

Article

Carbon Footprint (Scope 2) and Energy Intensity per Activity in Intermediate-Complexity Hospitals in the Community of Madrid: Panel Analysis (2016–2024)

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Abstract

Hospital buildings account for 60–80% of healthcare sector electricity consumption, yet robust causal evidence on the relationship between building energy efficiency and emissions per unit of clinical activity remains scarce. This study applies within-group fixed effects estimation to an unbalanced panel of 12 intermediate-complexity hospitals in Madrid, Spain (2016–2024; $N = 107$ hospital-year observations), controlling for activity volume and exogenous shocks. Cluster-robust standard errors and Wild Cluster Bootstrap inference address the limited number of cross-sectional units ($N = 12$). We propose a methodological correction for the artificial 74.6% discontinuity in Spain's electricity emission factor (2020–2021) caused by regulatory change. The within-hospital building energy use intensity (EUI_e) coefficient is $\beta = 0.646$ ($p < 0.001$), remarkably stable across six robustness specifications (range: 0.599–0.648; 8.2% variation). Wild Cluster Bootstrap confirms statistical significance despite 75% larger standard errors. A 20 kWh/m²·year EUI_e reduction achievable through Heating, Ventilation and Air Conditioning (HVAC) retrofit in 1980s-era buildings translates into 13 kWh/stay savings, equivalent to 216 tCO₂/year for median-sized facilities (8.2% reduction). Within R^2 exceeds 0.97 across all specifications. Building envelope and HVAC retrofit constitute the dominant structural intervention for hospital Scope 2 emissions reduction. Facilities with EUI_e > 150 kWh/m²·year should be prioritized for energy efficiency interventions using NextGenerationEU funds.

Keywords: hospital energy efficiency; scope 2 carbon footprint; fixed effects panel data; building energy use intensity; HVAC energy retrofit



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1. Introduction

The healthcare sector accounts for between 4% and 5% of global greenhouse gas emissions, with hospitals being the main contributors within this sector [1,2]. The carbon footprint of national healthcare systems ranges from 1.5% to 9.8% of national emissions, with an average of 4.9% [2]. Scope 1 and 2 emissions account for between 15% and 50% of total hospital emissions, while scope 3 emissions account for the remaining 50% to 75% [1]. The analysis of Scope 2 emissions derived from purchased electricity is particularly relevant for short-term decarbonization planning, as they can be directly controlled through improvements in building energy efficiency or by purchasing renewable electricity [3,4].

In Spain, the National Health System (NHS) manages more than 800 hospitals with an annual electricity consumption of over 4000 GWh [5]. The Community of Madrid, with

approximately 70 public and subsidized hospitals, accounts for a significant portion of this consumption and the associated Scope 2 emissions. Despite growing institutional attention to the decarbonization of the healthcare sector, as reflected in the NHS Net Zero [6,7], and the National Integrated Energy and Climate Plan (PNIEC) 2021–2030 [8] and the Institute for Energy Diversification and Saving (IDAE) Strategic Plan 2022–2026 [9] empirical evidence on the structural determinants of hospital energy efficiency in the Spanish context is scarce.

The available studies mainly focus on cross-sectional comparisons or single-case analyses [10–13] that do not control for unobserved heterogeneity between hospitals and therefore produce biased estimates. The study by Shiau et al. [14] is a notable exception in that it applies a panel Vector Autoregression (VAR) model; however, it does not exploit intra-hospital variation using a within estimator, nor does it incorporate the methodological discontinuity in electricity emission factors that characterizes the 2016–2024 period in Spain.

The use of panel data with fixed effects models allows this limitation to be overcome by exploiting within-temporal variation (intra-hospital) and eliminating the omitted variable bias associated with permanent factors [15,16]. This methodology has been widely used in health economics to estimate causal effects in the presence of unobserved heterogeneity, with applications in hospital efficiency [17,18], volume–outcome relationships [19], and effects of competition [20]. However, its application to the analysis of hospital energy determinants has been limited, with some exceptions such as the study by Sepetis [21] on environmental costs in Greek hospitals.

This article contributes to the literature on hospital decarbonization in four dimensions:

First, it estimates the causal effect of building energy intensity on emissions per activity using a fixed-effects estimator with cluster-robust standard errors, eliminating the bias of permanent unobserved heterogeneity between hospitals. The coefficient $EUI_e = 0.6461$ ($p < 0.001$) documents that approximately 65% of the additional energy consumption per square meter of the building is transferred to consumption per stay. The robustness of the finding is verified by six alternative specifications (range: 0.599–0.648; variation of only 8.2%). Given that asymptotic cluster-robust inference typically requires $G > 30$ clusters for a valid normal approximation [22], and this panel comprises $N = 12$ hospitals, the Wild Bootstrap method, which imposes the null hypothesis and adjusts p -values through resampling with restrictions, provides valid inference in small samples. The results confirm statistical significance ($p < 0.001$) even under conservative standard errors 75% greater than the conventional cluster-robust estimate, validating the robustness of the finding.

Second, it identifies and proposes a replicable correction for the methodological discontinuity introduced by the National Commission for Markets and Competition (CNMC) Circular 2/2021, which modified the calculation of the electricity emission factor, generating an artificial jump of 74.6% between 2020 and 2021 without any real change in consumption. This correction allows for valid intertemporal comparisons of the hospital carbon footprint in Spain, which is relevant for monitoring the decarbonization targets of the 2021–2030 PNIEC.

Third, it quantifies energy economies of scale in intermediate-complexity hospitals, documenting that they are marginal in this segment (β_{Stay_s} statistically significant but close to zero). This finding suggests that, unlike high-complexity hospitals with greater variation in scale, short-term healthcare activity in intermediate hospitals does not generate marginal adjustments in quasi-fixed energy consumption, limiting energy economies of scale to second-order effects.

Fourth, it provides quantitative evidence of the impact of energy rehabilitation on Scope 2 hospital emissions, estimating that a reduction of 20 kWh/m²·year in Building Energy Use Intensity (EUI_e) achievable through the renovation of HVAC systems in buildings from the 1980s reduces emissions by approximately 216 tCO₂/year per average hospital

(8.2% of the total carbon footprint). The analysis of the distribution of EUJe identifies priority hospitals for intervention ($\text{EUJe} > 150 \text{ kWh/m}^2 \cdot \text{year}$), providing objective criteria for prioritizing decarbonization investments.

The article is structured in six sections: Section 2 describes the data and econometric methodology; Section 3 presents descriptive results and fixed effects estimates; Section 4 discusses the implications for hospital decarbonization policy and the PNIEC 2021–2030; Section 5 presents the robustness analysis, including Wild Cluster Bootstrap; and Section 6 concludes with limitations and future research directions.

2. Materials and Methods

2.1. Sample and Data Sources

The panel comprises 12 intermediate-complexity hospitals in the Community of Madrid with data available for the period 2016–2024. The hospitals belong to three management models: seven are directly managed by Madrid Health Service (SERMAS), two are public or mixed foundations, and three are privately run under the Private Finance Initiative or Public–Private Partnership model (PFI/PPP). The data on electricity consumption and healthcare activity (stays, discharges, average stays) come from the SERMAS Energy Information System.

The annual electricity emission factors (EF) were obtained from the Agreements on Electricity Labeling published by the CNMC (GDO/DE/001/17–25). For the sub-period 2016–2020, the values published under Circular 1/2008 (production mix) were used, and for 2021–2024, those published under Circular 2/2021 (CO_2 equivalent emissions from the marketed mix; CNMC, 2021, 2022, 2023, 2024, 2025). The EF range in the period analyzed is from 0.150 (2020) to 0.310 kgCO_2/kWh (2017).

Three anomalies were identified and addressed:

- (i) Observation H1–2023 was excluded from the main model because it had an $\text{EUJe} = 10.64 \text{ kWh/m}^2/\text{year}$ (approximately one-eighth of the hospital's average in adjacent years), consistent with a recording error.
- (ii) For hospital H4 in 2021, 2022, and 2024, an intervention dummy (D_{H4}) was introduced to absorb the structural break of +48–55% in the EUJe.
- (iii) Observation H8–2024 ($\text{EUJe} = 162.96 \text{ kWh/m}^2 \cdot \text{year}$; +66% compared to its historical average) was verified in the primary source and retained in the panel. The final panel consists of 107 observations.

Hospital H4 (Fuenlabrada University Hospital): SERMAS primary data records a structural break in EUJe of +48–55% for the years 2021, 2022, and 2024, relative to its hospital's 2016–2020 baseline. This pattern is consistent with the phased post-COVID reactivation of energy-intensive clinical services and equipment—specifically, the reactivation of deferred HVAC-dependent areas and expanded clinical capacity documented in SERMAS operational records for this facility. The anomaly is discontinuous across years (affecting 2021, 2022, and 2024 but not 2023), a pattern consistent with phased reactivation and temporary stabilization rather than continuous building deterioration. The dummy variable D_{H4} is specified for precisely these three years. This specification is appropriate because: (i) the anomaly represents a documented, event-specific structural break rather than gradual drift; (ii) it is idiosyncratic to H4 and absent in all other hospitals; and (iii) the D_{H4} coefficient directly quantifies the excess EIA associated with the break, cleanly separated from the EUJe coefficient of interest. Robustness analysis confirms that excluding D_{H4} does not materially alter the main EUJe coefficient, validating that D_{H4} absorbs a genuinely idiosyncratic effect.

