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Under-spending, over-spending or substitution among services? Spatial patterns of unexplained shares of health care expenditures☆

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ABSTRACT

Using individual-level administrative data, we investigate the spatial patterns of unexplained shares of health care expenditures (HCE) at the municipality level. The focus is on the elderly population in the Italian Region Friuli-Venezia Giulia observed over the period 2017-2019. The empirical analysis comprises two steps. First, random-effects two-part models are estimated to analyze the effect of age, morbidity, and death on the probability and amount of positive individual total HCE and its components. Second, the unexplained shares of HCE at the municipality level are examined to identify areas with under- or over-spending and substitution among services. Results confirm the existing findings on the determinants of HCE and reveal geographic patterns in the unexplained shares of expenditures. We identify clusters of municipalities with observed HCE higher than predicted for each type of service and clusters with substitution between home care and all other services. These findings are associated with the degree of urbanization of these areas and, consequently, with the ease of access to health care. This is crucial from a policy perspective, as it indicates specific policy targets for public health intervention.

1. Introduction

The growth of health care expenditures (HCE) observed in the last decades is among the major concerns for public health sustainability [1]. This trend calls for continuous evaluation of the determinants of HCE and health system efficiency. In particular, unwarranted geographic variations not explained by population demographic structure and health care needs are often regarded as reflecting inefficiencies and are thoroughly assessed to identify under- or over-spending on health care services [2–4]. Such inefficiencies could be corrected, leading to potential savings with no adverse effects on quality of care and population health status [5].

This paper investigates the effect of the main determinants of individual HCE and studies the spatial patterns of unexplained shares of HCE at the municipality level. We focus on the over-65 population, typically characterized by more severe health conditions, frailty, higher care needs, and, consequently, higher HCE. Old individuals are also more likely to experience misuse of services [6,7]. The context of analysis is the Italian Region Friuli-Venezia Giulia (FVG), where the public health care system ensures universal coverage with a small share of services provided under co-payment schemes, allowing reliable comparisons of HCE patterns across municipalities. Moreover, with an average age of 47.31 years, a share of over-65 individuals equal to 29.08%, and a population that ranks as the second oldest region in Italy, FVG represents the ideal setting for analyzing the elderly cohorts.

Individual HCE depend on a wide range of factors, among which age, morbidity, and proximity to death are often regarded as the main determinants. According to the existing literature, expenses exhibit a J-shaped curve that increases slowly during adulthood and reaches its maximum around death [8,9]. Such a pattern is due to the fact that age acts as a proxy for underlying morbidity and proximity to death [10–13]. As age increases, the individual health condition deteriorates due to the onset of chronic diseases, especially at the end of life [14].

Despite the documented relevance of individual demographic and clinical traits, several studies find that a substantial share of individual HCE variability remains unexplained even after controlling for these factors and attribute part of it to the characteristics of the geographic areas where individuals live [15,16]. The spatial distribution of the

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share of unpredicted individual HCE represents the primary focus of our work. This is driven, among other factors, by differences in the supply of services [3,17,18], socio-economic characteristics [19], technology [4,20,21], and policy makers' behavior, political ideologies and other contextual factors [18,22].

In our study, we use individual-level administrative data and carry out a two-step analysis. In the first step, we follow the extensive literature on the determinants of HCE and estimate the effect of age, morbidity, and death on individual expenditures. To this end, we employ random-effects two-part models [23] to deal with clustered observations within individuals and the distribution of individual expenses, characterized by zero mass and over-dispersion. This strategy is adopted not primarily for the identification of HCE determinants, but rather for out ultimate goal of comparing actual expenditures with their predictions, the latter being embedded in the estimation of this class of models [24]. In the second step, we average the predicted HCE and derive the unexplained shares of expenses at the municipality level. The latter are then exploited to analyze their geographical variation across municipalities.

We contribute to the existing literature in several ways. First, estimating two-part models on individual-level data in the first step of our approach allows us to explain the heterogeneity in expenditures better than analyzing the variation in HCE with more aggregated data.

Second, while previous evidence focuses mainly on total or hospital expenses [10,13,25], this work examines separately expenses for hospital admissions, pharmaceuticals, outpatient, and home care services. Demographic and health-related traits are found to have heterogeneous effects on these HCE categories because of different health care profiles as age increases [26,27] and according to the severity of the underlying disease [25].

Third, we estimate the effect of morbidity by controlling for a selected set of chronic diseases and the Resources Utilization Band (RUB) index [28]. The RUB index is a measure of the severity of the individual health condition and represents a novel aspect compared to existing evidence, which mainly uses more common indices such as the Charlson Comorbidity Index [29].

