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Risk adjustment to improve fairness and efficiency of resource allocation: a case from the Emilia Romagna region in the decentralized Italian SSN

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ABSTRACT

Resource allocation formulas in National Health Systems (NHS) are crucial for distributing central funds to Regions/Local Health Authorities. However, under prospective capitation funding, resource constraints may generate incentives for selective rationing, as providers seek to contain costs within fixed budgets. While NHS features such as geographically based enrolment and funding limit explicit risk selection seen in competitive insurance markets, resource scarcity can lead to rationing in socially suboptimal ways, which might disproportionately affect vulnerable populations. This paper aims to quantify selective rationing incentives using the healthcare system in the Emilia-Romagna Region in Italy as a case study. We evaluate the current funding formula used in Italy and its impact on the Region and demonstrate how alternative formulas can be developed to minimize incentives for selective rationing in the Region while remaining feasible to implement, given heterogeneous data quality and availability across Regions that hinder formula development at a national level. Our results show that the current formula undercompensates specific population groups defined by age and sex and has inadequate responsiveness to need. Alternative formulas that risk-adjust using socioeconomic variables have low statistical fit but reduce funding disparities among deprived areas/poorer individuals. Nevertheless, they are less responsive to high-need individuals. Moreover, morbidity data, even at coarse granularity, contribute to more adequately funding high-cost groups like cancer patients. To explore broader implications, we simulate how these alternative formulas would alter allocations if applied at the national level, showing that accounting for risk variation would channel more resources to the Regions in need. Overall, we provide a rationale for transitioning from the current resource allocation formula to risk adjustment to reduce potential selective rationing incentives.

1. Introduction

Resource allocation formulas in National Health Systems (NHS) play a crucial role as the mechanisms by which central funds are distributed to Regions/Local Health Authorities (LHAs) to meet diverse population healthcare needs (Radinmanesh et al., 2021; Anselmi et al., 2022).

However, prospective capitation funding can create incentives for selective rationing as a cost-containment strategy when resources are scarce (OECD, 2024). NHS features (such as geographically based enrolment and funding) limit incentives for risk selection seen in competitive insurance markets with consumer choice and funding based on an individual's own risk (van Kleef et al., 2024). Nevertheless, when there are budgetary limitations, Regions/LHAs may be incentivized to ration resources through several mechanisms, such as the benefit package, provider supply limits, payment mechanisms, queuing, copayments, and gatekeeping, among others (Berezowski et al., 2023; Syrett, 2007). While funding formulas are typically set at the central level in both centralized (UK and Portugal) and decentralized (Italy, Spain, Canada and the Nordic countries) NHS, in decentralized systems where Regions and LHAs are granted greater autonomy to organize and deliver care, these problems might be particularly acute. Moreover, this rationing of resources may take place in socially suboptimal ways, disproportionately affecting vulnerable populations (Singh and Venkataramani, 2022), including those who cannot leverage supplementary insurance coverage or have independent access to private providers, and ultimately face the full risk of foregoing treatment in terms of the deterioration of their health status.

Italy's Servizio Sanitario Nazionale (SSN) exemplifies these

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challenges. Before the COVID-19 pandemic, Italy consistently spent 8.7 % of its GDP on average on healthcare. While the pandemic saw a rise in healthcare spending, 2025 estimates indicate a notable decline to below pre-COVID levels (OECD, 2025). This downward trend has intensified resource scarcity, making selective rationing more visible. According to official survey data (ISTAT, 2024) further analyzed by Spandonaro et al., 2024, 4.5 % of households lacked financial resources to pay for healthcare in 2022, with stark equity implications: 10.5 % of households in the first income quintile forewent treatment, compared to just 0.7 % in the highest quintile. Regional disparities are also evident, with southern regions averaging 5.9 % of families forgoing care versus 3.3 % in the North-East. Additionally, 8.6 % of households faced "catastrophic" health expenses exceeding 40 % of their disposable income, with this figure reaching 9.9 % in southern regions, 7.0 % in the North-West, and 17.7 % among households with seniors over 75.

The key question, therefore, is whether intensified resource scarcity may create incentives for selective rationing when budgets inadequately reflect the expected cost of care for certain groups (e.g. older adults, patients with chronic illness) in settings with underlying disparities. Italy presents a particularly relevant case given regional variations in health needs driven by demographic, socioeconomic, and morbidity factors leading to significant disparities in resource utilization (de Belvis et al., 2022). The working hypothesis is that when funding aligns with needs, there is less argument to make unintentional trade-offs between patients based on cost.

Despite the importance of this issue, there is a paucity of research that connects budget pressures and resource allocation formulas with incentives for selective rationing. One reason may be that, under geographically based enrolment and funding, incentives for selection are perceived to be weaker. In addition, national-level funding is often not strictly binding ex post for Regions/LHAs, that is, after spending has occurred, it is usual that Regions/LHAs receive supplemental income, thus not fully bearing the financial risk of deficits. Previous research has explored different technical aspects of resource allocation formulas. Studies from England have explored how socioeconomic (SES) factors influence mental healthcare costs, as well as addressed concerns about using historical utilization data to allocate resources as it could perpetuate unmet needs, introducing a "responsiveness of expenditure to need" measure as a potential solution to recalibrates payments by removing unresponsive organizations (Anselmi, et al., 2020, 2022; Urwin et al., 2024). Studies from Sweden have explored the effects of a reform that increased the primary care capitation payment for those chronically ill low-SES patients, finding significant increases in the number of private primary care centres setting up in areas with relatively high care need index values, but higher capitation for vulnerable patients failed to sustain these gains or to reduce inequalities (Anell et al., 2018; Anell et al., 2024).

This paper aims to quantify selective rationing incentives using the healthcare system in the Emilia-Romagna Region of Italy as a case study. Using a dataset of all Emilia-Romagna residents, we conduct a comprehensive analysis of the current weighted and unweighted resource allocation formula utilized in the Italian SSN and its impact in the Region. To assess the performance of the formula, we go beyond computing goodness of fit to assess over- and under-compensations for selected socioeconomic groups (e.g., age, sex, citizenship, income) and morbidity groups (e.g., cancer patients), which are of interest to the Region/LHA regarding potential incentives for selective rationing. In addition, we replicate the "responsiveness to need" metric as proposed by Urwin et al. (2024). Last, we also examine service-level distortions, such as underprovision, as a further indicator of incentives for selective rationing at the provision level.

We propose alternative formulas that vary in variable range and granularity, following Iommi et al. (2022),[1] aimed at appropriately funding population healthcare needs, thus mitigating incentives for selective rationing, while testing the feasibility of implementation. A key concern is Italy's implementation challenges due to heterogeneous data quality and availability across Regions (OECD, 2015; Skrami et al., 2020). The data of Emilia-Romagna allow us to simulate these challenges that hinder formula development at a national level.

Lastly, to explore broader implications, we simulate the allocation of central funds deriving from these alternative formulas across all 20 Regions by recreating their demographic structures. This simulation helps policymakers observe how each formula would affect the distribution of central funds among Regions.

