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Efficiency and Productivity in the Croatian Construction Sector: Trends and Challenges

Abstract

Croatian construction companies continue to struggle with inefficiencies and slow adoption of digital tools. Understanding the key drivers of efficiency and productivity is therefore crucial to ensure the long-term sustainability and competitiveness of the sector. This paper examines efficiency and productivity trends in the Croatian construction sector from 2019 to 2023, focusing on large and very large construction companies and the key challenges impacting their performance. Using Data Envelopment Analysis (DEA) and the Malmquist Productivity Index (MPI), the study tracks efficiency and productivity changes over time using a three-year window analysis of company accounting data. The results show that overall efficiency remains relatively low but stable, with a slight decline in 2023. The main causes of inefficiency are management practices and external factors rather than a (non-)optimal production size. In contrast, productivity has generally increased, especially between 2022 and 2023, due to improvements in technical efficiency and technological advances. These results underline the need for greater investment in digital tools and innovation to increase efficiency and productivity growth in the sector in the long term. The study provides valuable insights for policy makers, industry leaders and researchers and highlights the importance of digital transformation, workforce development and strategic investment. Eliminating persistent inefficiencies, accelerating technology adoption and addressing labor capacities will be critical to ensuring the sector's future competitiveness in both domestic and international markets.

Keywords: construction sector, window data envelopment analysis, Malmquist productivity index, efficiency, productivity, accounting data

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1. INTRODUCTION

The construction industry is one of the most important drivers of global economic development. According to the McKinsey Global Institute (2017), the sector accounts for 13% of global GDP and employs around 7% of the world's working-age population, which corresponds to an annual value added of around USD 10 trillion. The sector faces persistent challenges, including inefficient project delivery, labor shortages, and slow adoption of digital technologies (Denicol, Davie & Krystallis, 2020; Whyte, 2019). At the same time, sustainability has become a key priority, with circular and regenerative construction approaches gaining traction (Čegar, Drezgić & Čišić, 2024).

To address these challenges, the industry is increasingly integrating digital tools such as Building Information Modeling (BIM), automation, and artificial intelligence (AI) to enhance productivity and optimize resource management (Omotayo et al., 2024; Pan & Zhang, 2023). The Internet of Things (IoT) has also proven transformative, enabling real-time project monitoring and resource optimization, particularly for small and medium-sized enterprises (SMEs) (Gamil et al., 2020; Ghosh et al., 2021; Woodhead, Stephenson & Morrey, 2018). AI-driven predictive analytics and big data applications are further improving decision-making and project management (Abioye et al., 2021; Regona et al., 2022; Bilal et al., 2016). However, the construction sector has been slow to fully embrace digitalization, limiting its efficiency gains (Munawar et al., 2022).

The Croatian construction sector has experienced cycles of growth and crisis over the past two decades. After a prolonged downturn following the 2008 financial crisis, the sector began recovering in 2015, largely due to government investment and EU funding. However, this recovery has been hindered by a persistent labor shortage, exacerbated by the migration of skilled workers to more developed EU countries (Ceric & Ivic, 2020). The decline in skilled labor availability has increased costs and reduced productivity. In response, Croatia has implemented workforce retraining programs and expanded quotas for foreign workers, though structural inefficiencies remain (Ceric & Ivic, 2020). Additionally, Croatia's EU accession has intensified competition from foreign construction firms, pressuring domestic companies to expand internationally (Lovrenčić Butković & Mihić, 2019).

Despite modernization efforts, Croatian construction firms continue to struggle with inefficiencies and slow digital adoption, mirroring global resistance to technological change. This study examines efficiency and productivity trends in the Croatian construction sector from 2019 to 2023, focusing on large and very large firms. Using Data Envelopment Analysis (DEA) and the Malmquist Productivity Index (MPI), it assesses performance changes over time by analyzing company accounting data in a three-year window.

The paper is structured as follows: Section 2 reviews existing literature on efficiency and productivity measurement. Section 3 outlines the methodology, while Section 4 details data sources and variable selection. Section 5 presents and discusses the results, and the conclusion summarizes key findings, limitations, and future research directions.