Fourth, from a policy perspective, our work provides a practical and robust approach to characterize different health-economic scenarios and identify the geographic units showing critical discrepancies between observed and predicted HCE. The analysis of different HCE categories also allows us to verify the presence of substitutions among health care services.

On the one hand, our main results on the effects of age, morbidity, and death on the probability and the amount of positive HCE are in line with the existing literature. On the other hand, the geographic analysis shows clusters of municipalities in which HCE for each service are higher than expected and areas where substitution between home care and all other services is observed. We find that the degree of urbanization and, consequently, the ease of access to health care represent the main factors characterizing the two areas. From a policy point of view, these results are of great importance as they show that the population age structure and health care needs are not the sole drivers of HCE and their geographic distribution, raising concerns about the efficiency of the health care system.

The paper is organized as follows. Section 2 describes the institutional setting and data, reports the descriptive statistics, and illustrates the empirical strategy. Section 3 describes the results. Section 4 develops the discussion and conclusions.

2. Material and methods

2.1. Regional setting and data

The Italian Region Friuli-Venezia Giulia is in the North-East of Italy, occupies an area of 7845 km2, and is divided into 215 municipalities. Morphologically, the entire northern part of the region consists of mountainous territory. In contrast, the central and southern parts are characterized respectively by hilly and plain land, with the latter reaching the coastal area of the Adriatic Sea. Inhabitants are slightly more than one million, heterogeneously distributed across the territory. The northern part of the region is less densely populated than the central and southern parts (see Fig. A1, panel a, in the Online Appendix). In terms of demographic structure, FVG's population is the second oldest in Italy, with an average age of around 47 years between 2017 and 2019. The share of individuals under 30 is 25%, those aged 30-64 represent 48%, while those over 65 cover 27%. The elderly population presents a greater concentration in the mountainous and southeast coastal parts of the region (see Fig. A1, panel b). In several municipalities of these two areas, residents over 65 represent a share between 30 and 49% of the population. In contrast, the province of Pordenone has the lowest share of over-65s, with most southwestern municipalities showing percentages ranging from 18 to 26%. Regarding the institutional setting, FVG's health system is organized into three local health authorities responsible for providing preventive medicine, public health services, primary care, community services, and secondary and specialty care. The regional health service provides universal coverage, financed through taxes at the regional and national levels, with small shares funded through cost-sharing schemes [30].

In our analysis, we use two datasets collecting individual information on the entire population over 65 observed in the years 2017-2019. The first one is drawn from the Regional Health Care Information System (SISSR) and provides information on age, gender, survival status, the month of death, and the municipality of residence. It also includes expenditures for hospital, outpatient and home care services, and pharmaceuticals, which we aggregate into total HCE. As these expenditures are covered by the public health care system, they represent both a cost for the health system and an expense for citizens. For this reason, the words 'cost' and 'expense' are used as synonyms throughout the paper.

The second dataset provides information on resource use by assigning each individual to an Adjusted Clinical Group (ACG) [28]. ACGs are mutually exclusive health-status categories defined by the number and type of co-morbidities, disease duration and severity, diagnostic certainty, etiology, age, and gender [31]. Specifically, within each morbidity pattern, ACGs define clinical groups of individuals expected to require similar levels of health care resources. ACGs are combined into six Resources Utilization Bands (RUBs). Individuals with higher bands are expected to present higher clinical severity and consequently higher health care needs, being more likely multi-morbid. The merged dataset collects yearly information on more than 350,000 over-65 individuals, for a total of almost one million observations.

2.2. Descriptive statistics

The elderly population is about 330 thousand individuals yearly, with wide heterogeneity across the regional territory (see Table A1 in the Online Appendix). At the regional level, slightly more than half of the elderly population is female and about 65% is younger than 80, with cohort size decreasing as age increases. Regarding health status, 85% of individuals have at least one disease, with diabetes, hypertension and congestive heart failure being the most prevalent conditions. More than 18% of individuals are affected by diabetes, 66% by hypertension and 17% by congestive heart failure. Moreover, 18% of individuals are assigned to a RUB level 4 or 5 (RUB4;5), thus presenting high clinical severity and health care needs, and almost 4% die. Table 1 reports some summary statistics on total HCE and different types of health care services. At the regional level, the percentage of individuals 65+ with zero total HCE is almost 5%.