This paper makes three key contributions to the existing literature. First, our alternative formulas consider the introduction of individual level socioeconomic variables in a risk-adjustment model. This represents a novel contribution in the Italian context. Prior work in Italy has focused primarily on testing Adjusted Clinical Groups (ACGs) in the Veneto region (Corti et al., 2018). Moreover, building on recent work by Lux et al. (2025) on the implementation of socioeconomic variables in the German risk adjustment, we contribute to the understanding of the role of socioeconomic indicators in risk adjustment. Currently, there are mixed findings on whether these variables should or shouldn't be included in risk adjustment (Ellis et al., 2018). Second, our approach of testing a set of alternative allocation formulas with varying levels of variable range and granularity contributes to the literature on the optimal approach for resource allocation formula improvement, as a key concern is whether increased formula sophistication with 'more variables' represents the best avenue forward (Ellis et al., 2018). Broadly, this literature can be grouped into work concerned with the feasibility of implementation of risk adjustment formulas given data constraints. Key themes in this literature include the use of constrained regression to account for unobserved or incomplete information (Renker et al., 2025; Van Kleef, Eijkenaar, van Vliet and Nielen, 2020), the application of risk sharing to overcome data constraints (Henriquez et al., 2022), and the use of machine learning for variable selection (McGuire et al., 2021). Third, by employing a comprehensive set of evaluation metrics beyond goodness-of-fit, this paper introduces an NHS-oriented perspective into a literature that has largely applied these metrics in competitive insurance settings (Layton et al., 2018; Van Kleef, Eijkenaar and van Vliet, 2020). These metrics allow us to show how funding allocation formulas may create incentives for selective rationing that disproportionately affect certain population groups, and how a closer alignment of funding with need could reduce such incentives. This study does not claim to provide evidence of intentional selective rationing strategies.

The paper proceeds as follows. Section 2 describes the institutional context of the Italian SSN. Section 3 describes the data and methods, including the approach used to recreate the current resource allocation formula and the alternative risk adjustment models, the evaluation measures, and the simulation exercise. Section 4 presents the results of our estimations. Finally, in Section 5, we conclude with a discussion of our findings.

2. Institutional context: the Italian Servizio Sanitario Nazionale (SSN) and the resource allocation formula

The Italian Servizio Sanitario Nazionale (SSN) provides universal coverage, mostly free at the point of use, through a regionally organized system. In terms of resource allocation, the Ministry of Health allocates

[1] The various methods (OLS to ML) where evaluated using adjusted R2 and mean under/overcompensation by spending quintile similar to Park and Basu (2017). Results showed how ML algorithms are favored in simple models, compared to fine granularity scenario.

national funds from general taxation to the Regions. LHAs (Aziende Unità Sanitarie Locali, AUSL) are responsible for delivering the package of services (Livelli Essenziali di Assistenza – LEA) through a network of providers (Ferré et al., 2014).

This decentralized structure faces significant challenges due to North-South economic and social disparities (Bruzzi et al., 2022), affecting, among others, data availability and quality. While service-related data is collected at the hospital and local levels, heterogeneity in system accessibility, variations in information systems, and inconsistent data completeness and database quality across Regions hinder effective combination and utilization of the data (Skrami et al., 2020).

Since the establishment of the Italian NHS in 1978, the allocation formula has undergone several revision attempts. In 1996, the government formally required that allocations consider not only population, but also healthcare consumption by age and sex, mortality rates, and territorial and epidemiological indicators, though this was never fully implemented (Fantozzi et al., 2025). Since 2011, resources are allocated from the central Government to the Regions for three main levels of the package of services (LEA): prevention (5 %), hospital care (44 %), and community care (e.g., primary care, community pharmaceutical care, specialist outpatient care, and other district community health) (51 %). Allocation methods for each level vary: preventive care is population-based; hospital care combines population and age-weighted factors; and community care uses both approaches (e.g., family medicine, pharmaceutical is population based and specialist care is age weighted) (de Belvis et al., 2022). This process involves identifying three benchmark Regions based on efficiency and financial performance (Cichetti et al., 2021). 41 % of the allocation is determined through age-weighted capitation, while the remainder follows simple capitation (Ferré et al., 2014). Despite a 2014–2016 agreement proposing socioeconomic and quality-related parameters, the system largely retains its age-only component. In December 2022, 0.75 % of the National Health fund was allocated based on social deprivation indicators, and another 0.75 % on the premature mortality rate below 75. The rest of the funding (98.5 %) continues to be allocated according to the criteria adopted in previous years.

Despite age-weighting, disparities persist between the central/northern and southern Regions. Factors include variations in fiscal revenue and patient mobility. Patients seeking care outside their region exacerbate financial transfers from southern to northern Regions, as the Regions must pay for residents' care elsewhere while funding their own facilities. While local regional patients face budget caps, extra-regional patients provide unconstrained revenue (Berta et al., 2021). Efforts to reduce interregional mobility include setting tariffs near marginal costs.

3. Data and methods

3.1. Data

We utilize an administrative dataset of all residents from the Emilia-Romagna region in Italy for 2016. This anonymized dataset includes individual-level information on healthcare spending in specialist outpatient care and laboratory tests provided within the inpatient setting, hospital care, and pharmaceuticals (the standardized package of services - LEA). It also includes demographic data such as age, sex, citizenship, degree of urbanization (of the place of residence), exemption codes (which allow us to derive proxies to income), LHA of residence, and morbidity variables (DCGs), type of specialist outpatient care and laboratory tests, and pharmaceutical information coded into PCGs. The dataset comprises all beneficiaries with universal access to the Italian SSN in the Emilia-Romagna region. The sample, after data cleaning (excluding non-residents[2] of the Emilia-Romagna region and individuals with missing information), includes 4,262,377 individuals.

Table 1 presents the descriptive statistics. Average spending is 1,010 euros, with hospital care accounting for 549.8 euros, pharmaceuticals 289.8 euros, and specialist outpatient care and laboratory tests 170.6 euros. Most of the population is under 65 years old (74.5 %), female (51.8 %), holds Italian citizenship (91.7 %), and belongs to the LHA 7 (25.4 %) and 5 (19.1 %), resides in peri-urban areas (44.5 %), and falls into the low-income category (41 %).

The average number of hospitalizations is 0.15 (SD = 0.51), and the average number of prescription drugs is 10.1 (SD = 16.6). Additionally, 77.5 % of the sample used specialist outpatient care or laboratory tests, 32.2 % used pharmaceuticals (PCGs), and 11.2 % had at least one record in a diagnostic group (DCGs).

3.2. Methods

3.2.1. The current resource allocation formula

We approximate the current Italian resource allocation formula[3]

Table 1
Descriptive statistics of the sample.

