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DETERMINANTS OF TECHNICAL EFFICIENCY IN CROATIAN HOSPITALS

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Abstract

This paper evaluates the technical efficiency of 26 Croatian general hospitals, clinical hospitals, and clinical hospital centres, and examines its determinants across the pre-pandemic (2015–2016) and pandemic (2021–2022) periods. Technical efficiency is defined as a hospital's ability to maximise outputs from given inputs relative to the best-performing peers. An input-oriented Data Envelopment Analysis (DEA) with a BCC model and variable returns to scale is applied, using total expenditures (excluding investments in facilities) as the input and three outputs: weighted inpatient, day hospital, and outpatient cases. In the second stage, the Simar–Wilson bootstrap model assesses organisational and socioeconomic determinants. Population density and unemployment are negatively associated with efficiency, while bed occupancy, the share of disabled residents, and the share of the population under 15 show positive associations. The findings support more regionally adjusted resource allocation, improved bed management, and better data on treatment quality and complexity.

Keywords: technical efficiency determinants, Croatia, public hospitals, data envelopment analysis, Simar-Wilson

1. INTRODUCTION

National healthcare systems and population health are central determinants of a country's social welfare and economic performance. However, numerous authors argue that there are inefficiencies in public healthcare spending in EU countries (e.g., Škrabić, Kordić & Cikojević, 2025).

Hospitals are a crucial component of national healthcare systems (Dubas-Jakóbczyk et al., 2025). Assessing their technical (in)efficiency is essential for improving their performance, optimising resource use, and ensuring the sustainability of healthcare systems (Matranga et al., 2014). Technical efficiency refers to a hospital's ability to operate on its production frontier, producing a given level of output with the minimum possible inputs (Farrell, 1957).

Hospitals, which generally cannot refuse patients, may nonetheless improve efficiency by optimising resource use (Ramírez-Valdivia, Maturana & Salvo-Garrido, 2011). Accordingly, most studies apply an input-oriented DEA, a non-parametric technique for estimating production frontiers and benchmarking performance among decision-making units (Banker, Charnes & Cooper, 1984; Charnes, Cooper & Rhodes, 1978). DEA allows hospitals to be compared relative to a best-practice frontier, with efficiency scores indicating the potential for input reduction at given output levels.

As model specification depends critically on variable choice, the selection of inputs and outputs in this analysis follows established literature (Valdmanis, Rosko & Mutter, 2008). The BCC model is used to account for variable returns to scale (Banker et al., 1984). Based on the literature review and available data, this analysis covers general hospitals, clinical hospitals and clinical hospital centres for the years 2015, 2016, 2021, and 2022, using one input variable (total expenditures excluding investments in facilities) and three output variables (weighted inpatient cases, day hospital cases, and outpatient cases). We measure hospital performance by examining how many patients or cases are treated relative to the resources used.

This paper represents the first systematic analysis of external determinants affecting the technical efficiency of general hospitals, clinical hospitals and clinical hospital centres in Croatia. The primary objectives are to identify best-performing hospitals and to examine the socioeconomic and organisational factors contributing to efficiency. A two-stage methodological framework is employed: DEA is used to estimate efficiency scores in the first stage, and the Simar-Wilson model is employed as the primary specification in the second stage to assess the impact of selected determinants while accounting for the censored nature of DEA efficiency scores (Blank & Valdmanis, 2010; Campanella et al., 2017; Cavalieri, Guccio, Lisi & Pignataro, 2014; De Nicola, Gitto & Mancuso, 2013; Katharakis, Katharaki & Katostaras, 2013; Matranga et al., 2014; Rebba & Rizzi, 2006; Sielskas, 2021).

This study makes two contributions. First, this is the first analysis of external determinants influencing the technical efficiency of general hospitals, clinical hospitals, and clinical hospital centres in Croatia. Secondly, by applying multiple second-stage models, it reinforces the strength of its results and provides an important methodological advancement in DEA research.

The paper is structured as follows. Section 2 presents a review of the relevant literature and outlines the key determinants of hospital efficiency. Section 3 describes the data and methodology used in the analysis. Section 4 presents the results, and Section 5 discusses the empirical findings and their implications for health policy. Section 6 concludes the paper, outlining its limitations and offering policy recommendations and directions for future research.

2. LITERATURE REVIEW

Farrell (1957) defines technical efficiency as achieving the maximum output with available resources or producing a given output with the least input. Vrabková, Vaňková & Lee (2025) analysed general hospitals across 16 German states during 2018-2021, and highlighted the challenge posed by poorly defined prices in public services, which complicates technical efficiency assessment. Such issues can be addressed using specialised models (such as DEA) that fully or partially measure inputs and outputs in non-monetary units like quantities or weights.

Considering Farrell's definition, hospitals are viewed as production units where inputs include labour, capital, and supplies representing human resources, infrastructure, and materials (Zere et al., 2006). Thus, authors like De Nicola, Gitto & Mancuso (2011), for example, assessed the technical efficiency of the overall healthcare organization within a province (including hospitals) for 2004 and 2005, showing how effectively human and capital resources (doctors, nurses, and number of hospital beds) are used in relation to the number of patients and hospital days, which serve as output variables in the model.

While a hospital's efficiency in producing maximum output from given inputs is crucial, Matranga et al. (2014) stress that external and contextual factors beyond management's control also influence the technical efficiency of hospitals. Even effective resource use may not translate into high performance due to external conditions such as policy frameworks, demographic changes, or regional characteristics (e.g., unemployment). Thus, Banker, Natarajan & Zhang (2019) proposed a two-phase approach: the first explaining efficiency based on internal factors, and the second isolating inefficiencies caused by external influences.