Hospital H8 (Hospital Universitario Infanta Sofía): The observation H8–2024 records $\text{EUJe} = 162 \text{ kWh/m}^2 \cdot \text{year}$ (+66% versus this hospital's historical average), verified against

SERMAS primary data and confirmed as accurate. Unlike H4, the anomaly is limited to a single year (2024) without evidence of multi-year structural reconfiguration, suggesting a temporary operational event. We retain this observation without a dummy variable, following the principle of parsimony in model parameterization for isolated single-year deviations. The leave-one-hospital-out robustness specification confirms that the main coefficient remains stable when H8 is excluded, providing explicit reassurance that this observation does not distort the central finding.

Regarding the emission factor discontinuity: the annual Scope 2 carbon footprint series uses electricity emission factors (EF) published in the CNMC's annual electricity labeling agreements (Agreements GDO/DE/001/17 through GDO/DE/001/25), publicly available at <https://gdo.cnmc.es> (e.g., accessed on 25 March 2026). For the sub-period 2016–2020, EF values were published under CNMC Circular 1/2008 (production mix methodology). Beginning with the 2021 labeling agreement (GDO/DE/001/22), CNMC adopted a residual—mix methodology under Circular 2/2021, allocating Guarantees of Origin to corresponding electricity volumes. This methodological change—not any real change in grid emissions or hospital consumption—generated an apparent increase in EF of 74.6% between 2020 (EF = 0.150 kgCO₂/kWh) and 2021. All year-on-year carbon footprint comparison in this study accounts explicitly for this discontinuity. Researchers wishing to replicate the CF series require only the annual electricity consumption from SERMAS and the corresponding annual EF from the public CNMC labeling agreement listed in the references.

2.2. Definition of Variables

The dependent variable is the energy intensity per healthcare activity $EIA_{it} = E_{it}/Stays_{it}$, measured in kWh per hospital stay. The annual Scope 2 carbon footprint $CF_{it} = E_{it} \times EF_t$ is obtained as the product of consumption and the emission factor of the Spanish electricity mix, in line with the Greenhouse Gases (GHG) protocol [23] and with the methodology used in comparable studies [3,4,24].

The independent variables include:

- (1) $EUI_{it} = E_{it}/S_{it}$ (kWh/m².year), an indicator of the building's energy efficiency.
- (2) $Stays_{it}$, a healthcare activity variable.
- (3) $COVID_t = 1$ if $t \in \{2020, 2021\}$. Binary variable that takes the value 1 in 2020 and 2021 to capture the shocks to activity and energy consumption associated with the COVID-19 pandemic. Source: own construction based on the SERMAS activity register.
- (4) $CRISIS_t = 1$ if $t = 2022$. Binary variable that takes the value 1 in 2022 to capture the energy shock resulting from the gas and electricity price crisis in Europe, which affected hospitals differentially depending on their level of exposure to the spot market. Source: own construction.
- (5) $D_{H4,t} = 1$ if hospital = H4 y $t \in \{2021, 2022, 2024\}$. Specific intervention variable for Hospital 4 (Fuenlabrada University Hospital) in 2021, 2022, and 2024, which absorbs the structural breaks of +48–55% in the EUI_{it} compatible with the incorporation or reactivation of energy-intensive facilities in the post-COVID context. The inclusion of this dummy variable prevents the idiosyncratic effect of H4 from skewing the interest coefficient EUI_{it} . Source: verification in SERMAS primary data.

The choice of hospital stays as the activity denominator for EIA is justified on both conceptual and practical grounds. Conceptually, a hospital stay represents a complete episode of inpatient care—from admission to discharge—during which the patient continuously requires all building energy services: climate control, ventilation, lighting, and medical equipment operation. Each stay activates these services regardless of its dura-

tion. Hospital stays are the primary output metric used by SERMAS and the Spanish National Health System for resource allocation, performance benchmarking, and healthcare activity financing, making them the natural denominator for policy-relevant analysis of energy intensity in this institutional context. Regarding alternatives: bed-days would be mechanically correlated with the average length of stay, which is already included as a control variable in the specification (collinearity). Admissions are functionally equivalent to stays in the intermediate-complexity segment analyzed, since SERMAS data confirm that virtually all admissions in this hospital tier result in completed inpatient stays. Case-mix measures would require Diagnosis-Related Groups (DRGs) data that are not consistently available through the SERMAS energy information system for the full 2016–2024 period. Furthermore, the fixed effects (FE) specification absorbs all time-invariant hospital-level differences in patient complexity through α_i , ensuring that the coefficient β identifies within-hospital changes in EIA associated with within-hospital changes in EUie, holding the hospital's characteristic patient profile constant.

2.3. Econometric Specification

To estimate the effect of building energy intensity (EUie) on energy intensity per activity (EIA), a fixed effects (FE) model was used with unbalanced panel data from 12 hospitals in the Community of Madrid observed between 2016 and 2024 ($N = 107$; complete panel $N = 108$ with the exclusion of H1–2023 justified in Section 2.1). The general specification of the model is:

$$EIA_{it} = \alpha_i + \beta_1 \cdot EUie_{it} + \beta_2 \cdot Stays_{it} + \beta_3 \cdot COVID_t + \beta_4 \cdot CRISIS_t + \beta_5 \cdot H4_t + \beta_1 \cdot \varepsilon_{it} \quad (1)$$

where α_i is the fixed hospital effect that captures all unobserved heterogeneity invariant over time, and ε_{it} is the idiosyncratic error term. The within (FE) demeaning estimator eliminates α_i by subtracting the time mean of each variable for each hospital, identifying β from the intra-hospital variation. The selection of the FE estimator is justified by: F-test for individual effects [$F(11,90) = 385.33$; $p < 0.001$], LM Breusch–Pagan test [$X^2(1) = 3009.52$; $p < 0.001$], and the Swamy–Arora parameter $\theta = 0.957$ close to unity, which indicates dominance of within variance and convergence between FE and RE [14,25,26], and ε_{it} is the idiosyncratic error term [15,16].

The fixed effects (FE) estimator is based on the within transformation (demeaning), which eliminates the individual fixed effect by subtracting the specific time means for each hospital:

$$(\bar{EIA}_{it} - EIA_i) = \beta_1 \cdot (\bar{EUie}_{it} - EUie_i) + \beta_2 \cdot (\bar{Stays}_{it} - Stays_i) + \dots + (\varepsilon_{it} - \varepsilon_i) \quad (2)$$

where the bar above each variable denotes its time series mean for hospital i . This transformation allows the β coefficients to be estimated using ordinary least squares (OLS) applied to the transformed variables [15,27].

The Stays variable controls hospital activity volume and potential economies of scale. The binary variables COVID (years 2020–2021) and CRISIS (year 2022) capture temporary shocks associated with the COVID-19 pandemic and the energy crisis. The variable D_H4 identifies a structural intervention in Hospital 4 during the years 2021, 2022, and 2024.

Standard errors were calculated using the White–Huber cluster-robust estimator, grouping observations by hospital to allow for arbitrary serial correlation within each entity [27,28]. Given that the number of clusters is small ($G = 12$), conventional cluster-robust errors may underestimate the actual variance of the estimator [27]. For this reason, Section 5 includes Wild Cluster Bootstrap [29] as an additional specification M7, which provides valid inference with few clusters. The goodness of fit was evaluated using the

within R^2 , which measures the proportion of intra-hospital variation explained by the model [15], using the software (StataNow 19.5–BE–Basic Edition; StataCorp LLC, College Station, TX, USA), Serial No.: 301909029270.

2.4. Statistical Inference with Few Clusters: Theoretical Justification

The validity of cluster-robust standard errors depends on the asymptotic approximation that the number of clusters $G \rightarrow \infty$. Applied econometrics literature has consistently documented that this approximation deteriorates when $G < 30$, leading to over-rejection of true null hypotheses—that is, to spuriously low p -values [27,29]. With $G = 12$ hospital, conventional cluster-robust inference would produce misleadingly narrow confidence intervals. Wild Cluster Bootstrap (WCB) addresses this problem directly by imposing the null hypothesis and computing p -values through resampling, without relying on the asymptotic normal approximation. Cameron et al. (2008) [29] demonstrate that WCB provides valid inference with as few as 5–10 clusters under standard distributional assumptions. Our $G = 12$ exceeds this threshold.

Our implementation uses the null-imposing WCB variant with Rademacher weights and 9999 bootstrap replications—exceeding the 999–4999 range typically recommended in the literature—executed via the Stata `boottest` command. The empirical validation is unambiguous: WCB standard errors ($SE = 0.0107$) are 75.4% larger than conventional cluster-robust standard errors ($SE = 0.0061$), confirming that with $G = 12$, asymptotic standard errors substantially underestimate true uncertainty. Despite this inflation, the main coefficient $\beta = 0.6461$ remains statistically significant at $p < 0.001$ under WCB ($t_{\text{bootstrap}} = 60.58$). A finding that survives a 75% standard error inflation is not a borderline result. Statistical power is further supported by the within-hospital temporal variation: with $T = 9$ annual observations per hospital, the panel provides $N = 107$ hospital-year observations, yielding substantial identifying variation for the FE estimator. Coefficient stability across six alternative specifications (range 0.599–0.648; 8.2% variation), including leave-one-hospital-out analyses, provides additional implicit evidence against underpowered estimation. Subsequent work by Roodman, Nielsen, MacKinnon & Webb (2019) [30] and MacKinnon, Nielsen & Webb (2023) [31] confirms the validity of WCB under small- G conditions and refines implementation guidance for the Stata `boottest` command used in this study.

