.[1]

[1]ENTRCUEPC: total payments ("entregas a cuenta"). Million euro (per capita) (Table 1).

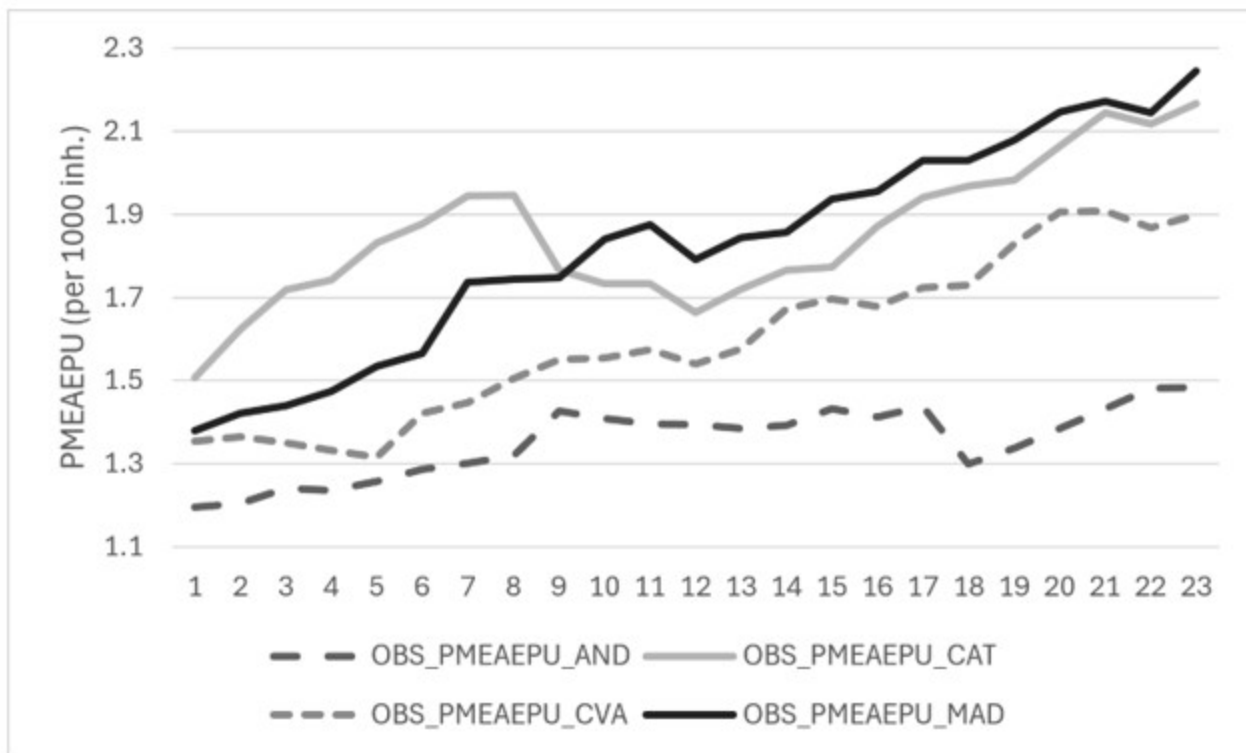


Figure 5

Observed PMEAEPU. Andalusia: OBS_ PMEAEPU _AND, Catalonia: OBS_ PMEAEPU _CAT. Madrid (Community): OBS_ PMEAEPU _MAD. Valencian Community: OBS_ PMEAEPU _CVA.[1]

[1] PMEAEPU: specialist care medical personnel per 1000 inhabitants (SNS) (Table 2).