As mentioned, the determinants of hospital efficiency can be categorized into internal and external factors. Internal determinants are variables under hospital management control, such as the number of hospital beds, outpatient/inpatient ratios, or the presence of specialised units. It is argued that larger hospitals with more beds tend to be more efficient (e.g., Mujasi, Asbu & Puig-Junoy, 2016, Giancotti, Guglielmo & Mauro, 2017; Rebba & Rizzi, 2006) and that hospital efficiency is often positively affected by higher outpatient/inpatient ratios (e.g., Ali, Debela & Bamud, 2017; Chowdhury & Zelenyuk, 2016). Tiehi (2020) argues that a higher number of doctors relative to other staff is associated with higher hospital efficiency. The bed occupancy rate has also been recognised as a significant determinant of technical hospital efficiency. It has been concluded that increasing bed occupancy rates improves hospital efficiency because hospitals with higher occupancy rates are more likely to match their target service capacity (e.g., Mujasi et al., 2016). On the other hand, hospitals with teaching status tend to be less efficient (e.g., Ali et al., 2017; Chowdhury & Zelenyuk, 2016; Schneider, Oppel & Schreyögg, 2020), as do hospitals with emergency departments or intensive care units, although these effects often depend on contextual and scale-related factors (e.g., Schneider et al., 2020; Sielskas, 2021). In addition, a longer length of stay is associated with lower hospital efficiency (e.g., Tiehi, 2020).

External determinants relate to factors outside hospital management control (e.g., demand for hospital services, competition in the hospital market, policies introduced by national regulatory healthcare bodies, and unemployment rate). Matranga et al. (2014) found a negative statistically significant relationship between the unemployment rate of younger men and the technical efficiency of hospitals. Unemployment is often associated with increased use of healthcare services partly due to worse mental health and higher risk behaviours (Flokou, Aletras & Niakas, 2017; Berg-Beckhoff, Gulis, Bak & Andersen, 2016). Although the proportion of elderly people is theoretically recognised as a factor that increases the burden on the healthcare system and reduces efficiency, this has been confirmed in the German context (Vrabková et al., 2025), but not in the Italian context (Campanella et al., 2017). The influence of hospital location, i.e., differences between urban and rural hospitals, has been recognised as a statistically significant external factor affecting technical efficiency, although the direction of this influence varies depending on the context (Ayiko et al., 2020; Chowdhury & Zelenyuk, 2016). Hospitals located in areas with a higher average population income (often densely populated urban centres) have, in some studies (Canada, Hong Kong), shown lower levels of efficiency (Ayiko et al., 2020; Guo, Zhao, Niu & Tsui, 2017). This is explained by higher demand for high-quality services, which increases both the volume and costs of input resources. In the literature, the effect of competition in the hospital market on efficiency is mixed (Schneider et al., 2020; Lindaas, Anthun & Magnussen, 2024). Policy and regulatory factors, such as payment mechanisms – DRG-based or prospective payment systems – are generally linked to higher technical healthcare efficiency compared to global budgeting systems (e.g., Cavalieri et al., 2014). Empirical research shows that the proportion of the population under 15 and over 65 can be a significant determinant of hospital efficiency, with a positive effect of these age groups being found (Alatawi, Niessen & Khan, 2020; Hu, Wang, Lu & Li, 2023), although the literature also highlights that the overall effect of age is often ambiguous due to its simultaneous impact on costs and outcomes (Baltussen, Leidl & Ament, 1996).

Domestic Croatian research on healthcare efficiency can be categorised into three groups. The first group includes studies examining the efficiency of the entire healthcare system. Jafarov & Gunnarsson (2008) compared the efficiency of social spending (including healthcare spending) among Croatia, the EU-15, the EU-10, Cyprus, Malta, and OECD countries and identified high expenditures, extended hospital stays, elevated drug costs, and minimal levels of private healthcare financing as key factors contributing to inefficiency. A similar approach was taken by Buljan & Šimović (2022), who assessed Croatia's healthcare efficiency relative to EU countries for the period 2013-2018. Their findings showed that Croatia demonstrated high-cost efficiency but low system efficiency, suggesting that inefficiencies arise not from the quantity of resources (inputs) but from how effectively they are used to produce desired health outcomes (longer life expectancy, lower mortality). These studies thus offer a broader, comparative view of the Croatian healthcare system at the macro level.

The second group focuses on hospital efficiency at the micro level. These studies analyse the performance of individual hospitals, emphasizing common sources of inefficiency such as resource surpluses, prolonged hospitalizations, high drug costs, and poor management practices. Rabar (2010, 2013) and Blecich, Dukić Samaržija & Samadžija (2024) highlight the surplus of resources, particularly hospital beds and medical staff, while Dukić Samaržija, Blecich & Najdek (2018) point to longer hospital stays and high material and drug costs as sources of inefficiency. Marijanović, Bronić & Prijaković (2025) examined the cost efficiency of 19 Croatian general hospitals during the pre-COVID and COVID periods, confirming that inefficiency stems not only from costs but also from poor resource management.

The third group comprises county-level research. Hodžić, Vuković & Muharemović (2019) analysed the efficiency of health expenditures across Croatian counties from 2010 to 2017. They emphasise the importance of effective primary healthcare services and the need for more patients to be treated at that level.

Although these studies have made significant contributions to understanding healthcare system efficiency in Croatia, none have empirically examined the external determinants of the technical efficiency of general hospitals, clinical hospitals, and clinical hospital centres. DEA indicates how efficient a hospital is, but it does not explain which external factors influence that efficiency. Buljan & Šimović (2022) and Marijanović et al. (2025) highlight that demographic changes (population decline and an increasing share of the elderly population), as well as smoking and alcohol consumption, pose challenges to the financial sustainability of the healthcare system in both Croatia and the EU. Nevertheless, external variables require deeper empirical testing regarding their impact on the efficiency of hospitals.

3. DATA AND METHODOLOGY

This section outlines data and methodological framework used to evaluate the technical efficiency of 26 Croatian general hospitals, clinical hospitals, and clinical hospital centres. Data were obtained from the State Audit Office's

Financial Audit Reports and the Ministry of Finance's Financial Reports for 2015, 2016, 2021, and 2022 (see Table 1).