Among services, the lowest percentage of null expenditures is observed for pharmaceutical costs (8.58%), while the highest regards home care (83.15%) and hospital expenses (81.87%). Considering individuals with positive HCE, inpatient stays represent the most costly services, with average expenditures equal to €7856. Note that, for those

Table 1
Summary statistics at the municipality and regional levels.

	(a) Individuals with HCE = 0 (%)		
	Municipality level		Regional level
	Mean	Min - Max	Mean
Total HCE	4.76	1.84 - 9.22	4.79
Hospital expenditures	81.97	75.96 - 87.40	81.87
Outpatient expenditures	15.58	9.94 - 22.38	15.58
Pharmaceutical expenditures	8.35	4.63 - 13.40	8.57
Home care expenditures	80.94	48.53 - 91.41	83.15

	(b) HCE for individuals with HCE > 0 (€)			
	Municipality level			Regional level
	Mean	SD	Min - Max	Mean
Total HCE	2996	367	1927 - 5457	2999
Hospital expenditures	10,390	1283	7048 - 18,177	10,231
Outpatient expenditures	477	73	339 - 1017	504
Pharmaceutical expenditures	540	107	261 - 1018	552
Home care expenditures	470	139	156 - 1078	417

Note: The table shows yearly averages of the percentage of individuals with zero health care expenditures (HCE) for different services (panel a) and the HCE amount for individuals with positive values for different services (panel b), at both the municipality and regional levels. It also reports minimum and maximum values at the municipality level for each HCE type.

who die, HCE are weighted by the months they live in the last year of life.

Observing Table 1, we note that averages at the municipality level do not differ significantly from those at the regional level. However, mean HCE and percentage of individuals with no expenditures vary largely across the territory, as described by minimum and maximum values at the municipality level. This is not only related to spatial heterogeneity in population health status. As shown in Fig. A2 in the Online Appendix, geographic variation in the percentage of individuals in poor health among municipalities is not followed by similar patterns of per-capita total HCE. Other factors are probably at play, and our goal is to study whether and how these unobservables shape the spatial distribution of individual HCE using the empirical strategy described in the next section.

2.3. Empirical strategy

In our empirical strategy, we investigate the determinants of individual HCE and compute the municipality-level unexplained shares of expenditures for each type of service.

In the first step, the effects of age, morbidity, and death are estimated through a two-part model with individual random effects. Two-part models are commonly used to model zero-censored dependent variables like HCE. Hospital and home care expense distributions are remarkably characterized by zero mass, with positive amounts observed in only a small portion of the population (see Table 1). The two-part model allows accounting for such a feature by permitting zero and positive values to be generated by different processes. On the one hand, a binary choice model is fitted for estimating the extensive margin, i.e., the probability of observing a positive-versus-zero outcome. On the other hand, several models are allowed for estimating the intensive margin, i.e., the amount of the outcome of interest, conditional on a positive outcome.

Our dataset includes observations that are nested within individuals. To account for correlation among them, we adopt random-effects two-part generalized linear models (hereafter GLMMs) [32]. Following the notation in [33], we specify a separate model for each type of HCE as follows. Let Y_{ijt} be a continuous variable with zero inflation for the i^{th} individual in the j^{th} municipality observed at time t. This measure can be better represented by splitting the problem in a dichotomic variable Z_{ijt}, assuming values 0 and 1 for $Y_{ijt} = 0$ and $Y_{ijt} > 0$, respectively, and the so-called intensity variable $g(Y_{ijt})$ given $Y_{ijt} > 0$. In the present work, the estimation is developed considering the following random-effects logit model [34] for the variable Z:

$$logit\{\Pr(Z_{ijt} = 1 | X_{ijt}, U_i)\} = X_{ijt}\beta + U_i \tag{1}$$

where X_{ijt} collects the explicative variables observed on individuals, β represents the parameters vector, and the term U_i identifies individual-specific effects.

Similarly, we consider a Gamma distribution with a log link function for the second part of the model. The natural logarithmic transformation of the condition mean (μ_{ijt}) is then modeled for positive expenditures as follows:

$$\log(\mu_{ijt}) = X_{ijt}\alpha + V_i \tag{2}$$

where α is the parameters vector, and V_i identifies the individual-specific effects in the conditional expectations model. The independent variables are the same for both models, assuming that the amount and the likelihood of positive HCE are affected by the same individual factors. These are selected to net out from the overall variation in HCE the share determined by individual specific traits and regional contextual factors, under the hypothesis that the unexplained part is driven by external forces.