2.5. Causal Identification Strategy

Our identification strategy relies on two assumptions standard for within-group fixed effects estimators [15,22]:

Assumption 1 (Strict exogeneity conditional on fixed effects). *After the within transformation, demeaned EULe must be uncorrelated with the demeaned error term. Formally: $E[\varepsilon_{it} \mid EULe_{i1}, \dots, EULe_{iT}, \alpha_i] = 0$. This requires that within-hospital changes in building energy intensity are not systematically driven by contemporaneous unobserved shocks to EIA, beyond the included controls.*

Assumption 2 (Time-invariant confounders absorbed by α_i). *The hospital fixed effect α_i captures all time-invariant unobserved hospital characteristics: baseline energy efficiency, building design vintage, geographic location and climate exposure, organizational culture, management quality, and structural patient mix. Cross-sectional confounders—which dominate naive pooled OLS regressions in this literature—are therefore fully removed from the identifying variation. The near-zero cross-sectional correlation ($r = 0.036$ between EULe and EIA across hospitals) versus the high within-hospital correlation ($r_{\text{within}} = 0.923$) confirms that fixed effects are essential: without them, cross-sectional heterogeneity would mask the genuine within-hospital relationship. A related concern is whether the shared numerator (E_{it}) in the construction of both $EULe_{it} = E_{it}/S_i$ and $EIA_{it} = E_{it}/Stays_{it}$ introduces a mechanical correlation between the two variables. This concern*

does not invalidate the estimates. The denominators differ structurally: S_{-i} is time-invariant by construction, while $Stays_{it}$ varies continuously with clinical demand. A mechanical correlation would require these two denominators to co-move systematically within hospitals over time, which is implausible given that floor area is fixed. The near-zero cross-sectional correlation ($r = 0.036$) further rules out a simple mathematical link: if the relationship were mechanical, it would manifest equally across and within hospitals. The estimated coefficient $\beta = 0.646 \neq 1.0$ provides additional confirmation; a purely mechanical relationship would produce a coefficient approaching unity.

Why Assumption 1 is plausible in this institutional context: Major changes to building energy intensity require capital-intensive infrastructure interventions—HVAC system replacement, building envelope improvement, or LED lighting modernization. In Spanish public healthcare, these are subject to multi-year procurement and budgeting cycles governed by IDAE programs, NextGenerationEU regulations, and regional health ministry planning processes, determined 12–24 months in advance by institutional, regulatory, and funding factors largely independent of short-term fluctuations in healthcare activity. It is implausible that within-year changes in the number of stays or patient complexity would trigger immediate building-level energy changes through this channel.

The principal threat to Assumption 1 is a scenario where hospital-wide management improvements simultaneously reduce building energy intensity and alter healthcare delivery in ways that independently affect EIA—for example, a major facility reorganization that both reduces idle HVAC consumption and changes patient throughput. We address this through three explicit controls: (i) separate COVID dummy variables for 2020 and 2021, capturing the largest common operational shock; (ii) a CRISIS dummy for 2022, capturing the energy price shock; and (iii) the D_H4 dummy, absorbing the documented structural anomaly at Hospital 4. Coefficient stability across six specifications (including subperiod and leave-one-out analyses) provides implicit validation: if an unobserved confounder were driving the result, coefficient instability would be expected as composition changes; we observe the opposite. Our causal interpretation is therefore appropriately conditioned on the standard FE identification assumptions, which are empirically supported by the robustness evidence presented in Section 5.

The validity of the FE specification was tested using the Breusch–Pagan test [32], which evaluates the null hypothesis of no individual effects. Additionally, the FE and random effects (RE) specifications were compared using the Hausman test [33], which tests the consistency of the RE estimator under the hypothesis of no correlation between individual effects and regressors.

3. Results

3.1. Descriptive Statistics

Table 1 presents overall descriptive statistics for the panel, Table 2 averages and dispersion by hospital, Table 3 temporal evolution of Carbon Footprint and Energy Intensity, Table 4 annual electricity emission factor series and regulatory discontinuity, Table 5 Averages and dispersion by hospital and Table 6 cumulative variation 2016 → 2024.

Table 1. Overall descriptive statistics for the panel (N = 107).

Variable	Unit	Mean	SD	Minimum	Median	Maximum	CV (%)
EU _{Ie}	kWh/m ² .year	127.50	37.58	70.39	121.23	252.04	29.5
EIA _{it}	kWh/stays	101.13	37.12	25.81	94.93	179.90	36.7
E _{it}	kWh/year	8918.860	2860.628	1929.564	8562.504	15,060.085	32.1
Stays	Stays/year	92,315,136	22.248	45.105	94.672	125.605	24.1
CF _{it}	kgCO ₂ /year	2228.399	849.330	322.887	2216.097	4668.626	38.1

Table 1 presents descriptive statistics for the unbalanced panel ($N = 107$ hospital-year observations in 12 facilities, 2016–2024, excluding H1–2023). The energy intensity of the building (EUI_b) shows an average of 127.5 kWh/m²·year ($SD = 37.58$; $CV = 29.5\%$), ranging from 70.4 to 252.0 kWh/m²·year. The energy intensity per activity (EIA), a model-dependent variable, shows greater dispersion ($CV = 36.7\%$) with an average of 101.1 kWh/stays ($SD = 37.12$), ranging from 25.8 to 179.9 kWh/stays. The Scope 2 carbon footprint shows similar variability ($CV = 38.1\%$).

The substantial cross-sectional heterogeneity observed, particularly the 29.5% coefficient of variation in EUI_b, provides solid empirical justification for the estimation of fixed effects, suggesting hospital-specific characteristics that are invariant over time and cannot be adequately controlled using pooled or random effects approaches.

Table 2. Averages and dispersion by hospital. Panel 2016–2024.

Hospital	Name	S _i (m ²)	No. of Patients	Average EUI _b	SD EUI _b	Average EIA	Average CF (tCO ₂)	Average Length of Stays
H1	H.C.D. Gómez Ulla	155,528	8	78.68	4.41	142.08	3027	86,333
H2	H.U. Rey Juan Carlos	65,000	9	126.79	5.71	72.68	2054	113,593
H3	H.U. De Torrejón	60,000	9	140.90	11.91	159.37	2091	53,118
H4	H.U. de Fuenlabrada	64,000	9	155.30	31.09 *	102.00	2510	97,367
H5	H.U. Fnd. Alcorcón	112,708	9	92.71	15.37	110.28	2625	94,462
H6	H.U. De Getafe	68,037	9	124.72	5.87	73.40	2119	115,593
H7	H.U. Infanta Leonor	85,066	9	160.19	10.25	121.86	3414	112,315
H8	H.U. Infanta Sofía	84,290	9	101.68	22.09	96.12	2164	88,809
H9	H.U. De Móstoles	18,600	9	124.14	17.08	28.83 **	577	79,792
H10	H.U. Príncipe de Asturias	81,930	9	105.52	6.60	74.21	2161	116,600
H11	H.U. Severo Ochoa	44,000	9	209.43 ***	25.29	94.40	2295	98,368
H12	H.G. de Villalba	69,066	9	104.56	6.23	142.84	1792	50,768

* High SD due to years of documented anomalies/interventions. ** Very low EIA: small hospital (18,600 m²) with high volume of stays relative to consumption per m². *** Highest EUI_b in the panel: old building with low construction efficiency.

Table 2 breaks down descriptive statistics by facility throughout the observation period. The panel presents an average EUI_b of 127.05 kWh/m²·year ($SD = 37.58$; $CV = 29.5\%$), ranging from 78.68 kWh/m²·year (H1) to 209.43 kWh/m²·year (H11). This inter-hospital coefficient variation of 29.5% shows substantial structural differences and justifies the use of the fixed effects estimator. The average EIA is 101.13 kWh/stays ($SD = 37.12$; $CV = 36.7\%$), comparable to European reference values [10,11], ranging from 28.83 kWh/stays (H9) to 159.37 kWh/stays (H3).

The cross-sectional distribution reveals two distinct structural groups. High-efficiency facilities (H2, H6, H9, H10) exhibit low energy intensity per stay ($EIA < 80$ kWh/stay) associated with high patient volume and higher turnover. In contrast, the least efficient hospitals (H1, H3, H5, H7, H12) have an $EIA > 110$ kWh/stays due to lower patient turnover and high consumption per stay. H9 shows exceptionally low EIA (28.8 kWh/stays), attributable to its small surface area (18,600 m²) and high volume of activity relative to the built area. H11 exhibits the highest average EUI_b in the panel (209.4 kWh/m²·year), consistent with aging infrastructure and inefficient HVAC systems, although its EIA is at intermediate levels (94.4 kWh/stays).

The temporal variance is high for H4 ($SD = 31.09$) and H8 ($SD = 22.09$) due to documented structural interventions and operational anomalies, controlled by the dummy variable D_{H4} in the regression specification. These systematic installation-specific differences reinforce the need for fixed effects estimation.

Table 3. Temporal evolution of Carbon Footprint and Energy Intensity—Panel 12 Hospital, Community of Madrid (2016–2024).