Variables	Mean (SD)
Number of observations	4,262,377
Spending (euros, per capita per year)	
Specialists ambulatory care and laboratory tests	170.6 (950.9)
Hospital care	549.8 (2,981.8)
Pharmaceuticals	289.8 (2,957.3)
Total spending	1,010.1 (4,614.7)
Sociodemographic variables	
Age	
≤19 years	14.6 %
20–64 years	59.9 %
≥65 years	25.5 %
Sex (=Female)	51.8 %
Citizenship (=Italian)	91.7 %
Place of residence	
1	10.1 %
2	6.17 %
3	11.7 %
4	8.13 %
5	19.1 %
6	16.5 %
7	25.4 %
8	2.93 %
Degree of urbanization	
Urban	36.3 %
Peri-urban	44.5 %
Rural	19.2 %
Income	
Low income	41.0 %
Medium-low income	13.7 %
Medium-high income	2.3 %
High income	9.3 %
Other	33.7 %
Morbidity variables	
Number of hospitalizations	0.15 (0.51)
Number of Prescription drugs	10.1 (16.6)
Specialist outpatient care and laboratory tests (=1)	77.5 %
DCGs (=1)	11.2 %
PCGs (=1)	32.2 %

[2] Recording of information is based on the official residential location. Individuals are regarded as residents if at the time of their access to the healthcare services (hospitalization, lab test, specialist visit, etc) are registered in the official registry of a municipality in the Region.

[3] As mentioned, around 1 % of the budget is redistributed based on social deprivation and mortality, which we do not include in our estimations.

used in the national procedure using regional data.

The current formula uses a procedure that is a combination of unweighted and weighted capitation for different spending areas. We begin by calculating the allocations related to the unweighted component, which applies to 50 % of hospital care spending and 100 % of pharmaceutical spending. For hospital care, we multiply the average hospital spending (549.8 euros per person per year) by 0.5, resulting in an equal allocation of 274.9 euros per individual per year. For pharmaceutical spending, everyone receives an allocation equal to the average spending (289.8 euros).

To compute the hospital care allocation, we create a fictitious population using the age-based weights such that, for instance, 3.184 for an individual under 1 year is treated as 3.184 individuals. We calculate the allocation by multiplying 0.5 by the sum of all hospital spending divided by this fictitious population, resulting in 239.4 euros per capita. This is multiplied by the respective weights from Table 2. Thus, an individual aged less than 1 year receives an allocation of 762.3 euros (239.4*3.184), while an individual aged 25–44 receives an allocation of 130.2 euros (239.4*0.544).

Similarly, for specialist outpatient care and laboratory test services, we calculate a fictitious population using the weights. Dividing the total outpatient and laboratory test services spending by this new population gives 152.1 euros per capita. This is multiplied by each age class's weight to determine the individual allocations. For example, an individual under 1 year receives 59.5 euros (152.1*0.391), while one aged 75+ receives 324.8 (152.1*2.136).

3.2.2. Alternative resource allocation formulas based on risk adjustment

We construct alternative resource allocation formulas that rely on risk adjustment, that is, on the use of indicators of expected health spending to redistribute resources. We use a concurrent risk adjustment, modelling 2016 spending against the same year individual characteristics.

We estimate, as is common (Ellis et al., 2018), an ordinary least squares (e.g., regression) model, where the dependent variable is "Total health care costs", equivalent to the sum of specialist outpatient care and laboratory tests, hospital care, and pharmaceuticals.

Table 3 describes six alternative formulas that vary in their range of variables (e.g., risk adjusters) from a demographic (poor range) to a rich range of variables (including morbidity indicators), and in their granularity (from coarse to fine, capturing aggregate healthcare encounters such as number of hospitalizations to specific morbidity indicators such as diagnosis groups (DCGs) or pharmaceutical groups (PCGs)). These formulas correspond to those in Iommi et al. (2022).

3.2.3. Evaluation measures

3.2.3.1. Goodness of fit. We utilize two summary measures to assess performance fit at the individual level: R-squared (R2) and the Cummings Prediction Measure (CPM) (Van Veen, Van Kleef, Van de Ven and Van Vliet, 2015). These measures allow us to evaluate how well a proposed option fits relative to the current formula or alternatives.

The R2 indicates the proportion of variance in spending explained by the formula, computed as 1-SSR/SST, where SSR is the sum of squared residuals, and SST is the sum of squared differences between spending and mean spending. Higher R2 indicate a better fit. R2 is sensitive to expense variance and outliers due to its basis on squared errors.

The CPM captures predictive accuracy in absolute terms, measuring the extent of observed value deviation from predictions. CPM is less sensitive to large outliers, as it does not involve squaring, and is calculated as 1 − (Mean Absolute Prediction Error)/(Mean Absolute Deviation from Average).

3.2.3.2. Over and under compensations. Our primary group-level measure is over/under compensations. This measure compares the average payments from the current resource allocation or the predicted values from the alternative formulas which use risk-adjustment, to the average actual costs for specific groups "g". Calculated as the per-person difference between expected and actual costs on a group level, in monetary terms (€), a negative sign (loss) indicates that the Region/LHA is undercompensated for group "g" (expected is less than actual), while a positive sign (gain) suggests overcompensation for group "g". Values close to zero imply greater fairness, and larger values mean increased incentives for selective rationing.

The rationale behind group level measures is that it allows us to answer the question, "Does the resource allocation funding formula adequately pay the Region for residents of a particular subgroup of the population?". The concern is that if the resource allocation formula does not adequately compensate a specific group, the Region might have incentives to exert selective rationing against this group. A group metric is also useful as economic analysis suggest discriminations would likely happen against groups of residents, not individuals (Layton et al., 2018). In Italy's SSN, Regions/LHA are committed to implementing strategic planning to meet population health needs. This serves as a basis to determine the relevant groups to monitor for selective rationing[4]. First, age and sex groups are considered to demonstrate the impact of risk adjustment versus the current procedure. Second, socioeconomic factors such as urbanization, citizenship, income, and LHA of residence are assessed to evaluate how changes in the formulas affect deprived areas/poorer individuals. Third, proxies for cancer groups monitored by the Region, such as breast cancer in women aged 45–74, neck of the uterus cancer in women aged 25–64, and rectal cancer in individuals aged 50–69. We use broader DCG groups to approximate these patient cohorts due to data limitations. Last, we consider specialist and laboratory tests related to cancer treatment (i.e., radiotherapy and chemotherapy). This focus on high-cost groups highlights how improved risk adjustment can address healthcare needs, aligning with Regions strategic planning goals to manage waiting lists.

3.2.3.3. Responsiveness to need. We compute the "responsiveness to expenditure need" metric as proposed by Urwin et al. (2024), which captures whether individuals with higher predicted need receive more resources, or whether allocations remain relatively flat regardless of need. We proceed by calculating this metric as follows:

(1) We compute the predicted expenditures for each individual for the current resource allocation formula, and the six alternative formulas as presented in Table 3. We term this predicted need.
(2) Individuals are sorted by predicted need. To assign a percentile-style rank, each individual's position in the sorting is then divided by the total population in the dataset to obtain a value that ranges from 0 (lowest need) to 1 (highest need).
(3) Then, we compute the gap in funding as actual costs minus predicted need for each of the seven formulas. Each gap is regressed against the rank computed in Step 2: ($gap_i = \alpha + \beta \cdot rank_i$).

This regression is interpreted as follows. The intercept captures the gap when the ranked need is 0 (the lowest). Negative values of the intercept would mean that the predicted need is higher than actual costs for those with the lowest need, and conversely, positive values would mean that actual costs are above predicted need for those with the lowest-ranked need.

The coefficient (slope) of the regression is the 'responsiveness to expenditure need' metric. It captures how much the actual costs – predicted need gap changes as you go from low-need to high-need individuals. If $\beta > 0$: gap rises *more than expected* for high-need people. If $\beta < 0$: gap rises *less than expected* for high-need people.