The demographic characteristics include gender (*Female*, dummy variable) and age (*Age*). As previous studies [8,9] suggest a quadratic life-cycle trend of HCE, we also include squared values of age. Then, given the documented role of death on the use and amount spent on health services [12,25,35], a dummy variable for the last year of life is also added (*Deceased*). Note that, as the analysis of determinants is instrumental to point out the explained variation of HCE, we consider the well-known issue of the endogeneity of time to death [13,27] negligible for this study. Regarding individual health status, we add to our specification a set of binary variables for the presence of the diseases listed in Table A1 in the Online Appendix, which are selected following the existing literature on the most costly diseases for the elderly [36–38] and after assessing their statistical significance. In addition, we include a dummy for RUB equal to 4 or 5 ($RUB_{4;5}$). We group these two categories to identify the individuals with the greatest clinical severity and health care needs. As shown in Table A4 in the Online Appendix, categories 4 and 5 identify the elderly with a mean number of co-morbidities and total HCE greater than the respective population averages (2.32 and €2855). A model considering the RUB as a factor can also be considered. Notwithstanding, the clustering of categories 0 and 1 is required because, in the logit model, the RUB level 0 is a perfect predictor of null HCE. We finally adopt the aforementioned dummy variable to focus on the elderly with severe co-morbidity. Note that the RUB index is an indicator defined by morbidity, age, and gender, among other factors. While multicollinearity may exist among all variables, the statistically significant role of all these individual characteristics (see Tables A2 and A3 in the Online Appendix) provides support for their simultaneous inclusion. It indicates that the RUB index represents a measure of overall clinical severity that goes beyond the sum of separate contributions of its components.

Finally, we add time fixed effects (time variable treated as a factor), which capture the impact of factors occurring within a particular year and affecting all observed individuals, and individual random effects (U_i and V_i in the logit model and Gamma GLM, respectively). The latter absorb, for example, the effect of temporary age-unrelated health shocks that do not generate increases in the RUB level and are not related to the pathologies included in the specification, as well as temporary falls in individual income that may hinder access to health services, and other aspects of individual behavior towards health service demand.

Once the two-part models are estimated for each HCE type, we derive the municipality-level averages of the unexplained shares of individual HCE. To this end, we first obtain the predicted values from the two-part model. Specifically, we calculate the predictions by combining the probabilities of positive HCE ($Pr(\widehat{Y_{ijt} > 0})$) predicted by the logit model and the so-called conditional expectations of HCE ($\widehat{Y_{ijt}}$), obtained from the Gamma model.

$$\widehat{Y^{*}_{ijt}} = \Pr\left(\widehat{Y_{ijt} > 0}\right) \times \widehat{Y_{ijt}} \tag{3}$$

Then, we calculate the averages of the observed ($\overline{Y_j}$) and predicted ($\overline{\widehat{Y^{*}_{j}}}$) values at the municipality level and their differences. The latter represent the unexplained shares of HCE in each municipality ($Z_j^{(k)}$ for each type of service k). These are finally exploited to study their spatial patterns and derive specific health-economic scenarios.

Note that the unexplained share of HCE variability at the municipality level could also be obtained more directly by estimating a multilevel model with individual and municipality random effects (nested three-level model). To verify whether our findings are robust to this alternative specification, we estimate the two-part GLMM with individual- and municipality-specific effects on total HCE. Fig. A3 in the Online Appendix compares the results of the two models (Models A and C). While the findings from the alternative specification are quite close to the baseline, it is worth noting that the advantages of the two-part model would be lost when considering the direct estimation of municipality random effects. The nested three-level model would produce independent predictions, and the municipality-specific effects would not account for the probability of positive HCE. For this reason, we follow the approach defined by Eqs. 1-3 and consider municipalities as administrative units that might share similar characteristics within larger geographic areas. As the present work represents a study on the entire population of the FVG region, the analyses based on model residuals can be considered relevant for the decision-making process, although a measure of uncertainty is not considered.

All results reported in the paper are obtained using Stata [39]. In particular, *xtlogit* and *meglm* commands are adopted to estimate the two parts of the model, respectively. R statistical software [40] and, in particular, library *glmmTMB* [41] have been used to check the model robustness only.