This analysis is focused on these four years because the State Audit Office's Financial Audit Reports are available only for those years, and that was the only source where we could find the outputs for all three types of hospital activities. Each hospital performs three main types of activities: inpatient hospital care (where patients stay in the hospital for longer periods), day hospital services (where patients receive treatment during the same day), and outpatient specialist-consultative care services (where patients come for consultations and examinations).

Hospitals Dubrovnik and Sisak were excluded from the analysis due to unavailable data for 2021-2022, while hospitals Nova Gradiška and Pakrac were excluded due to missing data for 2015-2016. In the first stage of analysis, DEA is used to obtain efficiency scores. In the second stage of analysis, four alternative regression approaches (Tobit, truncated, fractional logit, and Simar-Wilson) are employed to examine the determinants influencing individual hospital efficiency.

3.1. Croatian healthcare sector

The Croatian healthcare system, defined by the Law on Health Care (2024), is divided into primary, secondary, and tertiary care, as well as health institutes. Secondary care is provided by general and specialised hospitals. General hospitals deliver a wide range of medical services, including surgery, internal medicine, paediatrics, and gynaecology and obstetrics, along with patient accommodation and nutrition. Specialised hospitals focus on specific diseases or age groups. Tertiary care is provided by clinics, clinical hospitals, and clinical hospital centres, which manage the most complex cases, deliver comprehensive services, and are often involved in higher education and scientific research. Clinics perform the most complex forms of healthcare for one or more specialist-consultative activities. Clinical hospitals and clinical hospital centres represent more complex types of general hospitals, differing in the number of specialised activities they perform. This study analyses all three types of general hospitals in Croatia on the secondary and the tertiary care level (general hospitals, clinical hospitals, and clinical hospital centres).

3.2. Calculation of Technical Efficiency – DEA Method (First-stage Analysis)

For the purpose of assessing the technical efficiency of Croatian hospitals, this paper applies the BCC model (Banker et al., 1984) of the DEA method, with variable returns to scale and an input orientation. Since decision-makers in the healthcare sector have greater control over inputs (resources) than outputs (results), an input-oriented DEA model is used, as in similar studies (Zubir et al., 2024). The

BCC model, which assumes variable (non-constant) returns to scale, is applied because the healthcare sector operates under conditions of imperfect competition, where hospitals cannot freely adjust their scale of operations due to budgets and regulatory constraints (Buljan & Šimović, 2022). The model formulation is:

$$\max \theta = \sum_{j=1}^{m} u_j y_{j0} + u_0$$

$$\sum_{i=1}^{s} v_i x_{i0} = 1$$

$$\sum_{j=1}^{m} u_j y_{jk} - \sum_{i=1}^{s} v_i x_{ik} + u_0 \leq 0$$

$$v_i \geq 0; u_j \geq 0.$$

The model is used to obtain the efficiency values θ_j, as well as optimal input v_i, and output u_i weights.

The most common practice in DEA models is to combine financial inputs with physical inputs such as the number of doctors, nurses, and beds (e.g., Campanella et al., 2017; Cavalieri et al., 2014; De Nicola et al., 2011; Matranga et al., 2014; Rebba & Rizzi, 2006; Sielskas, 2021).

In this analysis, the input variable is total expenditures excluding investment in construction facilities. By excluding such investments, which can vary substantially across years, the analysis focuses on operating costs – those necessary for ongoing operations and service provision and over which hospital management has greater control. Expenditures represent both capital consumption and labour-related costs. Expenditures have been recognised in the international literature as a relevant input in the calculation of technical efficiency (Wang et al., 2016). Farra Fazria & Dhamayanti (2021) note that hospital expenditures routinely include the allocation of medical service costs, including wages, capital, and equipment depreciation. These authors also emphasize that they are often included in productivity analyses to provide a clearer comparison of units over time.

Defining output variables remains a key challenge in healthcare efficiency analysis, as it is difficult to capture healthcare outcomes (Hussey et al., 2009). Most studies use indicators such as hospital discharges, procedures, and patient visits (Hussey et al. 2009). Some adjust discharges using a case-mix index to account for patient complexity (e.g., Matranga et al., 2014; Campanella et al., 2017).

In this analysis, we use output variables from the State Audit Office (2018, 2024) and the Central Health Information System of the Republic of Croatia (CEZIH, 2026). While these sources provide reliable data on service volume, they do not include comprehensive information on case-mix or quality for all three types of hospital activities. Case-mix is available only for acute hospital treatment (CEZIH, 2026); therefore, adjustment is applied only to inpatient cases.

Accordingly, outputs are measured using three indicators: weighted inpatient cases (inpatient cases multiplied by case-mix), day hospital cases, and outpatient cases (similar like in e.g., Dukić Samaržija et al., 2018; Hodžić et al., 2019; Rabar, 2010). This approach ensures coverage of all hospital activities, although case-mix adjustment is limited to inpatient care. This limitation is consistent with previous research, as output measures are often constrained by data availability (Neri, Cubi-Molla & Cookson, 2022). The number of patients or cases is a standard indicator of hospital output, reflecting the volume of services provided. After defining the input and output variables, the DEA model was applied.

Table 1 Variables used in the DEA model

Variable		**Definition and measurement**	**Source**
Input			
Expenditures	x_{1j}	Total expenditures and outlays without investments in building facilities. Based on data from a hospital's financial reports (in mil. €).	MoF (2025)
Outputs			
Weighted inpatient cases	y_{1j}	Weighted inpatient cases are defined as inpatient cases multiplied by the case-mix weight for acute hospital treatment. Inpatient cases refer to the total number of hospitalized patients or cases admitted to inpatient care, including accommodation and treatment with one or more nights in the hospital (in 000).	SAO (2018; 2024) CEZIH (2026)
Day hospital cases	y_{2j}	The total number of patients or treatment episodes treated in a day hospital, where diagnostic or therapeutic services are provided during the day, without the patient staying overnight (in 000).	SAO (2018; 2024)
Outpatient cases	y_{3j}	The total number of healthcare services (examinations, diagnostic procedures or interventions) recorded in specialist-consultative health care (in 000).	

Source: Authors.