[4] It is important to note that relevant groups vary by context, and their identification should be tailored to each specific setting.

Table 2
Weights for outpatient and hospital care, 2016

National Weights by age groups	Average spending (euros)	<1 year	1–4 years	5–14 years	15–24 years	25–44 years	45–64 years	65–74 years	>75 years
Specialist outpatient care and laboratory test services	152.1	0.391	0.288	0.341	0.382	0.627	1.123	2.155	2.136
Hospital care	239.4	3.184	0.364	0.234	0.371	0.544	0.923	2.047	2.844

Table 3
Risk adjustment formulas estimated.

	Poor range of variables (Demographic – DEM)	Fair range of variables (DEM + Hospital Discharge Records – HDR)	Rich range of variables (DEM + HDR + Pharmacy Database – PD)
Coarse granularity (scarcely detailed)	Formula 1: Total healthcare costs = f (sex*age groups) Age groups: 0, 1–4, 5 year classes up to 90, 90+	Formula 2: Total health care costs = f (sex*age groups + n. of hospitalizations) HDR: n of hospitalizations	Formula 3: Total health care costs = f (sex*age groups + n. of hospitalizations + n. of drug prescriptions) HDR: n of hospitalizations PD: n of prescriptions
Fine granularity (highly detailed)	Formula 4: Total health care costs = f(sex*age groups + citizenship + degree of urbanization + income) Age groups: 0, 1–4, 5 year classes up to 90, 90+ Citizenship: Italian (yes/no) Degree of urbanization: urban, peri-urban, rural Income: low, medium-low, medium high, high	Formula 5: Total health care costs = f (sex*age groups + citizenship + degree of urbanization + income + group of ICD-9 codes) HDR: ICD-9-CM codes which can be classified into diagnosis related groups	Formula 6: Total health care costs = f (sex*age groups + citizenship + degree of urbanization + income + group of ICD-9 codes + group of ATC codes) HDR: ICD-9-CM codes which can be classified into diagnosis-related groups PD: ATC codes which can be classified into pharmaceutical groups

Note: Income level[a] is grouped into categories of low[b], medium-low[c], medium high[d], high[e] and other[f], following the exemption codes criteria in the footnotes. Income data used to construct the exemption codes is self-reported. The diagnosis related groups correspond to the 78 diagnoses based on Ash et al. (1989). The full list of these groups can be found in the Supplementary material. Similarly, the pharmaceutical cost groups included (36), have been detailed in the Supplementary material.

[a] Based on the exemption codes. If an individual is included in more than one income bracket, they are assigned to the lower one.

[b] Individuals need to meet one of the following criteria: be aged under 6 or over 65 with a family income of less than 36,151.98 euros; the unemployed - and their dependent family members - with a family income of less than 8,263.31 euros; benefit holders (former pension) social - and their dependent family members; minimum pensioners - over 60 years old - and their dependent family members - with family income <8,263.31; exemption for workers affected by the crisis; RE1 band - up to 36,151.98 euros.

[c] Includes the RE2 range - between 36,153 and 70,000 euros.

[d] Band RE3 - between 70,0001 and 100,000 euros.

[e] Those in the Maximum Quota range - over 100,000 euros; exemption code missing.

[f] Unspecified income, which includes individuals with only the exemption for pathology and/or other.

3.2.3.4. Service level distortion. Following Layton, Ellis and McGuire (2015) and Brammli-Greenberg et al. (2019), we construct a service distortion measure. We assume that resources are allocated across budget cells, varying by groups and services. This means individuals with the same healthcare needs using the same service may receive different levels of care if they're in different budget cells. We focus on how resources are distributed among these cells, assuming Regions/LHA adhere to budget and capacity limits. Suboptimal compensation may lead to under-allocating resources to expensive cells, easing budget constraints.

The formula for this measure is as follows:

$$\psi = 1 - \frac{\sum_q \left(\sum_i \widehat{\frac{x_i^q}{x^q}} \left(rev_{p,i} - x_i \right) \right)^2}{\sum_q \left(\sum_i \widehat{\frac{x_i^q}{x^q}} \left(\bar{x} - x_i \right) \right)^2}$$

Where q is a budget cell within a matrix, which is defined as:

- Three service categories: hospital care, pharmaceutical and specialist outpatient care and laboratory tests. As they are not mutually exclusive for each individual, meaning that an individual can have 1 or more of the spending categories, we construct the matrix for each one.
- Three classes of age: 0–24, 25–64, 65+.
- Sex (male/female)
– 5 Income groups (low, medium-low, medium, high, other)

x_i is total health care costs of individual *i*; $rev_{p,i}$ is the resource allocation received for individual i, coming from the formula p; $\bar{x}$ is the average spending among the population; x_i^q is the total health care costs of individual *i*, in the budget cell q (for example, males, aged 0–24, in the high income group); x^q is the total healthcare costs in cell q (across all groups). The ratio $\widehat{\frac{x_i^q}{x^q}}$ represents an individual's share of the overall spending on the cell q.

The interpretation of the index ψ is as follows: values closer to 1 indicate fewer incentives for service distortions (1 = no incentives, 0 = full incentives). If allocations equal actual expenditure, the result from the fraction is 0, and the index is 1, indicating no incentive for service distortion. Conversely, if the allocation is equal to the constant population average $\bar{x}$, not discriminating across individuals, the fraction equals 1, and the indicator is 0, suggesting potential incentives for service distortion.

3.2.3.5. Simulations. We conduct a simulation to estimate allocations across regions resulting from changes in the national resource allocation formula. This simulation provides a comprehensive understanding of various formula implications on different geographic areas, considering regional characteristics and specific needs.

We create the 20 Italian Regions based on their population size and age structure, broken down into 3 groups (percentage of the total population in the Region which falls into one of the following groups 0–14; 15–64; 65+) (ISTAT, 2023).

The simulation process involves: First, calculating each Region's percentage out of the total Italian population; second, multiplying the percentage of population in each Region-age group by the percentage of the total regional population over the total national population. This provides us with the percentage that a particular age group in a region represents of the total population of Italy; third, dividing our regional dataset into 3 age groups (0–14; 15–64; 65+); fourth, randomly selecting individuals without replacement for each group to allocate them across Regions according to the regional quota in each age group; fifth, summing up predictions from each formula (current and alternative), for each region based on the random sampling. This gives us the total resource allocation to each Region, with the sum of regional payments equaling the total spending in the dataset, as the budget is cleared.

4. Results: Comparison between the current resource allocation formula and the alternative formulas

4.1. Goodness of fit measures

Table 4 displays goodness-of-fit measures for the current and alternative resource allocation formulas. The current formula shows a higher R2 (11.4 %) compared to the alternative formula based on demographic risk factors only (Formula 1) (2.8 %). This difference could be attributed to better cost matching, separate accounting of spending items, and a higher proportion of actual costs shared. Formulas 2 and 3, which add the number of hospitalizations and drug prescriptions, show significant improvements over the current formula. Incorporating socioeconomic indicators (Formula 4) marginally increases R2 to 2.9 %, aligning with the literature, which indicates little statistical association between socioeconomic indicators and healthcare expenditures. Models with more detailed morbidity variables (e.g., DCGs and PCGs) (Formulas 5 and 6) enhance fit further by 2–7 percentage points. This is consistent with pharmacy data better capturing chronic illnesses and therefore explaining spending, and with more available pharmacy information across the included spending types of the LEA.