3. Results

3.1. Two-part models

This section briefly analyzes the results of the two-part models estimated for each HCE category separately. Table A2 in the Online Appendix shows the log odds ratios estimated from the random-effects logit model. In line with other studies [27,42,43], we find that the effect of age on the probability of having some HCE is always positive and marginally decreasing (except for the probability of positive home care expenses); moreover, elderly females are more likely to spend for out-of-hospital services and less likely for inpatient treatments than males. Hypertension and congestive heart failure (CHF) positively affect the probability of observing HCE for all types of services. At the same time, the other conditions show heterogeneous impacts, reflecting different care pathways and substitution among services. Individuals with RUB larger than three are more likely to incur some hospital, outpatient, and home care expenditures and less likely to spend on pharmaceuticals. As expected, in the last year of life, individuals are less likely to use outpatient services and pharmaceuticals and more likely to spend on hospital and home care services.

Table A3 in the Online Appendix reports the results of the Gamma GLMs. The effect of age on HCE is always positive and significant except for home care, for which it is not statistically significant. As the last result contrasts with other studies [27,44], we carry out further investigations and find that the effect of age becomes statistically non-significant when health-status variables are included in the model. This indicates that, for home care expenses, age strongly acts as a proxy for morbidity. Regarding gender differences, females spend less than males for each type of service except for hospital admission. In the latter case, average costs do not significantly differ between males and females. According to the existing literature [45], females tend to use significantly more outpatient services and pharmaceuticals than males, increasing prevention and reducing the onset of unexpected and costly health shocks. A second explanation is that, for specific diseases, men's health conditions are generally more severe than those of women [46,47]. Positive effects on HCE are observed for all types of services in the presence of hypertension, CHF, ischemic heart disease, renal failure, and high levels of RUB. Conversely, being affected by other diseases shows a distinct impact on the various HCE categories and points to different severity of the diseases or different costs of treatment. Finally, individuals dying during the reference period spend more on all types of services than survivors.

3.2. Spatial analysis

In this section, we present the results of the geographic analysis. First, we perform a Moran's I test for spatial dependence among yearly average unexplained shares of total HCE and expenses for different services at the municipality level. The test is performed using a spatial weighting matrix of rook contiguity, although similar results can be obtained with different types of spatial matrices. Results are reported in Table A5 in the Online Appendix. We find that spatial autocorrelation is present in the unexplained shares of hospital ($Z_j^{(H)}$, p-value 0.015), outpatient ($Z_j^{(O)}$, p-value <0.0001) and home care expenses ($Z_j^{(HC)}$, p-value <0.0001), but not in the unexplained shares of total HCE ($Z_j^{(Total)}$, p-value 0.9910) and pharmaceutical expenditures ($Z_j^{(Ph)}$, 0.6170). The geographic distribution of $Z_j^{(k)}$ for each service is plotted in Fig. 1, with darker shades of grey corresponding to increasing values. We note that hospital, outpatient, and pharmaceutical data share similar geographic patterns. They present low values in the mountainous area located in the northern part of the region and high values in the province of Pordenone and the plain area around the city of Udine (panels a, b, and c). These two areas also show low values of unexplained shares of home care expenditures, which, conversely, are high in the north of the region and the south of Udine province (panel d).

3.3. Health-economic scenarios

Previous results suggest a substitution between home care and all other services. They may also indicate under- or over-spending for all health care services. Fig. 2 identifies whether and where these cases occur. In panel a, we plot municipalities with positive $Z_j^{(k)}$ for all services and municipalities with negative $Z_j^{(k)}$ for all services (scenarios A). In municipalities with positive $Z_j^{(k)}$ for all services (scenario A1, blue tones), observed values are higher than predicted, indicating higher-than-expected HCE. On the contrary, there are no municipalities with negative $Z_j^{(k)}$ for all services (scenario A2). This means that observed expenses are always higher than expected for at least one service.

Panel b displays the spatial distribution of municipalities facing substitution between home care and all other services (scenarios B). Again, we distinguish between two cases. The first one is characterized by simultaneous positive unexplained shares of expenses for home care and negative unexplained shares for at least one of the other services ($Z_j^{(Ot)}$), respectively (scenario B1). The second presents a specular condition (scenario B2). Consistent with the insights drawn from Fig. 1, scenario B1 is more frequent in the mountainous area in the north of the region and the plains in the south of the province of Udine, for a total of 48 municipalities. In these areas, expenses for pharmaceuticals, hospital access, and outpatient services are lower than expected. However, higher-than-expected home care expenses cover part of the need for care