3.3. Regression Models (Second-stage Analysis)

Technical efficiency scores obtained from DEA range between 0 and 1, making the dependent variable bounded. To analyse determinants of efficiency, several regression models are applied.

Many studies use Tobit regression (Campanella et al., 2017; Matranga et al., 2014, Nistor, Ștefănescu, Sîntejudeanu & Crișan, 2017, Katharakis et al., 2013, Karma & Gashi 2023; Piubello Orsini, Leardini, Vernizzi & Campedelli, 2021). The Tobit model is defined as (Tobin, 1958):

$$y_i = \beta_o + \sum_{i=1}^{n} \beta_i X_i + \mu, \qquad i = 1,2 \dots n$$

$$0 \le y_i \le 1$$

In this case, y_i represents the technical efficiency, β_0 is the constant, X_i are the explanatory variables, which in this case are the factors that affect hospital efficiency, β_i are the coefficients.

The data can be right-censored, left-censored, or censored on both sides. In the standard Tobit model, the dependent variable is censored by zero (Henningsen & Toomet, 2011; Lamesgen, Miniyihun & Amare, 2022).

In this case: $y = \begin{cases} y*, & if\ 0 < y* < 1 \\ 0, & if\ y* \leq 0 \\ 1, & if\ y* \geq 1 \end{cases}$

In line with the approach of Jehu-Appiah et al. (2014), the dependent variable in our study also represents technical efficiency calculated using the DEA method. In DEA methodology, the result for each observation takes a value $0 < y_i \leq 1$ reflecting the relative efficiency of that unit within the sample, where $y_i = 1$ indicates efficient hospital and $y_i < 1$ an inefficient.

Hoff (2007) criticizes the inclusion of Tobit regression in DEA scores because it is limited to the interval (0,1], and the value 1 occurs with positive probability, whereas 0 never occurs.

Instead of Tobit, Hoff (2007) and Ramalho, Ramalho & Henriques (2010) recommend the use of fractional logit regression (Papke & Wooldridge, 1996). Unlike the Tobit model, which assumes a distribution for the dependent variable, this model does not assume any distribution for the dependent variable to yield reliable estimates. Therefore, the value of DEA efficiency depends on more explanatory variables through the logit function *G*, which is always between 0 and 1.

$$E(h_i \mid x_i) = G(x_i\beta)$$

$$G(z) = \frac{1}{1 + e^{-z}}$$

$$\ell(\beta) = \sum_{i=1}^{N} [h_i \ln G(x_i\beta) + (1 - h_i) \ln(1 - G(x_i\beta))]$$

In addition to the above regressions, in works on the study of external factors that affect efficiency, the most common, and so far one of the most widely used and methodologically robust approaches, is the Simar & Wilson (2007) double bootstrap (García-Cornejo & Pérez-Méndez, 2020; Piubello Orsini et al., 2021; Cavalieri et al., 2014; De Nicola et al., 2011; Lindaas et al., 2024; Schneider et al., 2020; Lindlbauer, Schreyögg & Winter, 2016; Tiemann & Schreyögg, 2012; Blank & Valdmanis, 2010; Blank & Van Hulst, 2011; Hoff, 2007; Katharakis et al., 2013).

In this regard, the authors Blank & Van Hulst (2011) study the influence of corporate governance characteristics on the cost efficiency of Dutch general hospitals. The analysis is carried out on a sample of 75 hospitals from 2007, and in the second phase they use the Simar-Wilson truncated regression with the bootstrap procedure to examine the influence of governance variables on DEA efficiency. The analysis in this paper was done according to the example of Blank & Van Hulst (2011). In performing the regression, it excludes all efficient hospitals, which have a value of one because they are cut off from the upper side. This assumes a dependent variable is lower than 1.

After this, a truncated regression model is estimated, where the dependent variable y_i (defined above) is regressed on explanatory variables Z_i:

$$y_i = \beta_o + \beta_1 Z_i + \cdots + \mu_i,$$

From this truncated regression, the Simar-Wilson model estimates standard deviations and generates new errors from a normal distribution respecting the previously specified condition $\mathrm{y}_i < 1$. For each hospital and for each bootstrap repetition $b = 1, \ldots, N$, Simar-Wilson forms an efficiency score:

$$y_i^{*(b)} = \beta_o + \beta_{i1}\mathrm{Z} + \cdots + \mu_i^{*(b)}$$

Where $\mu_i^{*(b)}$ are bootstrap errors from normal distribution truncated on 1. After generating these bootstrap efficiency scores, in the second part of the algorithm, the truncated regression is re-estimated on each bootstrap sample.

$$y_i^{*(b)} = \beta_0^{*(b)} + \beta_1^{*(b)}\mathrm{Z} + \cdots + \mu_i^{*(b)}$$

Bootstrap replicates of parameters form an empirical distribution from which the Simar-Wilson procedure constructs confidence intervals by sorting all bootstrap estimates, discarding the bottom and top 2.5% of values, and the remaining bounds represent the 95% confidence interval for each parameter. In this way, a reliable and consistent inference is obtained in the second phase of DEA analysis, because the bootstrap corrects the problems of bias, dependence and truncation that classical methods such as OLS or Tobit cannot. To assess robustness, we estimated four second-stage models: Tobit, fractional logit, truncated regression and Simar-Wilson bootstrap regression and provide an additional methodological contribution to DEA efficiency research.

Determinants of hospital technical efficiency are grouped into organisational and socioeconomic factors. These categories cover broad aspects of resource availability, patient demographic demand, and economic characteristics of counties that the hospital belongs to.

Table 2 Variables used in regression models

Variable	Definition and measurement	Source
	Dependent variable	
Technical efficiency	Technical efficiency scores calculated using the DEA method explained above.	Authors' own calculations
Organisational independent variables		
Medium	Indicator variable for hospital classified as medium (measured by the number of beds).	Authors' own calculations based on CIPH (2024)
Large	Indicator variable for hospital classified as large (measured by the number of beds).	Authors' own calculations based on CIPH (2024)
Bed occupancy	Bed occupancy rate in stationary hospital health care (%).	SAO (2018; 2024)
Socioeconomic independent variables		
Unemployment rate	Share of unemployed persons in the total population.	CBS (2025)
Population density	Population density (inhabitants per km²).	CBS (2025)
Share of disabled	Share of population with disabilities (%).	CIPH (2015, 2016, 2021, 2022)
Population under 15	Percentage of the population aged under 15 years in the total population.	CBS (2025)
Population over 65	Percentage of the population aged over 65 years in the total population.	CBS (2025)

Note: All variables used in the analysis are available upon request from the authors.