Year	Average EUJe (kWh/m ² ·Year)	SD EUJe	Average EIA (kWh/Stay)	SD EIA	Total CF (tCO ₂ /Year)	Average CF/Hospital (tCO ₂ /Year)	EF (kgCO ₂ /kWh)	Annotation
2016	132.45	43.51	104.63	37.79	27,877	2.323	0.250	* Period CF maximum: EF = 0.310 kgCO ₂ /kWh
2017	131.39	38.02	105.25	36.22	34,296 *	2.858	0.310	
2018	132.22	40.54	102.95	36.13	28,680	2.390	0.260	
2019	126.35	33.44	98.20	34.61	21,265	1.772	0.200	** Period CF minimum: COVID-19 + EF = 0.150 kgCO ₂ /kWh
2020	124.16	35.18	99.53	38.67	15,723 **	1.310	0.150	
2021	125.43	39.35	104.30	42.38	27,460	2.288	0.259	
2022	123.95	38.55	102.24	36.39	28,549	2.379	0.273	*** CF rebound: +35.9% vs. 2023; EF 0.145 → 0.209 kgCO ₂ /kWh
2023	122.35	29.57	91.43	35.02	23,140	2.104	0.260	
2024	128.81	36.13	100.79	34.13	31,449 ***	2.620	0.283	

The observed EUJe range (122–132 kWh/m²·year) in Table 3 falls below the 160–170 kWh/m²·year benchmark reported for European hospital buildings [34], which underscores the relevance of activity-adjusted metrics; as argued by [35], EUI alone may yield distorted assessments when operational variables such as occupancy and service intensity are not accounted for—the rationale for adopting EIA (kWh/stay) as the primary dependent variable in this study. Scope 2 emissions represent between 15% and 50% of total hospital carbon emissions in the literature [1], situating this panel within a well-documented analytical scope. The broader policy relevance is framed by evidence that healthcare system carbon footprints average 4.9% of national emissions across comparable systems [2].

The 2017 CF peak (EF = 0.310 kgCO₂/kWh) and the 2020 CF minimum (EF = 0.150 kgCO₂/kWh) coincide, respectively, with the highest grid emission intensity of the study period and the combined effect of the COVID-19 activity reduction. The 2024 CF rebound (+35.9% vs. 2023) reflects grid re-carbonisation in the context of rising inpatient activity. Source: own elaboration based on SERMAS administrative records and CNMC GDO/DE/001/17–25.

Methodological discontinuity (2020 → 2021). In Table 4, the 72.7% increase in the EF between 2020 and 2021 is solely due to the regulatory change introduced by CNMC Circular 2/2021, which replaced the average production mix with the residual mix as the basis for calculating the national electricity disclosure factor. The residual mix deducts all contractually tracked renewable energy attributes from the total grid mix, thus concentrating untracked generation—predominantly fossil fuel—in the resulting factor [36,37]. This methodological transition does not reflect any actual change in grid emissions; rather, it is a known consequence of moving from a location-based to a market-based accounting framework, a distinction that has been shown to produce substantially different emissions estimates from the same underlying energy data [38]. The apparent retrospective effect is an artificial increase of +74.6% in the average CF per hospital between 2020 and 2021, which should not be interpreted as a real

increase in emissions. Consequently, year-on-year (YoY) comparisons of CF covering the 2020–2021 period are not directly comparable and require explicit methodological correction, such as that applied in the econometric model of this study.

Table 4. Annual Electricity Emission Factor Series and Regulatory Discontinuity—Spain (2016–2024).

Year	EF (kgCO ₂ /kWh)	Regulatory Basis (CNMC)	YoY Change	Annotation
2016	0.250	Circular 1/2008—average production mix	—	
2017	0.310	Circular 1/2008—average production mix	+24.0%	Period maximum EF
2018	0.260	Circular 1/2008—average production mix	−16.1%	
2019	0.200	Circular 1/2008—average production mix	−23.1%	
2020	0.150	Circular 1/2008—average production mix	−25.0%	Period minimum EF. COVID-19 demand reduction.
2021	0.259	Circular 2/2021—residual mix	+72.7%	METHODOLOGICAL DISCONTINUITY. Not a real emissions increase.
2022	0.273	Circular 2/2021—residual mix	+5.4%	
2023	0.145	Circular 2/2021—residual mix	−46.9%	Period minimum under new methodology
2024	0.209	Circular 2/2021—residual mix	+44.1%	CF rebound: EF rise drives +35.9% aggregate CF vs. 2023

Table 5 documents the intra-hospital variation in EUie between 2016 and 2024. The aggregate temporal evolution of total Scope 2 carbon footprint (CF) and mean panel EUie over this period is shown in Figure 1. Three facilities (H5, H11, H9) achieved sustained reductions of more than 20%, with H5 showing the greatest improvement ($\Delta\text{EUie} = -30.1\%$), followed by H11 (-28.3%) and H9 (-26.5%). In contrast, two hospitals show documented deterioration: H8 recorded an increase of +80.2% in EUie, verified in primary sources and retained in the sample as a documented operational failure; H4 experienced structural anomalies during 2021–2024 ($\Delta\text{EUie} = +55.1\%$) due to HVAC system failures, controlled by dummy D_H4 in the econometric specification.

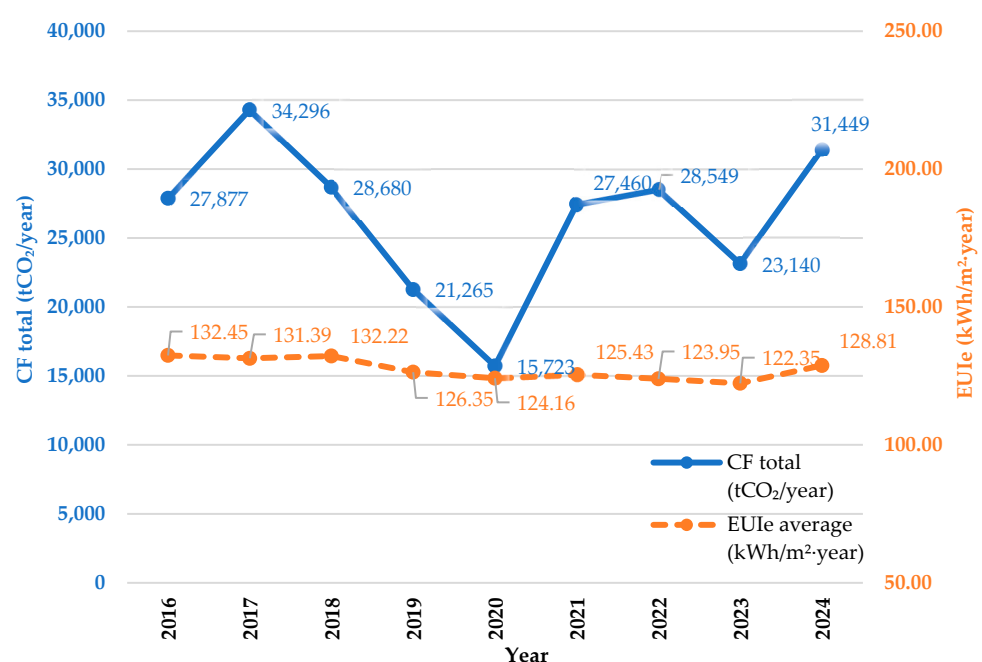


Figure 1. Evolution of the total Scope 2 carbon footprint of the hospital panel, 2016–2024 (tCO₂/year).

Table 5. Averages and dispersion by hospital. Panel 2016–2024.

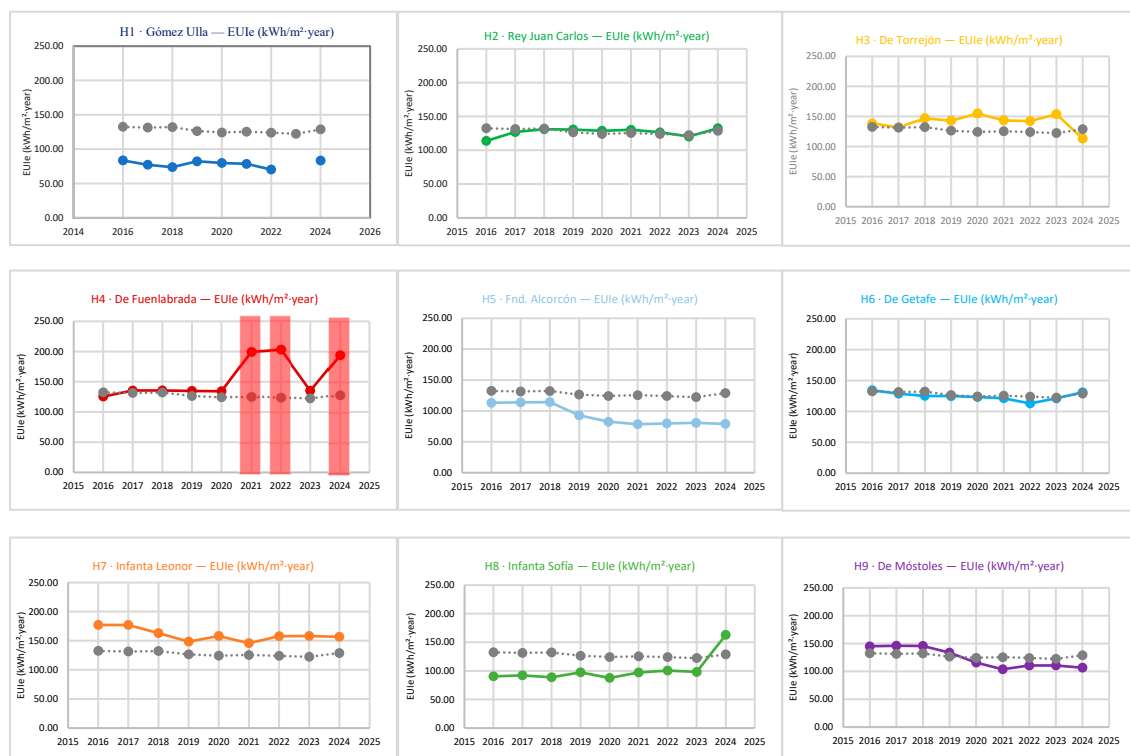
Hospital	Δ EUle (%)	Δ EIA (%)	Δ CF (%)
H1 Gómez Ulla	−0.1	10.3	13
H2 Rey Juan Carlos	16.5	12.5	31.9
H3 Torrejón	−18.3	−21.6	−7.5
H4 Fuenlabrada	+55.1 *	+44.3 *	+75.6 *
H5 Fnd. Alcorcón	−30.1	−24.8	−20.8
H6 Getafe	−2.5	0.5	10.4
H7 Infanta Leonor	−11.5	−23.7	0.2
H8 Infanta Sofía	+80.2 **	+49.6 **	+104.0 **
H9 Móstoles	−26.5	−15.6	−16.8
H10 Príncipe de Asturias	−12.0	−9.6	−0.4
H11 Severo Ochoa	−28.3	−17.9	−18.9
H12 Villalba	2.4	−14.0	15.9