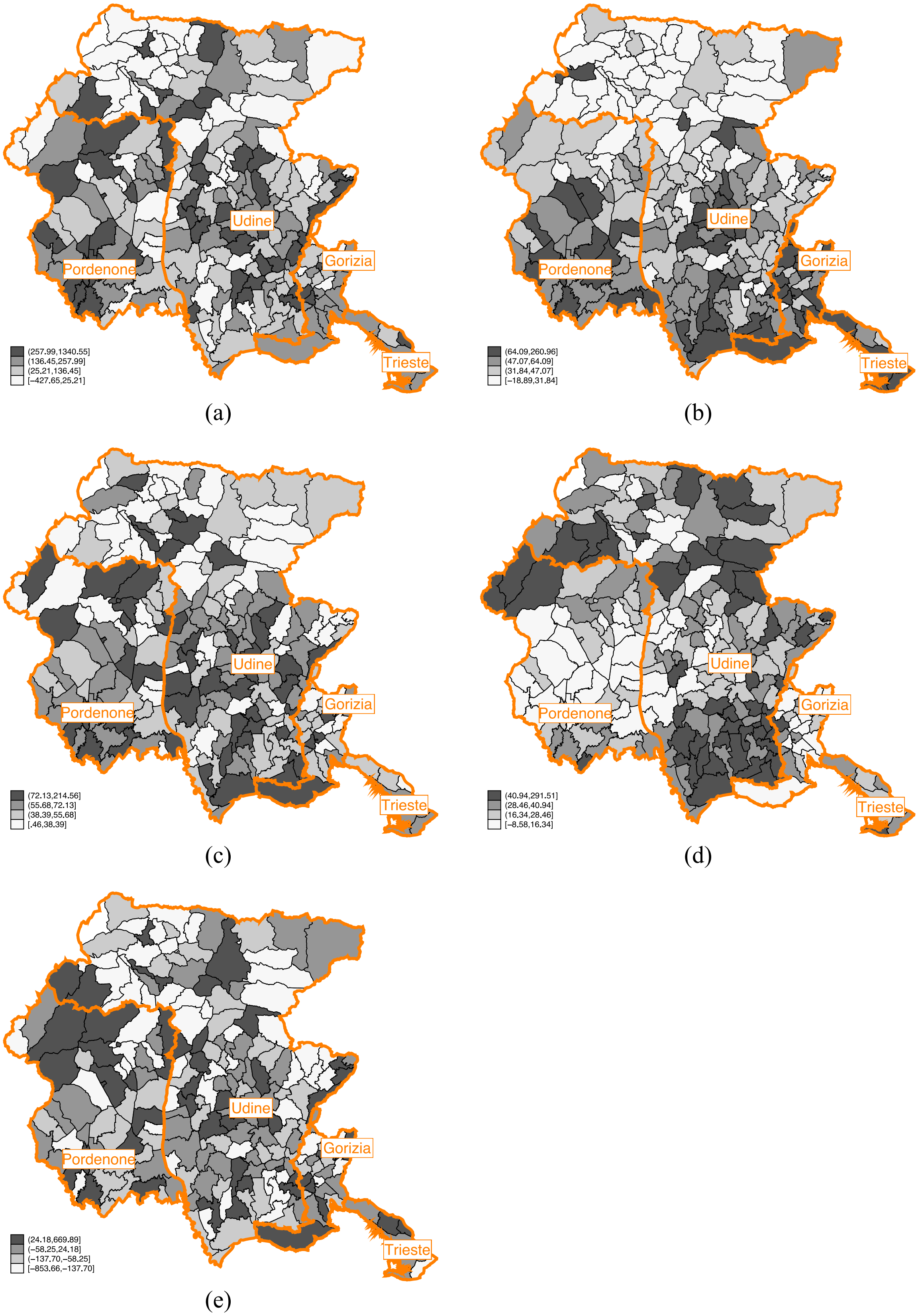

Fig. 1. Geographic distribution of yearly average unexplained values of total HCE and expenses for health care services at the municipality level. Increasing color intensity corresponds to rising values of total (panel e), hospital (panel a), outpatient (panel b), pharmaceuticals (panel c), and home care unexplained expenses (panel d). The distribution is divided into four quartile-bounded groups.