Small hospitals are Gospić, Knin, Našice, and Ogulin. Medium: Bjelovar, Čakovec, Karlovac, Koprivnica, Požega, Šibenik-Knin, Vinkovci, Virovitica, Vukovar, and Zabok. Large hospitals: KB Dubrava, KB Merkur, KB Sveti Duh, KBC Osijek, KBC Rijeka, KBC Sestre Milosrdnica, KBC Split, KBC Zagreb, Pula-Pola, Slavonski Brod, Varaždin, and Zadar.

Source: Authors.

The dependent variable is technical efficiency obtained from DEA. Sielskas (2021) analysed the determinants of efficiency of 110 Polish county hospitals. The author constructed a dummy variable for large and small hospitals, with the remaining hospitals serving as the reference group and representing medium-sized hospitals. Small hospitals are defined in this paper according to Sielskas (2021): the average bed count minus the standard deviation was calculated for each hospital, and all hospitals with lower values were designated as small. For large hospitals, the standard deviation was added to the average bed count. The number of beds in our study used to calculate hospital size was taken from the Croatian Institute of Public Health (2024) Statistical Yearbook. Medium-sized hospitals are between small and large, and a dummy variable for medium and large hospitals was used in the model, with small hospitals omitted as the reference category. The bed occupancy rate was included as an indicator of system workload and the efficiency of capacity management, capturing the extent to which actual utilisation corresponds with target service capacity.

The unemployment rate in the counties to which the hospital belongs was used as a socioeconomic indicator and reflects the local community's economic condition. Residents' income per capita was initially considered, but due to its high correlation with unemployment rate (r=-0.8) it was omitted to avoid multicollinearity. Population density was taken as an indicator that can affect accessibility and burden the demand for health services. The share of people with disabilities was also used as an indicator of service demand. Both indicators show the pressure of the population on hospital services, but population density may reflect higher demand that requires more complex hospital organization due to more urgent and expensive cases, while the share of people with disabilities represents clear and stable patterns of demand, due to which hospital capacities can be used predictably. The demographic variables used are the shares of the population aged under 15 and over 65 in the total population, capturing the age structure and the associated burden on hospital services.

4. RESULTS

The correlation table for input (expenditures) and independent variables for the analysed years is given in Table 3. It is important to note that the input variable from the DEA analysis was included in the correlation table. Johnson & Kuosmanen (2012) emphasize that correlation between input and independent variables may indicate potential endogeneity, which can affect the consistency of second-stage estimates. However, they also show that two-stage DEA models may remain statistically consistent even in the presence of some correlation, although some bias may still occur in finite samples. It is evident from the table that all the correlations of the variables used in the regressions and inputs are low to moderate and meet this condition. Accordingly, the results of the second-stage analysis should be interpreted with caution and considered indicative rather than strictly causal.

Table 3 Correlation matrix of input variable (DEA) and independent variables

	Expenditures	*Medium*	*Large*	*Bed occupancy*	*Unemployment rate*	*Population density*	*Share of disabled*	*Population under 15*	*Population over 65*
Expenditures	1	-0.38	0.59	0.09	-0.30	0.50	-0.01	0.21	-0.11
Medium	-0.38	1	-0.73	-0.10	0.20	-0.39	0.23	0.10	-0.02
Large	0.59	-0.73	1	0.22	-0.31	0.55	-0.33	0.24	-0.25
Bed occupancy	0.09	-0.10	0.22	1	0.26	0.24	-0.50	0.31	-0.54
Unemployment	-0.30	0.20	-0.31	0.26	1	-0.35	-0.35	0.09	-0.34
Population density	0.50	-0.39	0.55	0.24	-0.35	1	-0.10	0.45	-0.37
Share of disabled	-0.01	0.23	-0.33	-0.50	-0.35	-0.10	1	-0.24	0.55
Population under 15	0.21	0.10	0.24	0.31	0.09	0.45	-0.24	1	-0.75
Population over 65	-0.11	-0.02	-0.25	-0.54	-0.34	-0.37	0.55	-0.75	1

Source: Authors' calculations.

The technical efficiency analysis was conducted using the input-oriented DEA model for the pre-pandemic years (2015 and 2016) and pandemic years (2021 and 2022). The results are presented in Table 4. Hospitals with efficiency scores equal to 1 are considered fully efficient and form the efficiency frontier, while those with scores below 1 are less efficient.

Table 4 Results of first stage analysis: technical efficiency, ranked by technical efficiency in 2022