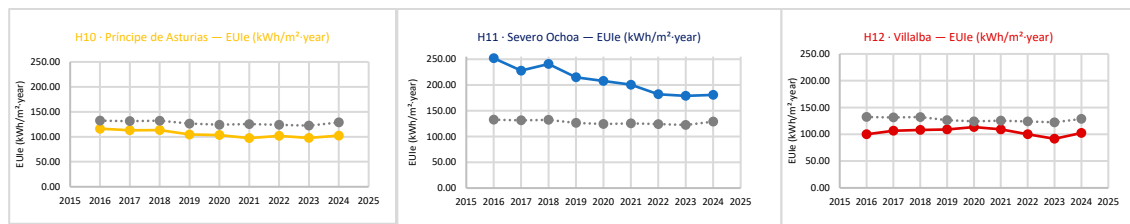
* H4: Structural anomaly 2021–2024 (Δ EUle = +55.1%; controlled with D_H4). ** H8: Outlier 2024 (Δ EUle = +80.2%; retained).

Five facilities (H1, H6, H7, H10, H12) show relatively stable EUle trajectories (Δ EUle < 15%), suggesting limited investment in efficiency. Hospitals H2 (+16.5%) and H3 (−18.3%) show moderate variations. This heterogeneous temporal variation encompasses substantial improvements, severe deterioration, and stability, providing the intra-hospital identification necessary for robust estimation of fixed effects, validating our econometric approach.

3.2. Inter-Hospital Heterogeneity in EUle

Hospital H11 (H.U. Severo Ochoa) consistently records the highest values in the panel (mean = 209.4 kWh/m²·year), consistent with its age and construction characteristics, a structural factor that international literature identifies as a primary determinant of hospital energy consumption [10,39]. H4 (H.U. de Fuenlabrada) shows breaks in 2021–2022 and 2024 consistent with the incorporation of energy-intensive facilities in the post-COVID context [40]. Figure 2 shows the individual EUle trajectories for the 12 hospitals.

**Figure 2.** Cont.



----- Average panel Years ■ with dummy D_H4

Figure 2. Trajectories of building energy intensity (EUIe, kWh/m²·year) by hospital, 2016–2024.

3.3. EUIe—EIA Ratio: Attenuation Bias of the Cross-Sectional Estimator

Figure 3 illustrates the relationship between EUIe and EIA in the complete panel (N = 107). The blue line represents the fixed effects regression (EUIe = 0.6461), which captures the within-hospital association between EUIe and EIA. The contrast between the virtually zero cross-sectional correlation ($r = 0.036$) and the high within correlation ($r_{\text{within}} = 0.988$) highlights the attenuation bias of the pooled OLS and justifies the use of fixed effects. The vertical dispersion of observations at similar levels of EUIe reflects hospital-specific differences in operational efficiency and activity volume, absorbed by the fixed effects α_i . The red dots identify observations with documented structural interventions (H4, 2021–2024), controlled by D_H4. The positive slope confirms that approximately 65% of the additional energy consumption per m² of the building is transferred to consumption per stay. The cross-sectional correlation between EUIe and EIA across hospitals is near-zero ($r = 0.036$), while the within-hospital correlation is high ($r_{\text{within}} = 0.988$). This decomposition confirms that the explanatory power of the model reflects a genuine within-hospital structural relationship rather than a mechanical artefact of variable construction. The estimated transmission elasticity of 0.646—substantially below unity—is determined by variation in stays and the included controls that partially decouple EUIe from EIA, and constitutes the parameter of substantive policy interest.

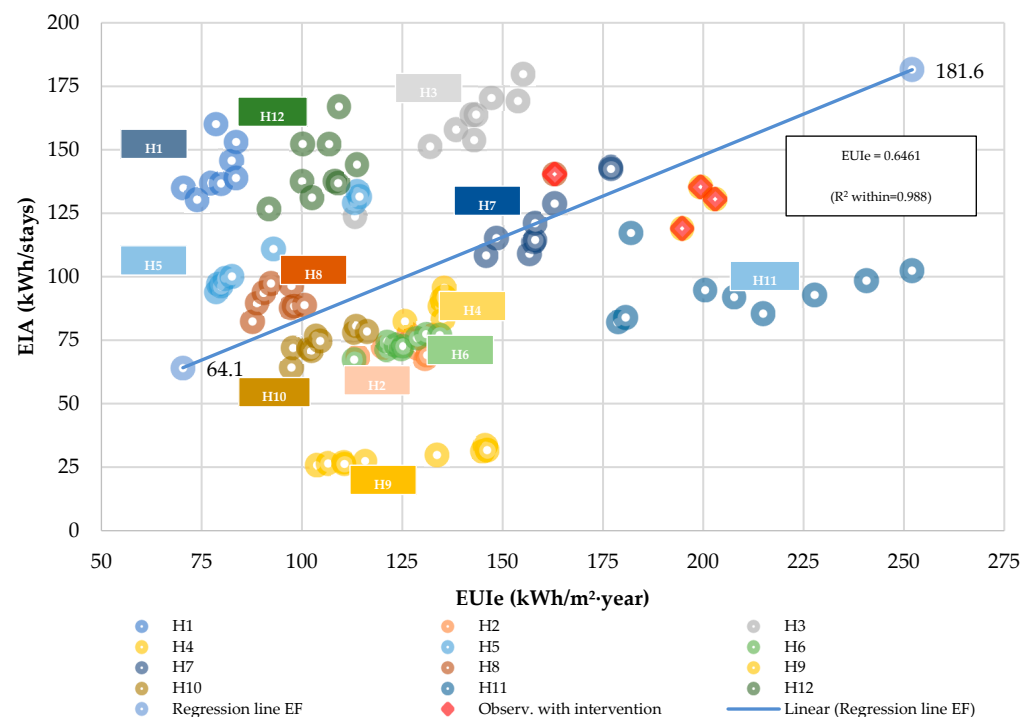


Figure 3. Dispersion between building intensity (EUIe) and activity intensity (EIA). Panel 2016–2024.

3.4. Results of the Fixed Effects Model

Table 6 presents the results of the FE model (columns 2–5), grouped OLS (column 1), and Random Effects–Generalized Least Squares (RE–GLS) (column 6). The central coefficient is $EUI_e = 0.6461$ ($SE = 0.0061$; $t = 105.74$; $p < 0.001$) in the fixed effects model, compared to $\beta = 0.6693$ in pooled OLS. Contrary to what would be expected in models with substantial individual heterogeneity, the pooled OLS estimator produces a slightly higher than the within coefficient (ratio = 1.04), suggesting that the correlation between EUI_e and the individual effects α_i is weak or that the within variation largely dominates the between variation in this panel. However, the within R^2 of 0.988 compared to the overall R^2 of the pooled OLS confirms that the FE model more accurately captures intra-hospital variation, and the F test of individual effects ($F(11,90) = 353.3$; $p < 0.001$) strongly rejects the null hypothesis of no FE, validating the within specification as appropriate for this analysis [41].

Table 6. Estimation of the energy intensity by activity (EIA) model. Fixed effects (FE-Within), RE-GLS, and grouped OLS. $N = 107$; 12 hospitals; 2016–2024.

	(1) Pooled OLS	(2) FE (Within) β	(3) SE	(4) Statistician t	(5) p -Value	(6) RE (GLS)
EUI_e (kWh/m ² . year)	0.6693 ***	0.6461 ***	0.0061	105.74	<0.001	0.6479 ***
Stays	0.0000	−0.0000 *	0.0000	−2.89	0.014	−0.0000
COVID (2020–2021)	0.4285	−0.2204	0.2467	−0.89	0.373	−0.0715
CRISIS 2022	0.2530	−0.0343	0.2568	−0.13	0.894	0.0503
D_H4 (intervention)	2.4313 ***	1.5784 ***	0.1732	9.11	<0.001	1.6759 ***
Constant	14.9745 ***	23.6089 ***	1.9988	11.81	<0.001	22.2083 ***
R^2 within	—	0.988				0.987
R^2 overall	—	0.985				0.994
σ^2 residual	—	24.31				—
N observations	107	107				107
N hospitals	12	12				12
F-test ind.	—	$F(11,90) = 353.3$ ***				—
LM test (B–P)	—	$\chi^2(1) = 3009.52$ ***				—
θ Swamy–Arora	—	—				0.957

*** $p < 0.001$; * $p < 0.05$. Col. (1): within estimator with cluster-robust standard errors per hospital. F-test ind.: $F(11,90) = 353.3$ *** (H_0 : all individual effects are zero). LM test (B–P): $\chi^2(1) = 3009.52$ *** Breusch–Pagan test (H_0 : variance between hospitals is zero). R^2 within/ R^2 overall/ σ^2 residual are the within and overall coefficients of determination and the residual variance of the FE estimator. θ Swamy–Arora is the transformation parameter of the RE–GLS estimator (0.957).