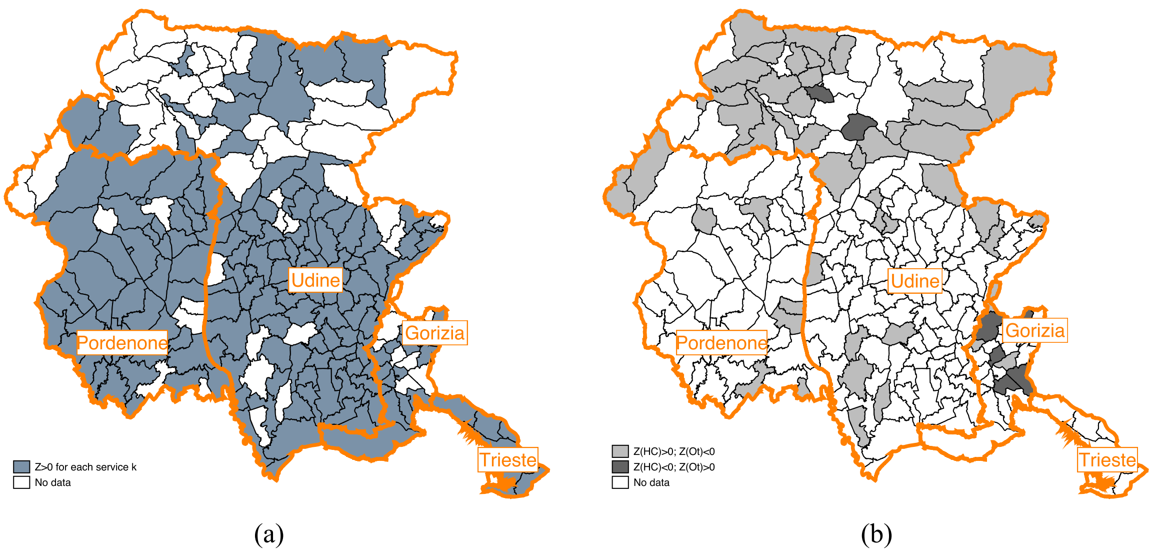

Fig. 2. Geographic distribution of different combinations of yearly average unexplained HCE for health care services at the municipality level. Panel a: municipalities with positive unexplained shares of expenses for each service (blue areas). Panel b: municipalities with positive unexplained shares of home care expenses and negative unexplained shares of expenses for all other services (light grey areas) and municipalities facing the opposite scenario (dark grey areas). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

that is not met by these services. Further investigations show that the most frequently replaced services are hospital treatments, with the substitution observed in 88% of municipalities facing scenario B1. Scenario B2 is not featured by any geographic pattern and characterizes a very low number of municipalities, indicating that outpatient and inpatient services and pharmaceuticals rarely substitute home care in providing health assistance. This result is not surprising for an elderly population, who rely on home care services to a greater extent than any other population group [48].

To this end, we carry out t-tests on several municipality features by comparing territorial units in scenario A1 ($Z_j^{(k)} > 0$ for each service) with those in scenario B1 ($Z_j^{(HC)} > 0$ and $Z_j^{(Ot)} < 0$). Scenarios A2 and B2 are excluded from the comparison as they include zero or a small number of municipalities, respectively. While data on demographic and health-related attributes are obtained from our merged dataset, those on geographic characteristics are drawn from databases of the Italian Institute of Statistics [49], those on population income classes from the open data of the Internal Revenue Service [50], and those on supply-side features from the open data of the Ministry of Health [51]. Results are reported in Table 2 and are twofold. On the one hand, in municipalities facing over-spending for all services, individuals are younger and healthier than those living in areas characterized by substitution. The former present a smaller percentage of over-65 residents and old individuals with a high RUB level. This result confirms that the amount of HCE depends not only on the need for care but also on other factors, such as those discussed in the following. Over-spending municipalities show a higher degree of urbanization and a higher percentage of medium- and high-income individuals. Therefore, their residents present weaker financial constraints. Moreover, these areas offer greater proximity to health care facilities and a higher level of health care supply, as suggested by the larger number of pharmacies and the lower distance from pharmacies and hospitals. As recent studies [52–54] describe, these factors correlate to frequent, technology-intensive, and expensive health care treatments, leading to observed values of HCE higher than expected.

On the other hand, compared with over-spending areas, municipalities with substitution show a higher percentage of elderly and individuals with more severe health conditions. In addition, such municipalities are mainly located in rural areas and present higher maximum altitude, lower population density, higher percentage of low-income individuals, poor health care supply, and greater distance to health care facilities. All these characteristics are found to be positively associated with higher expenses for home care. Older age is often accompanied by greater frailty and probability of living alone, which could translate into reduced outpatient or inpatient care due to difficulty in performing daily activities and the absence of support from informal care. To compensate for the lack of access to traditional care, the elderly may experience a greater need or preference to receive care at home in order to stabilize their clinical condition, limit functional decline, and improve the quality of life in their familiar environment [55–57]. In rural areas, another factor hindering access to traditional care is the low provision of health care. Any associated inadequacy or unavailability of public or private transportation, excessive travel time, or prohibitive transportation costs also explain higher-than-expected HCE for home care and lower-than-expected HCE for other services [53,58].