Overall, CPM exceeds R2, mainly due to error treatment, as CPM measures absolute predictive accuracy, handling large variations without squaring, resulting in relatively higher values. In the current model, values are closer, indicating smaller errors and similar R2 and CPM results.

4.2. Over and under compensations by selected groups

Fig. 1 shows the over and under compensations in the current formula by sex and age groups. The current formula significantly overpays the young and under pays the old. On average, young males between 1 and 54 are overpaid 336 Euros, and older males (55+) underpaid by −832 Euros. Females from 0 to 59 are overpaid on average 313 Euros, and those older underpaid by −481 Euros. Risk adjustment by construction precisely aligns payments with the average expenditure in each group, eliminating group-based over/under compensations (not shown).

Table 5 indicates the over/under compensations by socioeconomic groups, which serve as proxies of health status. Adding a simple morbidity indicator (number of hospitalizations as in Formula 2) significantly reduces the over/under compensations across various socioeconomic groups.

Low-income individuals (41 % of our sample) (with a caveat about the quality of the data on declared incomes, which we address in the discussion section), are undercompensated by 202.6 euros per person in the current formula. High income individuals (9 %) are also undercompensated, but by a much lesser extent (26 euros per person). On the other hand, middle income groups (16 %), are overcompensated by 121–133 euros per person. The number of hospitalizations indicator (Formula 2) nearly eliminates the largest under compensation for low income. The results indicate that risk adjustment results in a shift of funds towards specific groups.

In terms of over/under compensations according to the LHA of residence,[5] older, poorer and relatively more rural populations show the greatest improvement when the formula is enhanced (values closer to 0). Overall, LHA with relatively low levels of income, higher rural settings and older age (see Footnote 5) tend to be largely under compensated. More advanced risk adjustment models significantly reduce under/over compensations across LHAs.

Table 6 shows over/under compensation by selected cancer inpatient groups. Particularly, women aged 45–74 with breast cancer, women 25–64 with cervical cancer, and individuals aged 50–69 with rectal cancer.

Large under compensations are evident across our three groups. The most significant under compensation in the current formula is observed for rectal cancer patients aged 50–69, amounting to 16,250 euros per person (3,395 individuals in the sample). The current formula shows large under compensations, which worsen with Formula 1 (demographic variables only). Formula 2 (including number of hospitalizations) shows the most significant improvement, reducing under compensations to −6,693 euros per person. More granular formulas (5 and 6) further improve outcomes, with Formula 6 halving the under compensations of Formula 5 for breast cancer in women aged 45–74.

Last, Fig. 2 illustrates the under compensations for selected cancer groups related to specialist outpatient care and laboratory tests, specifically, chemotherapy and radiotherapy. Substantial under compensations are observed for both radiotherapy (8,313 euros) and chemotherapy (17,506 euros), in the current model. Formula 1 (age and sex only) shows even more pronounced under compensations. Incorporating the number of hospitalizations (Formula 2) significantly reduces under compensations, indicating a relationship between outpatient services and hospital episodes. The granularity of Formula 6 (attributed to PCG groups) approximately halves under compensations for radiotherapy and reduces them by 300 % for chemotherapy.

4.3. Responsiveness to need

Fig. 3 presents the results (intercept and slope) from the regressions, which capture how the gap between actual cost and predicted need varies across the ranked distribution of need, for each formula (current and alternatives). The Y-axis depicts the predicted gap (actual cost minus predicted need), and the X-axis the ranked need. Values below zero of the predicted gap reflect predicted need is higher than actual cost, indicating over-compensation, while values above zero reflect predicted need is lower than actual cost, indicating under-compensation. Moving to the right of the X-axis represents individuals with higher ranked needs. Each line reflects a different funding formula. An upward (positive) slope means the formula increasingly under-compensates people as need rises, while a downward (negative) slope means it increasingly over-compensates those with higher need. A flat line indicates a more neutral allocation across all levels of need.

Formula	Intercept	Slope
Current	−1,170.4	2,340.8
Formula 1	−42.3	84.5
Formula 2	343.2	−686.3
Formula 3	356.5	−713.1
Formula 4	14.4	−28.8
Formula 5	121.8	−243.6
Formula 6	125.0	−249.9

Note: Formula 1: sex*age groups; Formula 2: sex*age groups + n. of hospitalizations; Formula 3; sex*age groups + n. of hospitalizations + n. of drug prescriptions; Formula 4: sex*age groups + citizenship + degree of urbanization + income; Formula 5:

[5] Table 4 in the supplementary material contains the descriptive statistics per LHA of residence with the purpose of identifying their level of deprivation simplified by rurality, low income and age population structure.

Table 4
Comparison between the current resource allocation formula, and the alternatives based on risk adjustment which vary in terms of granularity and range of variables.

	Current	Formula 1	Formula 2	Formula 3	Formula 4	Formula 5	Formula 6
R2	11.4 %	2.8 %	29.3 %	30.5 %	2.9 %	32.8 %	38.0 %
CPM	12.2 %	6.9 %	39.0 %	41.6 %	7.2 %	43.9 %	50.2 %

Note: Formula 1: sex*age groups; Formula 2: sex*age groups + n. of hospitalizations; Formula 3; sex*age groups + n. of hospitalizations + n. of drug prescriptions; Formula 4: sex*age groups + citizenship + degree of urbanization + income; Formula 5: sex*age groups + citizenship + degree of urbanization + income + group of ICD-9 codes; Formula 6: sex*age groups + citizenship + degree of urbanization + income + group of ICD-9 codes + group of ATC codes.

Fig. 1. Over and under compensations in the current formula, by sex and age groups. Note: M: Males, F: Females. Green = Over compensations; Red = Under compensations. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 5
Over and under compensation by socioeconomic indicators.

		Current	Formula 1	Formula 2	Formula 3	Formula 4	Formula 5	Formula 6
Degree of urbanisation	Urban	−25.8	−27.1	−11.5	−28.0	0	−16.0	−18.5
	Peri-urban	34.3	29.0	11.4	15.7	0	9.4	9.4
	Rural	−30.7	−15.8	−4.7	16.6	0	8.5	13.1
Citizenship	Italian	−20.8	−1.8	−8.19	−5.6	0	0	0
Income	Low	−202.6	−159.0	−19.68	50.2	0	0	0
	Medium low	121.0	134.8	139.2	143.9	0	0	0
	Medium high	133.2	168.9	175.1	113.1	0	0	0
	High	−25.9	−113.5	−86.1	−181.7	0	0	0
LHA of residence								
	1	−11.9	−17.7	3.4	−1.2	−25.1	−2	−10
	2	−131.5	−125.2	−4.0	−65.7	−129.7	−26	−42
	3	20.8	−21.0	−18.8	−7.5	−24.7	−40	−19
	4	−67.5	−54.0	−35.4	−18.0	−27.0	−7	1
	5	−13.2	2.3	4.3	−0.9	5.3	6	5
	6	35.1	11.8	−8.1	−2.6	2.1	17	7
	7	38.9	57.8	34.3	30.0	62.0	19	21
	8	−26.1	−24.2	−26.0	−18.1	−50.3	−57	−58

Note: Formula 1: sex*age groups; Formula 2: sex*age groups + n. of hospitalizations; Formula 3; sex*age groups + n. of hospitalizations + n. of drug prescriptions; Formula 4: sex*age groups + citizenship + degree of urbanization + income; Formula 5: sex*age groups + citizenship + degree of urbanization + income + group of ICD-9 codes; Formula 6: sex*age groups + citizenship + degree of urbanization + income + group of ICD-9 codes + group of ATC codes.