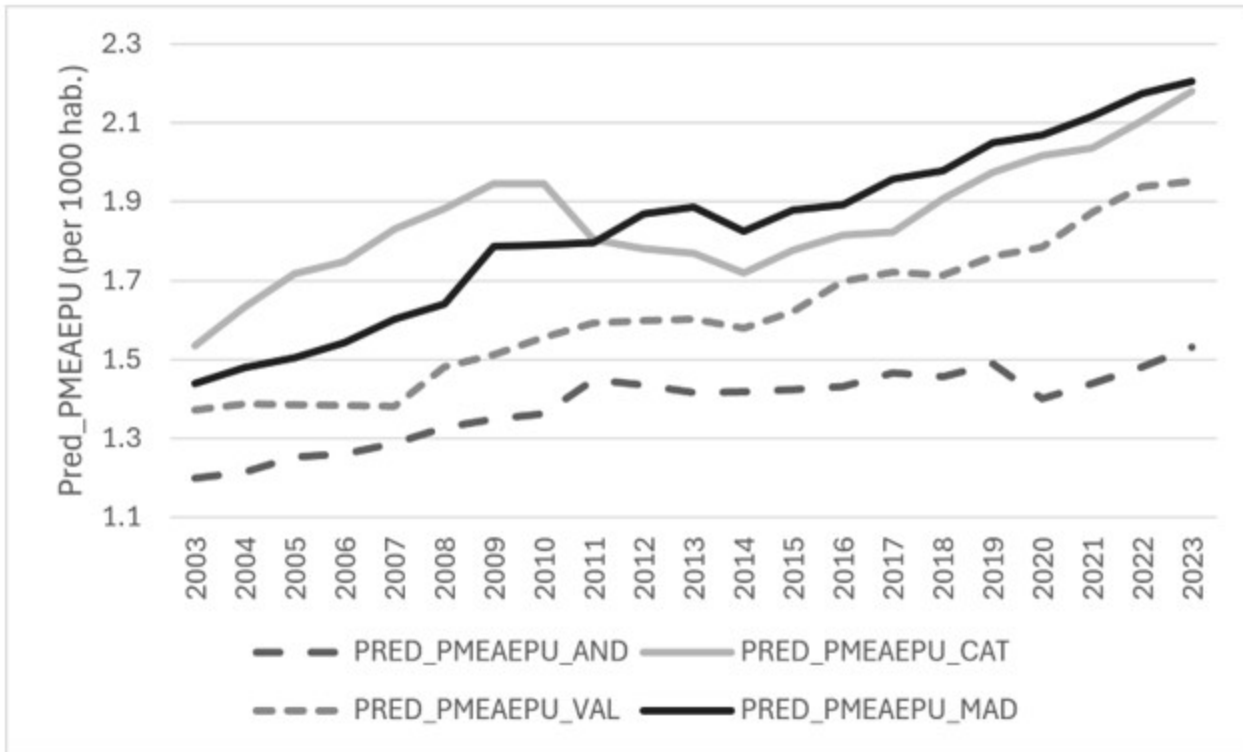


Figure 6

Predicted values of PMEAEPU based on average GSANATEPC of ACs and estimated coefficients (Table 3). Andalusia: PRED_ PMEAEPU_AND, Catalonia: PRED_ PMEAEPU_CAT. Madrid (Community): PRED_ PMEAEPU_CVA. Valencian Community: PRED_ PMEAEPU_MAD.[1]

[1] GSANATEPC: expenditure on specialist care services (per capita) (Table 1).