Although our analysis concerns the elderly regional population that may not be representative of other areas, the findings shown in this

Table 2
T-test on municipality characteristics by health-economic scenario.

	(1) $Z_m^{(k)} > 0$	(2) Substitution	(3) Difference
Demographic and health-related:			
Over-65 individuals (%)	28.10	30.33	-2.23***
Individuals with RUB= 4; 5 (%)	18.04	20.15	-2.11***
Socio-economic:			
Low-income individuals (%)	19.47	23.28	-3.81***
Middle-income individuals (%)	46.09	45.24	0.85**
High-income individuals (%)	1.16	0.65	0.51***
Geographic and supply-side:			
Population density (pop./km2)	217.01	89.24	127.77***
Maximum altitude (m)	545.75	1288.44	-742.69***
Distance to hospital (km)	12.97	24.35	-11.38***
N. pharmacies	1.99	0.80	1.19 **
Distance to pharmacy (km)	0.26	0.98	-0.72***

Note: The table shows yearly averages of some demographic, health-related, socio-economic, and supply side characteristics for municipalities with positive unexplained shares of HCE for all services (column (1)) and those with simultaneous positive unexplained shares of home care expenses and negative unexplained shares of expenses for at least one other service (column (2)). Column (3) reports the differences between the averages of the two groups and the respective p-value levels. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

section are in line with those in other studies [55,56,59] and are, therefore, consistent with other settings.

4. Discussion and conclusions

In this paper, we investigate the determinants of individual HCE for different health care services and identify their unexplained shares. The latter are then averaged at the municipality level to study their spatial patterns. The main findings on the effect of age, gender, morbidity, and death are in line with previous evidence. Age generally shows positive effects on the probability of positive expenditures and HCE levels, while gender and high RUB levels exhibit heterogeneous effects by type of health service. Differences in the type of treatments used are also observed by survival status, while dying individuals always spend more than survivors, regardless of the type of service.

The geographic analysis shows spatial clusters of over-spending municipalities (scenario A1) and groups of units with substitution between home care and the other services (scenario B1). The primary difference between the two scenarios lies in the degree of urbanization they exhibit and, consequently, in the ease of access to health care. Over-spending/urban municipalities have a larger percentage of medium- and high-income individuals, greater proximity to health care facilities, and a higher level of health care supply. In contrast, opposite conditions are associated with increased use and expenses for home care services, which, in rural areas, substitute other distant and expensive services.

From a policy perspective, these results are of great importance and can be instrumental in directing health policy intervention. They show that the population's age structure and health care needs are not the unique drivers of HCE and their geographic distribution, raising concerns about the efficiency of the health care provision. Relevant implications concern, in particular, access to care in rural areas and appropriateness of care in urban areas. On the one hand, continuous monitoring of whether the quantity and quality of home care services are meeting population needs is required to increase and improve access [60,61]. In the presence of unmet needs, we believe that policies should promote adequate supply and distribution of health care services throughout the territory or, if not possible, address financial barriers to care and improve tele-health [62]. On the other hand, addressing the appropriateness of care in urban areas is necessary for value-for-money considerations. In this regard, more attention could be paid to transition and integrated care, which can improve co-ordination while reducing duplicative and unnecessary care [1].

Although our analysis concerns a specific elderly population, the findings shown in this paper are in line with those found in other studies. One comparative advantage of our research is the use of individual-level data, which is crucial to obtain reliable estimates of unwarranted variations in HCE. Moreover, our work proposes a practical and robust approach developed through the use of administrative data, which are always available at the regional level and potentially at the national level. Consequently, such a method can be applied to all settings to identify the territories showing unwarranted levels of HCE or substitutions among different services and characterize different health-economic scenarios and the associated factors.

CRediT authorship contribution statement

Irene Torrini: Data curation, Formal analysis, Investigation, Software, Visualization, Writing – original draft. **Luca Grassetti:** Conceptualization, Formal analysis, Investigation, Methodology, Project administration, Supervision, Writing – review & editing, Funding acquisition. **Laura Rizzi:** Conceptualization, Formal analysis, Investigation, Methodology, Project administration, Supervision, Writing – review & editing, Funding acquisition.

Declaration of Competing Interest

None.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.healthpol.2023.104902.

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