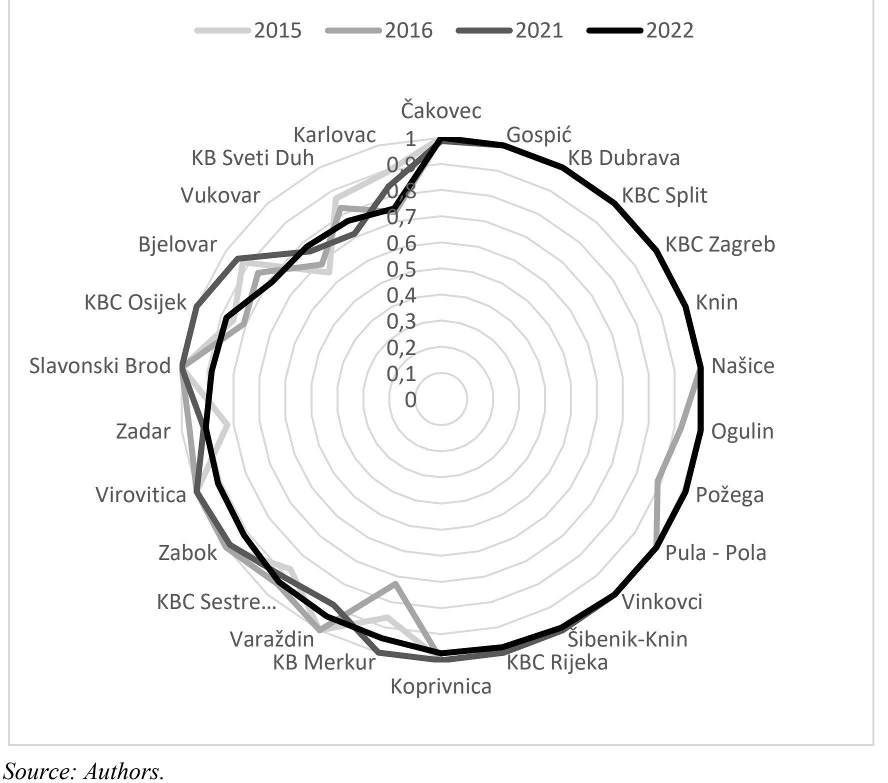
Hospital	**Technical efficiency**			
	2022	**2021**	**2016**	**2015**
Čakovec	1	0.9875	1	1
Gospić	1	1	1	1
KB Dubrava	1	1	1	1
KBC Split	1	1	1	1
KBC Zagreb	1	1	1	1
Knin	1	1	1	1
Našice	1	1	1	1
Ogulin	1	1	0.9238	1
Požega	1	1	0.8858	0.9960
Pula - Pola	1	1	1	1
Vinkovci	1	1	1	1
Šibenik-Knin	0.9877	1	1	1
KBC Rijeka	0.9777	1	1	1
Koprivnica	0.9732	1	1	1
KB Merkur	0.9434	1	0.7290	0.8608
Varaždin	0.9399	0.8889	1	1
KBC Sestre Milosrdnice	0.9357	0.9093	0.9448	0.8693
Zabok	0.9170	0.9825	1	1
Virovitica	0.9133	1	1	1
Zadar	0.9073	0.9150	0.9699	0.8234
Slavonski Brod	0.8849	1	1	1
KBC Osijek	0.8782	1	0.8083	0.8501
Bjelovar	0.7877	0.9457	0.8505	0.9222
Vukovar	0.7775	0.7554	0.6878	0.6463
KB Sveti Duh	0.7693	0.7137	0.8263	0.8671
Karlovac	0.7509	0.8382	0.7371	0.8908

Source: Authors' calculations.

By analysing technical efficiency, the efficiency frontier is defined as the set of hospitals that reach the efficiency limit of 1. A large number of hospitals achieved maximum technical efficiency (PTE=1) in all four reference years (Gospić, KB Dubrava, KBC Split, KBC Zagreb, Knin, Našice, Pula – Pola, and Vinkovci). During the pandemic years, some hospitals achieved significant efficiency improvements. For example, Ogulin improved from 0.9238 in 2016 to a PTE of 1 in 2021 and 2022, while Požega rose from 0.8858 to 1 over the same period. Similarly, KB Merkur increased its PTE from 0.7290 in 2016 to 1 in 2021, and KBC Osijek from 0.8083 in 2016 to 1 in 2021. Lower-performing hospitals such as Vukovar showed lower technical efficiency throughout the period of analysis.

However, it should be emphasised that these results should be interpreted with caution. Firstly, 2001 and 2022 were pandemic years when hospitals were not operating under normal conditions. Secondly, after the earthquake in 2020 in the City of Zagreb and Petrinja, many hospitals in the City of Zagreb and surrounding areas needed reconstruction and were not operating under normal conditions. Thirdly, the absence of case-mix and quality-of-care indicators for day hospitals and outpatient specialist-consultative health care services in this analysis reduces full comparability across hospitals and limits the interpretation of efficiency, as hospitals treating more complex patients in day hospitals and outpatient specialist-consultative health care may appear less efficient. For example, KB Merkur might be one of the hospitals that has high expenditures for a relatively low number of patients due to complex patient cases (since it is the leading Croatian and globally recognized transplant centre, especially for the liver, kidney, and pancreas). Future research should address this important limitation when comprehensive and comparable data about case-mix and/or quality-of-care indicators for all hospital activities for each general hospital become publicly available.

Figure 1 Hospital technical efficiency ranked by 2022 performance



Source: Authors.

In the second stage analysis, four types of regression models were applied. The first model is a Tobit model in which the dependent variable is doubly censored $0 \leq y_i \leq 1$. The second model is a truncated regression that includes only those hospitals for which the condition $y_i < 1$ is met. The third regression is Papke & Wooldridge (1996), which represents $E(y_i \mid x_i) = G(x_i\beta)$, where G represents the logit function. After that, the Simar & Wilson (2007) truncated bootstrap model represents a truncated regression but includes a bootstrap procedure for bias correction. Therefore, we present one regression model for all four regressions, but these conditions should be kept in mind for each of these regressions

$$y_{it}^* = \beta_0 + \beta_1 Medium_{it} + \beta_2 Large_{it} + \beta_3 Bed\ occupancy_{it} + \beta_4 Unemployment\ rate_{it} + \beta_5 Density_{\boldsymbol{it}} + \beta_6 Share\ of\ disabled_{it} + \beta_7 Population\ under 15_{it} + \beta_8 Population\ over\ 65_{it} + \mu_{it}$$

Where y_{it} depends on model:

(a) Tobit model (0-1)

$$y_{it} = \min(1, \max(0, y_{it}^*))$$

(b) Truncated model without bootstrap (y_{it}<1)

$$y_{it} = y_{it}^*, \quad \text{where } y_{it}^* < 1$$

(c) Fractional logit model

$$E(y_i \mid x_i) = \frac{e^{x_i\beta}}{1 + e^{x_i\beta}}$$

(d) Simar-Wilson model

$$y_{it} = y_{it}^*\ with\ bootstrappe\ truncated\ model\ (2000)$$

Considering the limited sample size and potential deviations from the assumption of homoscedasticity, all models except Simar-Wilson were estimated using robust standard errors. Simar-Wilson standard errors come from the bootstrap distribution, which is methodologically a completely different variance model. This approach reduces the sensitivity of the results to heteroscedasticity, thereby improving the reliability of statistical conclusions. This approach is in line with Kalina (2012) suggestions.