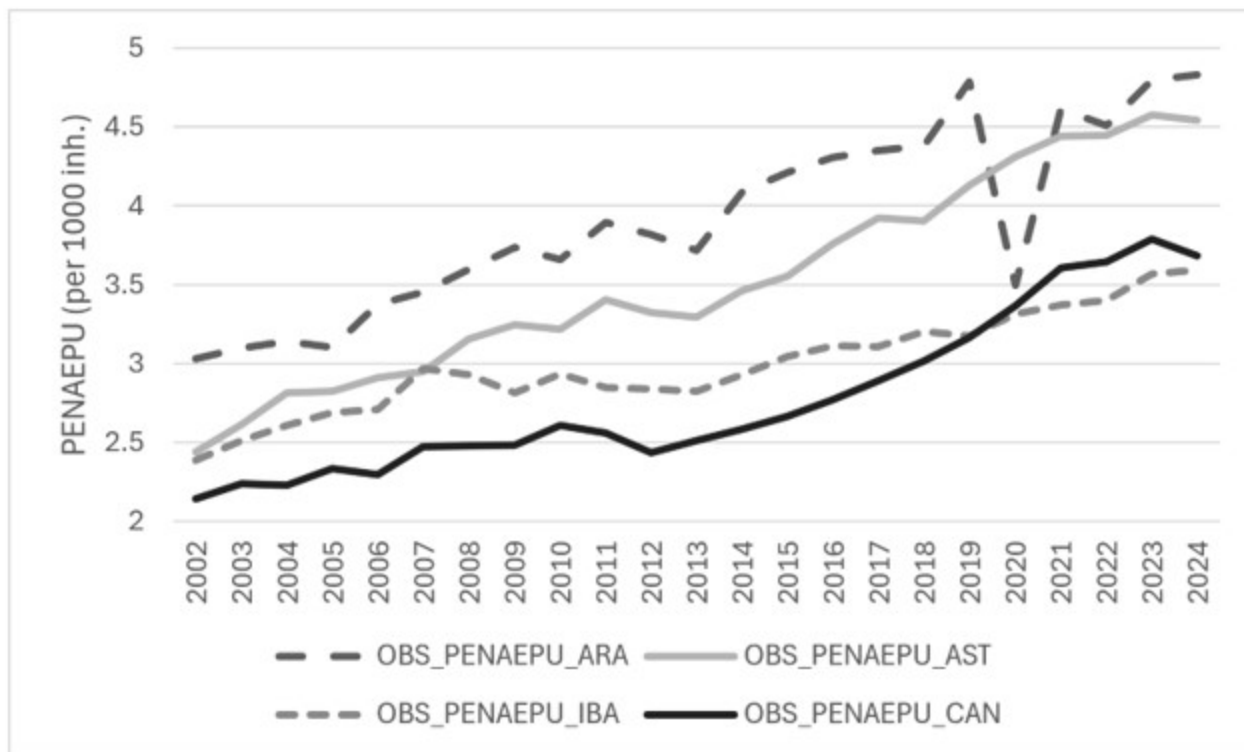


Figure 7

Observed PENAEPUs. Aragon: OBS_PENAEPU_ARA. Asturias: OBS_PENAEPU_AST. Balearic Islands: OBS_PENAEPU_IBA. Canary Islands: OBS_PENAEPU_CAN.[1]

[1] PENAEPUs: specialist care nursing staff per 1000 inhabitants (SNS) (Table 2).

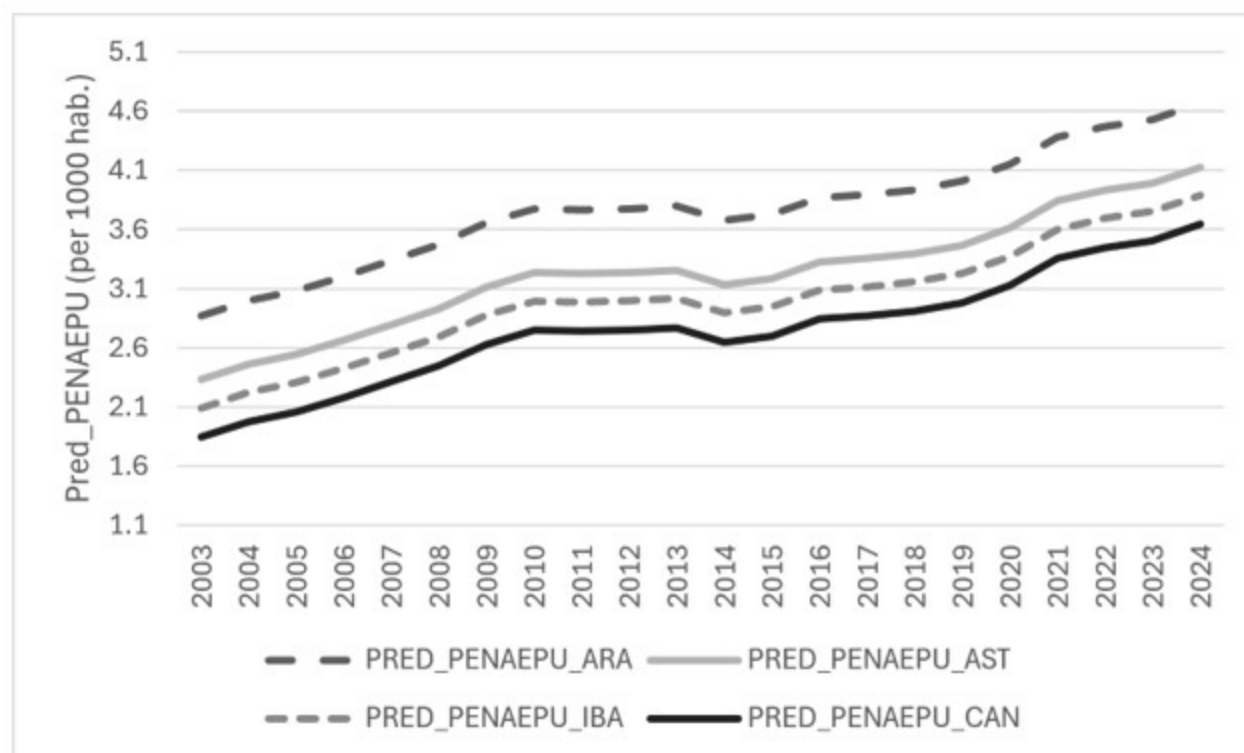


Figure 8

Predicted values of PENAEPUs based on average GSANATEPCs of ACs. Estimation method: IV panel, IV RNFNEPC. Aragon: PRED_ PENAEPUs _ARA. Asturias: PRED_ PENAEPUs _AST. Balearic Islands: PRED_ PENAEPUs _IBA. Canary Islands: PRED_ PENAEPUs _CAN. [1]

[1] GSANATEPC: expenditure on specialist care services (per capita) (Table 1).

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [Appendixv2.docx](#)