Table 6
Under compensations for selected cancer inpatient groups.

	Frequency	Current	Formula 1	Formula 2	Formula 3	Formula 4	Formula 5	Formula 6
Breast cancer in women 45–74 year old	4,632	−7,534	−9,565	−1,956	−1,895	−9,546	−1,076	−515
Cervical women 25–64 year old	1,246	−10,995	−12,612	−2,068	−2,110	−12,575	−2,373	−1,812
Rectal 50–69 (men and women)	3,395	−16,250	−17,502	−6,693	−6,638	−17,474	−2,892	−2,314

Note: Formula 1: sex*age groups; Formula 2: sex*age groups + n. of hospitalizations; Formula 3; sex*age groups + n. of hospitalizations + n. of drug prescriptions; Formula 4: sex*age groups + citizenship + degree of urbanization + income; Formula 5: sex*age groups + citizenship + degree of urbanization + income + group of ICD-9 codes; Formula 6: sex*age groups + citizenship + degree of urbanization + income + group of ICD-9 codes + group of ATC codes.

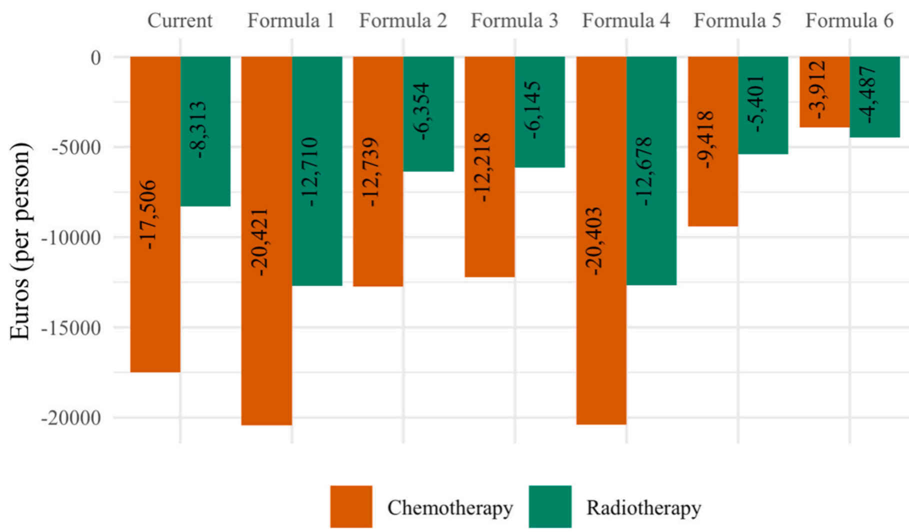

Fig. 2. Under compensations for selected oncological groups specialist ambulatory care and laboratory tests. Note: Formula 1: sex*age groups; Formula 2: sex*age groups + n. of hospitalizations; Formula 3; sex*age groups + n. of hospitalizations + n. of drug prescriptions; Formula 4: sex*age groups + citizenship + degree of urbanization + income; Formula 5: sex*age groups + citizenship + degree of urbanization + income + group of ICD-9 codes; Formula 6: sex*age groups + citizenship + degree of urbanization + income + group of ICD-9 codes + group of ATC codes. The frequency of radiotherapy: 10775 individuals, The frequency of chemotherapy: 3127 individuals.

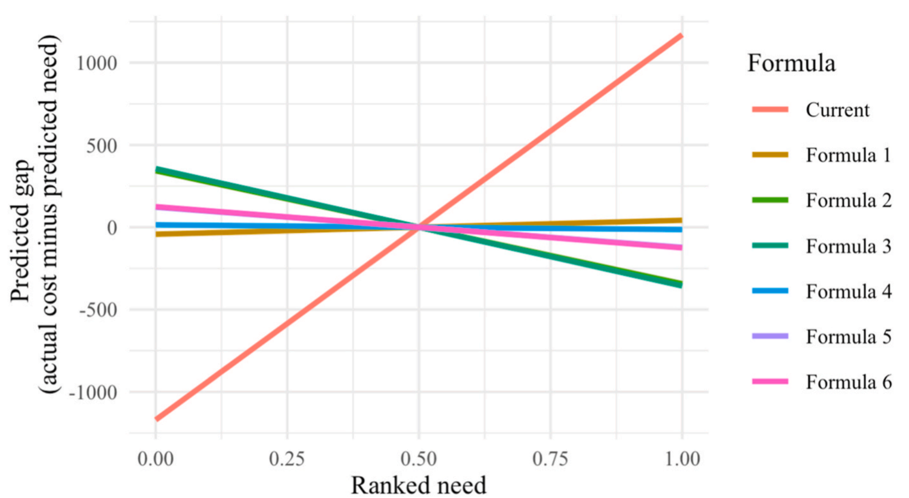

Fig. 3. Responsiveness to need measure.

sex*age groups + citizenship + degree of urbanization + income + group of ICD-9 codes; Formula 6: sex*age groups + citizenship + degree of urbanization + income + group of ICD-9 codes + group of ATC codes.

For the current formula, the intercept indicates that individuals ranked at zero in the relative need distribution are overcompensated by approximately 1,170 Euros, as predicted spending exceeds actual spending. The positive slope shows that this pattern reverses as need increases, leading to substantial under-compensation among individuals with the highest levels of need. This suggests a misalignment between funding and underlying health needs.

Formula 1, which adjusts for sex and age, has a small positive intercept of around 42 Euros, indicating slight under-compensation among individuals with low need. Its slope is close to zero, with values remaining near zero across the distribution. This suggests the formula is largely unresponsive to variation in need, as the gap between predicted and actual spending remains relatively constant.

Formulas 2 and 3, which add a coarse measure of morbidity, in the number of hospitalizations and number of drug prescriptions, respectively, reveal a higher responsiveness to need as low-need individuals are under-compensated, and the slope of the line is negative and large, indicating progressively better compensations for higher-need individuals.

Interestingly, Formula 4, which adds age, sex, citizenship + degree of urbanization + income, is relatively flat, as the intercept is 14 Euros and the slope is negative but moderate, meaning those with the greatest needs do not significantly receive more resources.

Finally, Formulas 5 and 6 fall between these extremes, indicating moderate responsiveness to need, with smaller and more balanced deviations across the distribution.

4.4. *Service level distortion*

Mitigating service-level selection incentives is an important rationale for risk adjustment. The Psi index allows us to compare various formulas in terms of their incentives for service distortion. This index is applied across formulas (current and alternatives).