Our interpretation of the results in Table 5 is primarily based on the model Simar-Wilson (2007) because of its bootstrap procedure, which corrects for bias in estimates. It is important to note that the Simar-Wilson and truncated models without bootstrap are based only on inefficient hospitals (43 observations), whereas the Tobit and fractional logit models use the entire sample (104 observations). Although the analysis focuses on the results of the Simar-Wilson procedure, other models are included to assess their robustness and because of their frequent use in the literature.

Table 5 Results of second-stage analysis

Variables	**(a)**	**(b)**	**(c)**	**(d)**
	Tobit	**Truncated**	**Fractional Logit**	**Simar-Wilson**
Medium	**-0.2687*** (-3.11)**	**-0.1574*** (-3.31)**	**-3.0572*** (-2.92)**	-0.1574 (-0.52)
Large	**-0.2353*** (-2.66)**	**-0.1137*** (-2.58)**	**-2.7623** (-2.57)**	-0.1137 (-0.38)
Bed occupancy	0.0022 (1.24)	**0.0054*** (4.37)**	**0.0326** (2.35)**	**0.0054*** (3.80)**
Unemployment rate	-0.5549 (-1.44)	**-0.8235** (-2.09)**	**-7.6583** (-2.25)**	**-0.8235* (-1.79)**
Population density	**-0.0001** (-2.00)**	**-0.0002*** (-2.82)**	**-0.0013*** (-2.74)**	**-0.0002*** (-2.77)**
Share of disabled	-0.0036 (-0.47)	**0.0160* (1.81)**	0.0036 (0.05)	**0.0160* (1.78)**
Population under 15	0.0206 (0.68)	**0.0532* (1.67)**	0.3115 (0.93)	**0.0532* (1.70)**
Population over 65	0.0004 (0.03)	0.0082 (0.64)	0.0134 (0.11)	0.0082 (0.56)
Constant	0.9407 (1.39)	-0.3532 (-0.55)	-0.0771 (-0.01)	-0.3532 (-0.44)
Observations	104	43	104	43

Note: z-statistics are in parentheses, * p<0.1, ** p<0.05, *** p<0.01.

Source: Authors' calculations.

According to the Simar-Wilson model, hospital size has no statistically significant effect on technical efficiency. In the other three models, hospital size shows a negative effect on efficiency, with medium-sized hospitals exhibiting a stronger negative relationship than large hospitals.

The results from three models (excluding the Tobit model) indicate that bed occupancy rate is a statistically significant and positive predictor of technical efficiency improvements. The proportion of people with disabilities is statistically significant and positive in two models (Simar-Wilson and truncated). The percentage of the population under 15 years is positive and statistically significant in the Simar-Wilson and truncated models, while the population over 65 years shows no statistically significant effect in any model.

The unemployment rate is a negative and statistically significant determinant of technical efficiency in the truncated regression, fractional logit, and Simar-Wilson model. Population density also reduces technical efficiency, but it has the smallest effect among the included determinants across all four models.

The DEA results show that a significant number of hospitals are technically efficient (PTE = 1), while for those below the efficiency limit, analysed through a robust Simar-Wilson model to correct for bias, efficiency increases statistically significantly with bed occupancy, share of disabled, and the share of population under 15 years. At the same time, it decreases with the unemployment rate and population density.

5. DISCUSSION

Previous Croatian studies on hospital efficiency at the individual hospital level (e.g., Rabar, 2010, 2013; Hodžić et al., 2019; Dukić Samaržija et al., 2018) have focused primarily on efficiency assessment using DEA analysis. The key contribution of this study is the inclusion of external determinants, specifically socioeconomic and sociodemographic characteristics at the county level, in explaining variations in hospital technical efficiency.

The bed occupancy rate has a positive effect on the technical efficiency of Croatian hospitals. This finding is consistent with international studies (e.g., García-Cornejo & Pérez-Méndez, 2020; Cheng et al., 2015; Chowdhury & Zelenyuk, 2016; Mujasi et al., 2016). The bed occupancy rate is a widely used indicator of capacity utilization in hospitals. For example, García-Cornejo & Pérez-Méndez (2020) highlight that it reflects the presence or absence of excess capacity, while Chowdhury & Zelenyuk (2016), analysing hospitals in Ontario, Canada, show that higher occupancy indicates that hospitals operate closer to their service capacity, whereas lower occupancy suggests underutilization. Higher occupancy rates therefore, reduce excess capacity and lower costs per unit of service, leading to higher measured efficiency.

In contrast, population density is found to negatively affect technical efficiency. This result partially aligns with findings from Canadian studies, which show that hospitals in densely populated urban areas may be less efficient than those in less populated rural areas. One possible explanation lies in differences in case complexity: hospitals in urban areas are more likely to treat complex and emergency cases, which require more resources and increase costs, thereby reducing measured efficiency. By contrast, rural hospitals tend to treat less complex cases, which may contribute to higher efficiency scores within the DEA framework.

Unemployment is also negatively associated with hospital efficiency. Our finding is consistent with Matranga et al. (2014), who report a negative relationship between unemployment rate of younger men and the technical efficiency of Italian hospitals at the regional level. Existing research shows that unemployed individuals tend to use more healthcare services than employed persons (Kraut, Mustard, Walld & Tate, 2000; Åhs, Burell & Westerling, 2012), partly due to worse mental health and higher risk behaviours (Flokou, Aletras & Niakas, 2017; Berg-Beckhoff, Gulis, Bak, & Andersen, 2016). When unemployed persons use hospital services, they are more likely to be more complex hospital cases since unemployment is associated with higher rates of overall mortality (Jin, Shah & Svoboda, 1995). Additionally, job loss may reduce access to private healthcare, shifting patients toward public hospitals and additionally increasing pressure on public hospital resources (Flokou et al., 2017; Kaitelidou et al., 2016).