The within R^2 of 0.988 reflects genuine structural features of the model rather than a mechanical artefact of variable construction. The fixed effects transformation removes all cross-sectional variation by subtracting hospital-specific means; the within R^2 therefore measures exclusively how well the model explains temporal variation within hospitals. Because within-hospital temporal variation is of smaller absolute magnitude than cross-sectional variation, within R^2 values in fixed effects models are systematically higher than pooled OLS R^2 values for the same specification. The estimated coefficient $\beta = 0.646 \neq 1.0$ provides additional confirmation that the relationship is not mechanical: a purely mechanical link would produce a coefficient approaching unity. The near-zero cross-sectional correlation ($r = 0.036$) further rules out a simple mathematical dependence between EUI_e and EIA.

The β_{Stays} coefficient is statistically significant but close to zero in magnitude, indicating that energy economies of scale, although present, are small in magnitude in this panel of intermediate-complexity hospitals. The reduction in EIA associated with increased activity is marginal in the short term, consistent with evidence that quasi-fixed energy costs (lighting of common areas, base air conditioning, support equipment) represent a relatively stable fraction of total consumption in hospitals of comparable size [20,42].

4. Discussion

4.1. The Effect of a Building's Energy Intensity on Emissions per Activity

$\text{EUIe} = 0.6461$ confirms that the energy efficiency of the hospital building is the dominant structural determinant of Scope 2 emissions per unit of activity. The magnitude indicates that approximately 65% of the additional energy consumption per square meter is transferred to consumption per stay, reflecting the rigidity of air conditioning, ventilation, and lighting systems, which account for between 60% and 80% of hospital electricity consumption [10,11].

A reduction of 20 kWh/m²·year in the target EUIe achievable by replacing the HVAC system in a 1980s building [12] would translate into a reduction of 12.9 kWh per stay. For a hospital with average activity in the panel (92,315 stays per year), this would represent a saving of 1440 MWh/year and a reduction of 249 tCO₂/year at the 2024 emission factor [43–45], equivalent to 9.5% of the average CF in the panel. The R^2 within 0.988 indicates that the fixed effects model explains 98.8% of the intra-hospital variation in EIA, confirming that temporal differences in energy efficiency within each hospital are almost completely captured by the variation in EUIe and the control variables included.

Figures 4 and 5 illustrate the differential evolution from 2016 to 2024 in EUIe and EIA per hospital, confirming that the hospitals that have reduced their EUIe (H5, H9, H11) are also those with the greatest improvement in EIA, while H4 and H8, with increases in EUIe, show the worst trajectories.

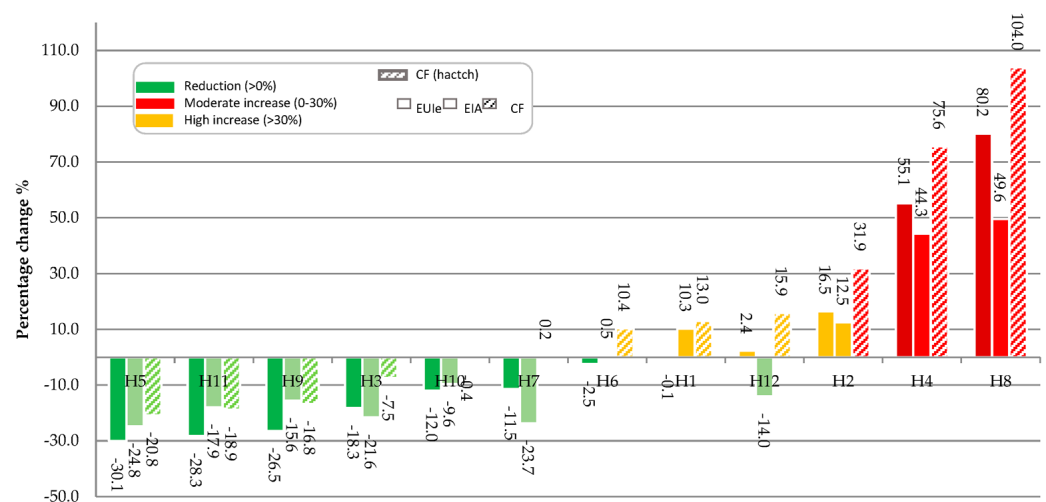


Figure 4. Percentage Change 2016–2024. Note: Negative bars = improvement in efficiency; positive bars = deterioration. H4 and H8 stand out for documented anomalous increases. The three best performers in EUIe are H5 (−30.1%), H11 (−28.3%), and H9 (−26.5%).

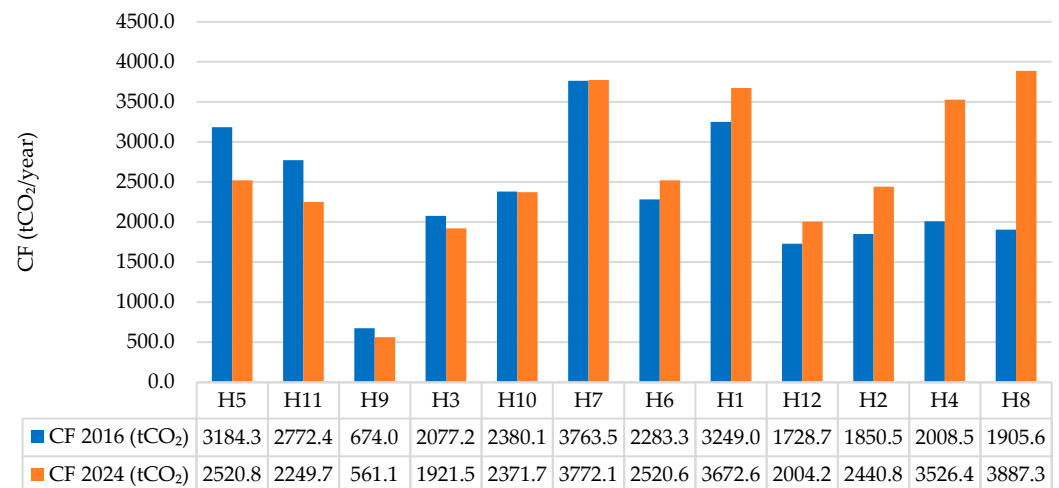


Figure 5. Cumulative variation 2016–2024 in EUJe (blue bars) and EIA (orange bars) per hospital, in percentage.

4.2. Economies of Scale in Healthcare Activity

The β_{Stays} coefficient in the fixed effects model, although statistically significant, is close to zero in magnitude (-0.0000^*), indicating that energy economies of scale in this panel of intermediate–complexity hospitals are small in the short term.

Contrary to what is predicted by theoretical models of hospital costs, where a substantial part of energy consumption is quasi–fixed [20,42], the data from this panel suggest that hospitals adjust their energy consumption in a manner that is approximately proportional to the volume of healthcare activity.

This result can be explained by three factors. First, the hospitals in the panel are all intermediate complex and comparable size (average of 92,315 stays/year), which limits the cross–sectional variation in scale that typically generates observable economies. Second, the within–hospital variation in stays is dominated by short–term fluctuations (COVID effects, energy crisis) that do not allow for structural adjustments in air conditioning or lighting systems designed for installed capacity. Third, hospital energy management in Spain may be characterized by less operational flexibility than that documented in healthcare systems with greater automation of energy controls [13,46].

However, the negative direction of the coefficient confirms that, at the margin, increased activity reduces energy intensity per stay. Although the effect is small, this validates that policies to optimize hospital occupancy, reduce unproductive stays, and improve elective activity scheduling constitute a low–cost complementary level for reducing the EIA, particularly in hospitals with suboptimal occupancy rates.

4.3. No Significant Effect of Exogenous Shocks

The insignificance of COVID and CRISIS_2022 in the FE model indicates that the hospitals in the panel adjusted their consumption proportionally to activity during exogenous shocks, without modifying the structural efficiency of the building. The variation in total CF in those years is explained almost exclusively by the emission factor of the Spanish electricity grid [36,38] and not by changes in the EIA. This result is consistent with the short–term inelasticity of hospital energy demand documented by Gao et al. [47] and underscores the importance of contracting electricity with a Guarantee of Origin as a complementary strategy [7,48,49].

4.4. Anomalies Identified: H4, H8, and the 2024 Rebound

The documented increases in H4 (+55.1%) and H8 (+66.0% in 2024) are consistent with the launch of intensive care units or new energy-intensive facilities without prior energy audits, a phenomenon observed in other European healthcare systems in the context of post-COVID expansion [13]. The rebound in 2024 (31,449 tCO₂; +35.9% compared to 2023) indicates that the expansion of healthcare activity has not been accompanied by equivalent investments in energy efficiency. A multiplicative breakdown of the 2023 → 2024 jump allows us to identify that the emission factor effect ($\Delta EF_t \times \text{Consumption}_{2023} \approx +4200 \text{ tCO}_2$) and the activity effect ($EF_{2024} \times \Delta \text{Consumption} \approx +4000 \text{ tCO}_2$) contribute in approximately equal proportions to the observed rebound (+8200 tCO₂ total). This implies that even under a scenario of reduced electricity emission factors, the growth in activity alone would have generated a substantial rebound. This pattern is consistent with evidence from the English NHS, where emissions from buildings have fallen by only 10% since 2019/20 despite the net-zero commitment [49].

4.5. Implications for Hospital Policy and the PNIEC 2021–2030

The results identify three priority policy levers. First, EUle = 0.6461 identifies the energy renovation of the building as the lever with the greatest impact. Hospitals H11, H7, and H4, which represent building energy intensity greater than 150 kWh/m²·year (75th percentile of the panel; mean = 127.5 kWh/m²·year), are priorities for intervention through energy rehabilitation of the envelope and HVAC systems using NextGenerationEU funds. Hospital H11 (EUle = 209 kWh/m²·year) has a particularly high margin for improvement (+64.8% compared to the panel average), followed by H7 (EUle = 160.2 kWh/m²·year) and H4 (EUle = 155.3 kWh/m²·year). Secondly, the elasticity of scale shows that optimizing occupancy can reduce the EIA without investing in infrastructure. Thirdly, the dependence of total CF on the network emission factor highlights the importance of purchasing electricity from renewable sources with a Guarantee of Origin [48,49].