The results in Table 7 capture the index ψ (“psi”) that ranges from

Table 7
Psi index of service level distortion across models.

	Current	Formula 1	Formula 2	Formula 3	Formula 4	Formula 5	Formula 6
Hospital	0.089	0.009	0.257	0.271	0.006	0.243	0.314
Pharmaceuticals	0.080	0.015	0.405	0.393	0.011	0.394	0.424
Specialists	0.064	0.013	0.444	0.445	0.010	0.412	0.454

Note: Formula 1: sex*age groups; Formula 2: sex*age groups + n. of hospitalizations; Formula 3; sex*age groups + n. of hospitalizations + n. of drug prescriptions; Formula 4: sex*age groups + citizenship + degree of urbanization + income; Formula 5: sex*age groups + citizenship + degree of urbanization + income + group of ICD-9 codes; Formula 6: sex*age groups + citizenship + degree of urbanization + income + group of ICD-9 codes + group of ATC codes.

0 (strongest incentive for service distortion) to 1 (no incentive for service distortion) and a change in the payment mechanisms that results in an increase in the index, decreases the incentive for service distortion.

The index is higher under the improved formulas, but it is far from 1, suggesting that some pressure for service distortion remains even when more refined formulas are implemented. The best formula to reduce this pressure is Formula 6 (which includes DGC and PCG groups), where the index ranges from 0.455 in outpatient spending to 0.314 in hospital services. However, even the introduction of the simplest morbidity measure (Formula 2) changes significantly the hospital index, from 0.089 to 0.257.

4.5. Simulation

Table 8 presents the total (not per-person) resource allocation payments (in million Euros) each Region would receive from the central fund under the current and alternative formulas. Columns 2,3, and 4 show the age structure of the regions.

Results show that formulas accommodating regional population structures better distribute resources based on varying risks. For instance, in Region 6 with the highest percentage of 65+, payments increase by 4.5 %–5.2 % in sociodemographic Formulas 1, 4, and 5 compared to the current formula, reaching 120.11 million euros in Formula 5. Conversely, in regions with lower elderly percentages (Regions 11 and 17), indicative of lower healthcare needs, payments consistently decrease by 2.7 %–3.4 % from the current formula.

5. Conclusions and discussion

This paper quantified selective rationing incentives using the healthcare system in the Emilia-Romagna Region of Italy as a case study. In evaluating the current funding formula used in Italy and its impact on the Region, we compare it with alternatives that rely on risk adjustment to improve alignment between funding and healthcare needs, while considering feasibility constraints that limit formula development at the national level.

The results showed that the current formula exhibits large sex and age over and undercompensation. Moreover, little statistical association between spending and age, sex and the socioeconomic variables (such as income, degree of urbanization, citizenship) was observed, aligning with findings from the literature (Cid et al., 2016; Gravelle et al., 2003; McWilliams et al., 2023). Despite their limited predictive power, their feasibility for incorporation remains high. Their contribution to improving alignment of resources to healthcare needs, observed in the elimination of over and under payments, provides a rationale for moving away from the current unweighted/weighted resource allocation system towards risk adjustment to diminish underpayments.

This is echoed for the case of socioeconomic variables, which revealed important reduction in disparities between richer and poorer individuals/areas, and in occasion these differences would be neutralized, similar to what has been argued in previous research (Irvin et al., 2020; Schokkaert, Guillaume and van de Voorde, 2018; Ash et al., 2017; Holster et al., 2024; Lux et al., 2025). These variables offer advantages, such as resistance to manipulation by the Region/LHA/providers and therefore efficiency in resource allocation. However, they introduce complexity, relying on potentially incomplete self-reported data and facing challenges in tax-based systems, like underreporting of income. Moreover, because risk adjustment is based on observed spending, underlying socioeconomic factors such as the persistent North–South divide in Italy and its correlation with under/over utilization might have

Table 8
Payment to each region based on the current and alternative formulas (in millions, Euros).

Region	0–14	15–64	65+	Current formula	Formula 1	Formula 2	Formula 3	Formula 4	Formula 5	Formula 6
Region 1	12.6	64.2	23.2	414.22	411.18	408.39	409.03	410.97	409.92	410.62
Region 2	11.8	62.2	25.9	109.66	111.83	112.42	112.63	111.84	112.66	112.47
Region 3	11.6	62.1	26.2	272.01	277.21	275.93	275.88	277.22	275.95	276.48
Region 4	11.7	61.6	26.8	63.67	65.33	65.32	65.54	65.34	64.94	64.80
Region 5	12.1	62.9	25.0	9.03	9.15	9.32	9.31	9.13	9.41	9.39
Region 6	10.7	60.4	28.9	114.19	119.30	119.70	119.46	119.28	120.11	119.80
Region 7	12.8	63.8	23.4	724.22	718.75	717.91	718.23	718.78	720.26	719.42
Region 8	11.7	61.8	26.4	316.49	322.88	322.55	322.46	322.93	321.24	320.51
Region 9	12.4	63.1	24.5	325.47	326.08	326.15	326.25	326.21	326.39	327.32
Region 10	11.4	61.7	26.9	88.89	91.50	91.57	91.20	91.38	91.95	92.74
Region 11	14.4	63.8	21.8	77.35	75.23	75.24	75.14	75.23	75.00	75.06
Region 12	12.4	63.5	24.1	353.62	354.15	354.64	354.33	354.30	354.85	354.39
Region1 3	11.9	62.8	25.3	94.02	94.87	93.90	93.95	94.82	93.55	93.57
Region 14	12.3	63.9	23.8	285.04	284.20	284.04	283.88	284.14	283.53	283.97
Region 15	11.3	63.8	24.9	39.39	39.95	40.51	40.35	39.95	40.72	40.45
Region 16	12.8	63.6	23.6	134.62	133.70	134.16	134.06	133.75	133.40	133.47
Region 17	13.8	65.6	20.6	397.56	384.18	386.18	386.37	384.27	385.68	384.51
Region 18	10.8	62.7	26.5	21.34	22.22	22.30	22.12	22.25	22.24	22.26
Region 19	10.4	63.3	26.3	117.20	120.31	120.38	120.38	120.26	120.01	120.02
Region 20	13.3	63.8	22.9	347.70	343.52	345.36	345.38	343.44	343.08	342.98
Total				4,305	4,305	4,305	4,305	4,305	4,305	4,305

Note: Formula 1: sex*age groups; Formula 2: sex*age groups + n. of hospitalizations; Formula 3; sex*age groups + n. of hospitalizations + n. of drug prescriptions; Formula 4: sex*age groups + citizenship + degree of urbanization + income; Formula 5: sex*age groups + citizenship + degree of urbanization + income + group of ICD-9 codes; Formula 6: sex*age groups + citizenship + degree of urbanization + income + group of ICD-9 codes + group of ATC codes.

non-trivial implications for resource allocation, potentially perpetuating existing disparities through the risk adjustment models. These issues have been noted in the risk adjustment literature (van de Ven and Ellis, 2000). Proposed solutions in the literature take two forms: ex post correction through risk factors, and some proposals have suggested transforming underlying data toward efficient and fair spending levels rather than observed spending (see van Kleef et al. (2020) and Bergquist et al., 2019; Bergquist et al., 2019 for a comprehensive review of this literature). While we do not examine this in the paper, these approaches may address observed unfairness and inefficiency, particularly regarding socioeconomic variables, in shifting utilization incentives.