Our results also indicate that a higher proportion of the population under 15 years of age has a positive and statistically significant effect on hospital efficiency. This finding is consistent with previous papers (Alatawi et al., 2020; Hu et al., 2023), which show that efficiency rises with a larger proportion of younger populations. This can be explained by the way that healthcare demand is structured: children, especially those who are younger, need regular, relatively standardised, and less resource-intensive services like immunisations and outpatient care for acute illnesses. These services require comparatively constant inputs but produce larger output quantities. Such an increase in output with unaltered resources results in higher measured technical efficiency within the DEA framework.

Although the disability rate has not been analysed so far, Croatia is in the context of the Homeland War and there is an increased number of disabled people. Although disabled people increase demand for health services, they usually receive mostly repetitive, fixed, and predictable services. This creates stable, easily forecastable demand, which can improve technical efficiency. In contrast, higher population density can bring more complicated health cases and thus reduce hospitals technical efficiency because emergency cases are more often and they are more expensive.

6. CONCLUSION

This paper represents the first systematic analysis of external determinants that affect the technical efficiency of 26 general hospitals, clinical hospitals, and clinical hospital centres in Croatia. The study is important for hospital managers who, in addition to internal hospital factors, should also consider external socioeconomic and demographic factors when allocating resources. In addition to practical implications, the paper also offers methodological progress. In the second stage of the analysis, it offers four regression models most frequently used in the literature for the analysis of efficiency determinants, but also uses them as a robust check for the research results.

The most robust results of the analysis are bed occupancy rate, the unemployment rate, and population density, which are statistically significant and relevant in almost all models. Bed occupancy rate increases efficiency by reducing unused capacity and lowering fixed costs per patient, in line with existing literature. The negative impact of unemployment on technical efficiency most likely stems from the increased and more complex demand for healthcare services. Population density also reduces efficiency, likely due to a higher frequency of emergency cases, which increases the cost per patient, although this effect is relatively small. A larger share of the population under the age of 15 has a positive effect on technical efficiency, as it increases demand for standardized and less resource-intensive services. The share of disabled individuals also increases technical efficiency, most likely due to the predictability of demand and the routine nature of services required by this group.

The finding that higher bed occupancy rates significantly increase technical efficiency suggests that the key problem of the Croatian hospital system is not a lack of capacity, but its insufficient utilization. Therefore, in the context of

Croatian long waiting lists for medical services in the hospitals, to increase bed occupancy the focus of management should be on optimizing patient flow (eliminating administrative and organizational delays). Existing studies indicate that ICT can significantly improve efficiency in healthcare systems by enabling real-time access to information and facilitating communication, thereby streamlining workflows and increasing productivity (Pira & Pira, 2025), thus this should be an important topic for future research. Targeted reduction in inpatient capacity makes sense only in hospitals with chronically low bed occupancy, which is in line with the findings of Rabar (2010) and Buljan & Šimović (2022) that further emphasize the need to strengthen day care and rationalize hospital infrastructure in the Croatian context.

Since a negative impact of the unemployment rate on technical efficiency has been identified, it is recommended to strengthen preventive programs for unemployed persons. Considering that higher population density reduces efficiency, probably due to more complex cases and greater demand, the Ministry of Health should think about targeted organizational improvements and increased funding in hospitals in highly populated areas.

Regarding limitations, it should be emphasised that this analysis represents only one perspective on the efficiency of the analysed hospitals and not a definitive assessment. The output variables used in this study are not perfect measures; they reflect the best available data at the hospital level. A key limitation is the lack of detailed output data, particularly regarding hospital case-mix and quality-of-care indicators, which would enable more accurate measurement of efficiency. Future research should address this limitation, but firstly, the Ministry of Health should publish comprehensive case-mix and quality-of-care data (e.g., waiting times for operations) for all public hospitals.

Future research should also include other types of public hospitals (such as specialised hospitals and clinics), as well as private hospitals and primary healthcare providers. Lower-performing hospitals identified by the DEA analysis should be further investigated. Combining quantitative methods with qualitative approaches (surveys, interviews, and/or case studies) would provide a more comprehensive understanding of hospital performance. Additionally, cross-country comparisons (especially within the EU) and the application of alternative methodological approaches, such as panel DEA or Stochastic Frontier Analysis (SFA), would further enhance the robustness of findings.

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ODREDNICE TEHNIČKE EFIKASNOSTI U HRVATSKIM BOLNICAMA

Sažetak

Rad analizira tehničku efikasnost 26 hrvatskih općih i kliničkih bolnica te kliničkih bolničkih centara i ispituje njezine odrednice u razdobljima prije (2015.–2016.) i tijekom pandemije (2021.–2022.). Tehnička efikasnost promatra se kao sposobnost maksimiziranja izlaza iz zadanih ulaza u odnosu na najbolje ustanove u uzorku. U prvoj fazi primijenjena je DEA metoda orijentirana na ulaze (BCC model s varijabilnim prinosima na opseg), uz jedan ulaz i tri izlaza. U drugoj fazi korišten je Simar-Wilsonov bootstrap za procjenu organizacijskih i socioekonomskih odrednica. Rezultati pokazuju da su gustoća naseljenosti i stopa nezaposlenosti negativno povezane s efikasnošću, dok su popunjenost kreveta, udio osoba s invaliditetom i udio mlađih od 15 godina pozitivno povezani. Rad donosi prvu sustavnu analizu tih odrednica u Hrvatskoj te naglašava potrebu prilagodbe zdravstvenih politika regionalnim uvjetima, bolje upravljanje popunjenosti bolničkih krevetima i poboljšanja dostupnosti podataka.

Ključne riječi: determinante tehničke efikasnosti, Hrvatska, javne bolnice, analiza omeđivanja podataka, Simar-Wilson.

JEL klasifikacija: H75, I11, I18.