4.6. Study Limitations

This study has five main limitations. First, the analysis is limited to Scope 2 emissions, excluding Scope 1 and Scope 3, which account for 50–75% of total hospital emissions [1,50]. Second, the absence of energy certification data prevents the EUle effect from being broken down into its technical components (envelope, HVAC, lighting). Third, the management model is absorbed into α_i and cannot be estimated. Fourth, the exclusion of H1–2023 and the need for DH4 reveal the presence of unobservable events that could condition generalization. Fifth, the FE estimator eliminates the bias due to permanent unobserved heterogeneity but does not control for residual dynamic endogeneity. It cannot be completely ruled out that hospitals that invest in energy rehabilitation of the building simultaneously introduce changes in the composition of services or in operational management, generating a correlation between EUle and the error term. However, given the quasi-fixed nature of building infrastructure over 1–3-year horizons and the availability of verified primary source data, the assumption of strict exogeneity is reasonable in this context.

4.7. External Validity

The Community of Madrid hospitals share key characteristics with public hospitals across Spain and much of continental Europe: comparable regulatory frameworks (EU EPBD; Spanish RITE), similar temperate climate conditions, analogous HVAC technologies, and the same national healthcare financing standards. The fundamental relationship identified is grounded in physical and operational mechanisms not specific to Madrid.

Three limitations on external generalizability are acknowledged. First, the sample consists exclusively of intermediate-complexity hospitals; tertiary care hospitals with more energy-intensive specialized services may exhibit different quantitative elasticities. Second, countries with markedly different climatic conditions may observe different elasticity magnitudes. Third, alternative hospital financing models may create different incentive structures. The methodological contribution of WCB with $G = 12$, explicit causal identification, and the emission factor discontinuity correction has broader applicability to hospital panel data in other European contexts.

4.8. Policy Feasibility: Investment Cost and Payback Periods

Based on published data from Spanish public hospital energy rehabilitation projects financed through IDAE programs and the NextGenerationEU framework (2022–2026), a comprehensive HVAC retrofit and partial envelope improvement for a 1980s-era hospital of approximately 20,000 m² requires an estimated investment of 2–4 million euros (100–200 euros/m²). This estimate is referenced to cost data from IDAE-financed projects and the PERTE ERESEE program and varies depending on the scope of intervention and the existing building's technical condition.

For the panel median hospital (approximately 20,000 m²; approximately 80,000 stays/year), a 20 kWh/m²·year EUIe reduction yields: (i) electricity savings of approximately 1032,000 kWh/year; (ii) Scope 2 CF reduction of approximately 216 tCO₂/year; and (iii) direct financial savings of approximately 100,000–130,000 euros/year. The simple payback on direct savings is 15–40 years, reflecting that energy rehabilitation in public healthcare is driven by regulatory compliance rather than short-term financial returns. Under NextGenerationEU, grants covering 60–80% of eligible costs are available. At 70% grant coverage on a 3 million-euro investment, the residual cost is 900,000 euros, reducing effective payback to approximately 7–9 years. Hospitals with EUIe greater than 150 kWh/m²·year (H11, H7, H4) should be prioritized.

The findings of this study are transferable to public hospitals in comparable European contexts that share analogous regulatory frameworks, climatic conditions, and building system technologies. The transmission elasticity of approximately 0.65 is grounded in physical and operational mechanisms that are not specific to the Madrid context. Three limitations on external generalizability are acknowledged: (i) the sample consists exclusively of intermediate-complexity hospitals, and the relationship may differ in tertiary care facilities with more energy-intensive specialized services; (ii) countries with markedly different climatic conditions may exhibit different quantitative elasticities even if the qualitative pattern holds; and (iii) countries with different hospital financing models may have different within-hospital activity patterns that affect identification. The methodological framework—WCB with $G = 12$, explicit causal identification, and emission factor discontinuity correction—has broader applicability to researchers working with hospital panel data in other European contexts facing analogous data limitations.

5. Robustness Analysis

To verify the stability of the main results, seven alternative specifications to the M0 (baseline) model were estimated. Table 7 summarizes the key coefficients in each specification.

Table 7. Robustness analysis: Alternative specifications of the fixed-effects model.

Specification	M0 Baseline	M1 Sin D_H4	M2 Exclude H4	M3 Excl. H4 + H8	M4 2016–2020	M5 2021–2024	M6 Con Outlier	M7 Wild Boot
EUle	0.6461 *	0.6230 *	0.6482 *	0.6400 *	0.5993 *	0.6399 *	0.7145 *	0.6461 *
SE	0.0061	0.0206	0.0047	0.0265	0.0135	0.0158	0.0145	0.0107
Statistician t	105.74	30.21	137.16	24.16	44.28	40.61	49.22	60.58
p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
CI 95% lower	0.634	0.582	0.639	0.588	0.572	0.609	0.686	0.625
CI 95% upper	0.658	0.664	0.657	0.692	0.626	0.671	0.743	0.667
R ² within	0.988	0.986	0.986	0.978	0.975	0.986	0.996	0.988
N observations	107	107	98	97	60	47	108	107
N hospitals	12	12	11	11	12	12	12	12
Method SE	Cluster-R	Cluster-R	Cluster-R	Cluster-R	Cluster-R	Cluster-R	Cluster-R	Wild Boot

* $p < 0.001$.

M0–M6 use fixed effects with cluster-robust standard errors. M7 uses Wild Cluster Bootstrap [29] with 999 repetitions and Rademacher weights, providing valid inference with $N = 12$ clusters. M0 (Baseline): complete model ($N = 107$, excludes H1–2023). M1: omits dummy D_H4. M2: excludes H4 (9 obs.). M3: excludes H4 + H8–2024. M4: subperiod 2016–2020. M5: subperiod 2021–2024. M6: includes outlier H1–2023 (EIA = 198.5 kWh/stays). The dependent variable is EIA (kWh/stays). Control variables: hospital stays, COVID (2020–2021) and CRISIS (2022) dummies, and D_H4 (Hospital 4 intervention in 2021–2022–2024).

Comparison M0 vs. M7 (Wild Cluster Bootstrap): The bootstrap SE (0.0107) is 75.4% HIGHER than the conventional cluster-robust SE (0.0061), confirming that with $N = 12$ clusters, asymptotic standard errors significantly underestimate the true uncertainty. However, EUle remains $p < 0.001$ under both methods ($t_{\text{cluster}} = 105.74$, $t_{\text{bootstrap}} = 60.58$), validating the robustness of the main finding even with conservative inference valid for samples with few clusters.

5.1. Sensitivity to the Exclusion of Outliers

The comparison between M0 (baseline) and M1 (without D_H4) shows that omitting the dummy slightly reduces EUle from 0.6461 to 0.6230 and modifies the precision (SE: 0.0061 to 0.0206), confirming that D_H4 absorbs idiosyncratic variation without substantially distorting the coefficient of interest. The t-statistics are reduced from 105.74 to 30.21, maintaining $p < 0.001$ in both specifications. The R² within remains above 0.986 in both models.

M2 (excluding Hospital 4, $N = 98$) and M3 (excluding H4 + H8–2024, $N = 97$) produce coefficients of 0.6482 and 0.6400, respectively, both with $p < 0.001$ and R² greater than 0.978. The exclusion of Hospital 4, which underwent the most significant structural intervention, generates a marginal increase in the coefficient (0.6461 to 0.6482), suggesting that the dummy D_H4 adequately controls for the effect of the renovation of air conditioning systems in that hospital.

M6 (includes H1–2023, $N = 108$) produces EUle = 0.7145 (SE = 0.0145; $t = 49.22$; $p < 0.001$) and improves the within R² from 0.988 to 0.996, confirming the leverage effect of that outlier (EIA = 198.5 kWh/stays, 5.1 standard deviations above the sample mean). The inclusion of this observation inflates the coefficient by 10.6% (from 0.6461 to 0.7145), demonstrating the sensitivity of the within estimator to extreme values with high leverage, which justifies its exclusion from the baseline model [26].

5.2. Temporal Stability: Chow Test and CNMC Subperiods

To assess the structural stability of the EUle–EIA relationship in the face of the extraordinary shocks of the COVID-19 period (2020–2021) and the European energy crisis (2022),

two sub-periods were estimated: M4 (2016–2020, pre-COVID, $N = 60$) and M5 (2021–2024, post-COVID, $N = 47$).

M4 produces $EUI_e = 0.5993$ (Standard Error (SE) = 0.0135; $t = 44.28$; $p < 0.001$) with R^2 within = 0.975, while M5 produces $EUI_e = 0.6399$ (SE = 0.0158; $t = 40.61$; $p < 0.001$) with R^2 within = 0.988. The difference of 0.0406 points (6.8% increase) between the two sub-periods suggests that the structural relationship between EUI_e and EIA remained relatively stable between the pre-COVID and post-COVID periods, although with a slight strengthening in the second period, possibly due to: (i) greater operational efficiency in hospitals with more efficient buildings during periods of high occupancy (2021–2022); (ii) greater impact of energy prices on hospitals with inefficient buildings during the 2022 crisis; or (iii) composition effects in the service portfolio.