At the same time, we show that incorporating morbidity variables, even at coarse granularity, such as the number of hospitalizations, results in important improvements in fit, and becomes more compelling when examining high-cost groups, such as those with cancer, as under compensations in these groups is considerably higher. Despite challenges like upcoding (Geruso and Layton, 2020), morbidity data significantly aid in allocating resources to those in greater need.

Interesting results are revealed by the responsiveness to need measure. While findings support the inadequacy of the current resource allocation formula in responding to increasing levels of need, it provides novel results related to the role of socioeconomic and deprivation metrics, as formulas that only add these risk adjustors show low responsiveness to need, further suggesting these indicators are not able to fully capture health needs. Meanwhile, formulas which also add coarse measures of morbidity through the number of hospitalizations and number of drug prescriptions outperform more complex formulas, exhibiting a large responsiveness to need, channeling more resources to those ranked in highest need.

Following our service level distortion measure application, we show how, in the dimensions specified, deemed to be at risk of incentives for selective rationing on the provision side, better risk adjustment is more effective at reducing potential distortions (Berta et al., 2010). Nevertheless, the persistence of some degree of distortion suggests that even the most refined models cannot entirely mitigate the risk of service manipulation under the current data constraints, and broader institutional measures might be needed in line with regulations such as expanding the benefit package and instilling minimum services standard (availability, quality and intensity). This metric adapts previous work by Layton et al. (2015) and Brammli-Greenberg et al. (2019). It is important to note that the cells ("budget cells") are defined to reflect how Regional/LHA managers plausibly allocate resources in practice, rather than fine-grained clinical distinctions. Cells could be split more finely or more coarsely. Although the absolute level of the metric depends on the cell definition, such that with finer cells the metric would go down, and up with coarser cells, comparisons across resource allocation formulas, like in our case, reflect the impact of formulas on profit heterogeneity across cells.

Last, the regional simulations showed that alternative formulas, particularly those incorporating morbidity variables, proved to be more effective in allocating funds, thus directing resources towards Regions with higher risk profiles.

This paper is not without limitations. Our analysis relies on data from a single region in Italy, Emilia-Romagna, which has distinct socioeconomic and supply-side health characteristics. Overall, the population in Emilia-Romagna is relatively older and better off than the national average, even if in relative terms it is placed in the middle of the ranking for both demographic and economic indicators. According to ISTAT in 2024, the average age in Italy was 46.7, compared to 47.7 in Emilia-Romagna (the 6th oldest region over all 20 regions). In 2021, the prevalence of relative poverty in Italy was 11.1 % (North 7.5 %, Center 10.5 %, South 20.1 %), compared to Emilia-Romagna in which it was 8.7 % (again 6th out of 20). In terms of supply side characteristics, utilizing metrics that can be compared across regions, the Emilia-Romagna Region is endowed with 3.1 hospital beds per 1000 inhabitants, which is very near the national average of 2.9. Moreover, there are 2.14 doctors per 1000 inhabitants, while the national average is 1.85 (ANAP Confartigianato, 2025; Fondazione GIMBE, 2025). While comparable to other Italian regions in some respects, our work remains geographically focused.

To enhance external validity, we therefore use a simulation approach, yielding results consistent with studies that rely on survey data to approximate regional allocations (Fantozzi et al., 2025). This reflects common practice in international research on risk adjustment, where analytical datasets often differ from those used in actual policy implementation. An important direction for future research would require a national database covering a representative sample of regions, with information on healthcare spending and the demographic and health profiles of residents, to assess how these formulas could be operationalized in practice.

Our models excluded supply-side risk adjusters, such as provider density, distance, and waiting times, which are sometimes used to allocate funds geographically or to provider groups, as they are typically not available at the individual level (Ellis et al., 2018). While such variables can in principle be incorporated using aggregated or small-area information, these were not available in our dataset. Conceptually, the inclusion of supply-side factors is also debatable. Many countries, including Switzerland, Germany, and the Netherlands, do not adjust for these factors, as doing so risks compensating for inefficiencies or provider-induced demand (McGuire and Van Kleef, 2018). The main argument for including them is that supply characteristics can influence utilization, potentially biasing estimates of health needs. However, utilization differences do not always reflect true need: some groups may access care more easily or have different thresholds for seeking treatment. Evidence from the UK suggests that diagnosis-based risk adjustment already captures most demand- and supply-side variation (Dixon et al., 2011). Ultimately, adjustment should target factors outside regional control (e.g., health risk) rather than those reflecting provider performance (Panturu et al., 2025).

This paper has important implications for the design of risk adjustment models in Italy and broadly. Our findings contribute to the Italian SSN's growing interest in incorporating deprivation into resource allocation following the 2022 reforms. Fantozzi et al. (2025), in their review of the reform, argue for moving away from the current discretionary approach towards a needs-based risk adjustment mechanism that explicitly integrates deprivation indicators, where weights are determined by the distribution of need rather than judgment is needed. Our results support this shift and suggest that moving towards a prospective risk-adjusted formula, and away from unweighted/weighted capitation, could enhance efficiency and fairness by appropriately funding high-cost/high-risk cases, alongside a simple morbidity indicator. Overall, improvements in such a direction would have the potential to adequately fund Regions/LHAs to meet patient needs, and reduce incentives for selective rationing, improving equity and efficiency in production. This contributes to the overall literature on the design of equitable, feasible and efficient resource allocation, showing that simple adjustments can be successful in aligning funding and adequately responding to high-cost needs population. This has been argued in Henriquez et al. (2023) for Australia, finding that a risk adjustment formula that includes age, sex, prior hospitalization indicator, and reinsurance would outperform the existing age-only based risk sharing formula.

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Ethics

The datasets analyzed during the current study follow Iommi et al., 2022 and as such the same data statement applies. The data analyzed are property of a third party that is Emilia-Romagna Regional Health Agency (https://assr.regione.emilia-romagna.it/) and, although they are anonymized, datasets are not publicly available due to the current regulation on privacy. The description of the administrative databases is available from the website https://salute.regione.emilia-romagna.it/siseps/sanita/asa/documentazione. Other researchers can obtain access to the data through a formal request based on a research project to the Emilia-Romagna Regional Health Agency. We obtained the access to the data in the framework of a research agreement between the University of Bologna and the Local Health Authority of Bologna entitled "New funding mechanisms for the Italian National Health Service and the Emilia-Romagna Regional Health Service".

CRediT authorship contribution statement

Josefa Henriquez: Conceptualization, Data curation, Formal analysis, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Gianluca Fiorentini:** Conceptualization, Funding acquisition, Methodology, Writing – original draft, Writing – review & editing. **Francesco Paolucci:** Conceptualization, Funding acquisition, Writing – review & editing.

Declaration of competing interest

None.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.socscimed.2026.119032.

Data availability

Other researchers can obtain access to the data through a formal request based on a research project to the Emilia-Romagna Regional Health Agency.

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