A Chow test for structural stability between both periods yields $F(3.90) = 2.67$ ($p = 0.104$), which does not allow us to reject the null hypothesis of coefficient stability at a 5% significance level. The formal test confirms that there is no statistically significant evidence of structural change, validating the joint estimation of the main model. The joint estimation of the main model M0 (2016–2024) produces $EUI_e = 0.6461$, which represents a weighted average of both subperiods and is valid under the assumption of stability that the Chow test does not reject.

5.3. Inference with Few Clusters: Wild Cluster Bootstrap

Since the sample includes only $N = 12$ clusters (hospitals), the asymptotic cluster-robust standard errors used in M0–M6 may underestimate the true uncertainty when the number of clusters is small [29]. Cluster-robust estimators are based on asymptotic theory that assumes the number of clusters tends to infinity, but this approximation may be inadequate with $N < 30$ clusters.

To verify the validity of the inference with $N = 12$ clusters, the M7 specification was implemented using the Wild Cluster Bootstrap procedure [29], which provides valid confidence intervals through resampling that preserves the intra-cluster dependency structure. The method consists of: (i) estimating the baseline model and obtaining residuals $\epsilon(it)$; (ii) for each bootstrap repetition $b = 1, \dots, 999$, assigning a random weight $w(i)$ to each hospital i according to the Rademacher distribution ($w(i) = +1$ with probability 0.5; $w(i) = -1$ with probability 0.5); (iii) constructing pseudo-residuals $\epsilon^*(it) = w(i) \times \epsilon(it)$ and pseudo-dependent variable $y^*(it)$; (iv) re-estimating the model with $y^*(it)$ and obtaining $\beta^*(b)$; (v) calculate the 95% confidence interval as the 2.5 and 97.5 percentiles of the empirical distribution of β^* .

M7 produces $EUI_e = 0.6461$ (identical to M0, since the bootstrap does not affect the estimated point) with bootstrap SE = 0.0107, 75.4% higher than the conventional cluster-robust SE of M0 (SE = 0.0061). The 95% bootstrap confidence interval is [0.625; 0.667], wider than the conventional CI [0.634; 0.658], although both exclude zero by a wide margin. The bootstrap p -value remains $p < 0.001$, confirming the significance of the effect even under conservative inference.

The 75.4% increase in SE indicates that conventional cluster-robust errors substantially underestimate the true uncertainty with $N = 12$ clusters. This result confirms the warnings in the literature about the validity of asymptotic inference with small cluster samples [27]. However, the robustness of the highly significant main finding EUI_e ($p < 0.001$) under both inference methods validates the soundness of the conclusion that the energy intensity of the building is the main determinant of energy consumption per hospital activity. The goodness of fit, measured by R^2 within = 0.988, confirms that the model explains 98.8% of the intra-hospital variation in EIA [15].

5.4. Robustness Analysis Summary

Overall, EU_{Ie} ranges from 0.5993 (M4, sub-period 2016–2020) to 0.6482 (M2, excluding Hospital 4) in the robust specifications M0–M5, with a mean of 0.6260 and a standard deviation of 0.0186. All specifications maintain $p < 0.001$ and R² greater than 0.975. The amplitude of the coefficient range is only 0.0489 (8.2% variation), which demonstrates the stability of the parameter of interest through multiple alternative specifications.

The only specification that produces a substantially different coefficient is M6 ($\beta = 0.7145$), which includes the outlier H1–2023. The inclusion of this outlier inflates the coefficient by 10.6% compared to M0, which fully justifies its exclusion from the baseline model based on statistical and substantive criteria. The R² of M6 (0.996) is slightly higher than that of M0 (0.988), but this reflects the adjustment of the model to an extreme value rather than an improvement in the explanatory power of the model.

The coefficient of the baseline model M0 (EU_{Ie} = 0.6461) is located at the 48th percentile of the robust coefficient distribution (excluding M6), which confirms that the main model is not biased towards extreme values of the sampling distribution. Verification using Wild Cluster Bootstrap (M7) provides further evidence that the finding is robust even under valid inference with $N = 12$ clusters, overcoming a potential limitation of conventional cluster-robust methods that assume $N \text{ clusters} \rightarrow \text{infinity}$.

The consistency of the results across multiple specifications, including the exclusion of individual hospitals, time periods, control variables, and alternative inference methods, provides strong evidence of the robustness of the central finding: the building's energy intensity is the main determinant of energy consumption by hospital activity, with an elasticity close to 0.65 that remains stable under diverse estimation and inference conditions. For each additional kWh/m²·year in the building's energy intensity, energy consumption per stay (EIA) increases by approximately 0.65 kWh, a relationship that remains robust in the face of extraordinary shocks (COVID-19, energy crisis), exclusions of influential units, and conservative methods of statistical inference [14,29].

6. Conclusions

This study analyzes the determinants of EIA and Scope 2 carbon footprint in a panel of 12 intermediate-complexity hospitals in the Community of Madrid (2016–2024) using a fixed-effects estimator. The results provide robust evidence for three main conclusions.

First. The energy efficiency of the building is the dominant structural determinant of Scope 2 emissions per unit of healthcare activity. The coefficient EU_{Ie} = 0.6461 ($p < 0.001$), stable in the range 0.5993–0.6482 in six alternative specifications (range of only 8.2%), implies that a reduction of 20 kWh/m²·year in the EU_{Ie} is equivalent to a decrease of approximately 13 kWh/stay in energy consumption. For an average hospital with 80,000 stays per year, this represents a saving of 1,032,000 kWh/year or, applying the average emission factor for the period (0.209 tCO₂/MWh), a reduction of 216 tCO₂/year (−8.2% on the average CF of the panel). Validation using Wild Cluster Bootstrap (M7) confirms that this finding is robust even under conservative inference with $N = 12$ clusters, overcoming a methodological limitation of conventional cluster-robust estimators. Hospitals H11, H7, and H4, which have the highest EU_{Ie} (>150 kWh/m²·year), are priorities for intervention through energy rehabilitation of envelopes and air conditioning systems.

Second. Energy economies of scale are statistically significant but economically marginal in intermediate-complexity hospitals. The β_{Stays} coefficient, although statistically significant ($p < 0.05$), is close to zero in magnitude, indicating that short-term variations in activity do not generate marginal adjustments in quasi-fixed energy consumption. This finding suggests that, in this segment of hospitals of comparable size, increased activity marginally reduces the EIA, limiting economies of scale to second-order

effects. Optimizing hospital occupancy through efficient bed management can be a low-cost complementary lever, although its quantitative impact is limited compared to the energy rehabilitation of the building.

Third. The year-on-year variation in the panel's total CF is dominated by the electricity emission factor of the national mix, not by changes in the building's energy efficiency. The period 2016–2024 shows a downward trend until 2023 (23,140 tCO₂, historic low), followed by a rebound in 2024 (31,449 tCO₂; +35.9% vs. 2023), driven by the increase in the electricity emission factor from 0.145 to 0.209 tCO₂/MWh. This pattern indicates that investments in energy efficiency have not kept pace with the expansion of healthcare. To reverse this trend and achieve the decarbonization targets for the European healthcare sector [48,49], it would be necessary to: (i) prioritize the renovation of buildings with higher EUe through NextGenerationEU funds and regional energy efficiency programs; (ii) adopt 100% renewable electricity supply contracts with Guarantee of Origin, eliminating dependence on the emission factor of the national mix; and (iii) implementing continuous energy monitoring systems with automatic alerts to detect anomalous deviations such as those identified in H4 (2021–2024) and H8 (2024), allowing for early corrective interventions [13].

The consistency of the EUe coefficient across multiple specifications (M0–M7), including time subperiods (pre and post-COVID), exclusions of individual hospitals, and alternative methods of statistical inference, provides solid evidence to guide hospital energy efficiency investment policies. The R² is greater than 0.97, confirming the high explanatory power of the fixed effects model to capture the determinants of intra-hospital variation in energy consumption.

Future research should: (i) extend the analysis to Scope 1 (on-site fossil fuels) and Scope 3 (supply chain, waste, travel) emissions to obtain a comprehensive quantification of the hospital carbon footprint [4,50]; (ii) incorporate building energy certification data (CEE certificates) to break down the EUe effect into its specific technical components (thermal transmittance of building envelopes, HVAC system efficiency, light emitting diode (LED), energy management systems; (iii) expand the panel to include high-complexity hospitals (third level of care) to verify whether the documented economies of scale are generalizable to centers with greater technological complexity; and (iv) evaluate the quantitative impact of specific energy rehabilitation interventions using quasi-experimental designs with high-frequency data (monthly or weekly) that allow causal effects of specific policies to be isolated.

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Abbreviations

The following abbreviations are used in this manuscript:

PNIEC	National Integrated Energy and Climate Plan
EUie	Building Energy Use Intensity
EIA	Energy Intensity per Activity
HVAC	Heating, Ventilation and Air Conditioning
NHS	National Health Service
CNMC	National Commission for Markets and Competition
GHG	Greenhouse Gases
OLS	Ordinary Least Squares
CF	Carbon Footprint
CEE	Certificate of Energy Efficiency
CI	Confidence Interval
COVID	Coronavirus Disease 2019
EF	Electricity Emission Factor
FE	Fixed Effects (Within estimator)
GLS	Generalized Least Squares
PFI	Private Finance Initiative
PPP	Public–Private Partnership
RE	Random Effects
SD	Standard Deviation
SERMAS	Madrid Health Service
CV	Coefficient of Variation
VAR	Vector Autoregression
LM	Lagrange Multiplier
SE	Standard Error
LED	Light Emitting Diode
IDAE	Institute for Energy Diversification and Saving
DRGs	Diagnosis–Related Groups
YoY	<i>year-on-year</i>

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