2. LITERATURE REVIEW

The profitability of construction companies has been studied extensively in the literature, with many studies focusing on financial ratios and profitability indicators as key performance measures. Financial ratios such as return on assets (ROA) and return on equity (ROE) are often used to evaluate the profitability of companies in this sector. Lafuente et al. (2017) emphasized the importance of access to trade credit as an important source of liquidity as a key factor influencing the financial performance (measured by ROA) of Spanish construction companies. Halian et al. (2020) found that a decline in GDP and a reduction in the cost of revenue lead to an increase in ROA and ROE in the construction subsector. Similarly, rising inflation combined with lower costs improves profitability, with the highest gains observed when GDP declines, inflation rises and costs fall at the same time. Škuflić, Mlinarić & Družić (2018) examined the determinants of profitability of Croatian construction companies. Their study shows the significant influence of factors such as company size, concentration index, growth and lagged profitability on profitability. The authors emphasize the role of the construction sector in Croatian economic growth and the impact of the global financial crisis on the performance of the industry.

Despite the emphasis on financial ratios, these indicators have their limitations when viewed in isolation. They often fail to capture the full range of operational and strategic factors that contribute to a company's financial performance. Recent studies also recognize the importance of external factors such as regulatory changes (Azman et al., 2023) and technological advances (Musa et al., 2024). In addition, the importance of organizational, human capital-related and operational factors was emphasized in connection with Croatian construction companies. For example, Šandrk Nukić & Šuvak (2013) demonstrated that HR managers' perception of organizational success is significantly influenced by the adequacy, quality and quantity of employee training, the effectiveness of storing and accessing business information and the efficiency of knowledge acquisition from partners. Complementing this internal perspective, Nahod & Knezović (2017) identified key factors that influence labor productivity from the client's perspective and found that economic factors such as regularity and salary level are the most important motivators in Croatia, while socio-psychological factors such as job satisfaction and relationships with colleagues also play an important role. This combination emphasizes that success is not only a function of financial management, but also depends on strategic human resource practices, knowledge management and effective motivation of local employees.

In contrast to profitability, efficiency and productivity are more comprehensive measures that capture a company's operational performance over time. Efficiency is defined as the optimal use of resources, including labor, capital, and technology, to achieve maximum output. Various methodologies have been employed to assess efficiency, with DEA being a predominant tool. Ersoy & Tehci (2024) conducted an efficiency analysis of construction companies using DEA models, including the input-oriented CCR model and the Super Efficiency SE-CCR model. Their study found that only three out of ten companies analyzed were operating efficiently, with inefficiencies attributed to suboptimal resource utilization and financial constraints. They conducted Tobit regression models in the second stage analysis to determine the influencing factors on efficiency and identified that net sales positively impacted efficiency scores, while an excessive workforce and high asset values led to inefficiencies. Similarly, Hu & Liu (2018) applied DEA to assess efficiency trends in the construction industry, highlighting the importance of improving construction efficiency and management effectiveness, with regional performance disparities mainly driven by technical efficiency differences. Procel (2021) used DEA to evaluate the efficiency of construction companies in the Spanish region of Catalonia and found that efficiency fell significantly during the economic downturn (2009-2012), but began to recover after 2013, although the rate of recovery varied between companies. In addition, company size plays an important role in the differences in efficiency, as micro companies have lower efficiency levels compared to small, medium and large companies.

Productivity is usually measured using the MPI, which breaks down the total productivity change into an efficiency change (TEC) and a technological change (TC). The MPI is often used to monitor productivity fluctuations in the construction industry over time. Cristea et al. (2021) evaluated the productivity changes of Romanian construction companies between 2006 and 2019 using the MPI. The results showed that most Romanian companies recorded improvements in TC, while their TEC decreased. Nazarko & Chodakowska (2015) used DEA and Tobit regression to analyze the productivity of the construction industry in Europe, comparing differences and similarities across countries. The results highlight significant productivity disparities across Europe, and the regression analysis confirms that disregarding a country's economic conditions when interpreting efficiency scores could lead to incorrect conclusions. Similarly, the same authors (2017) examined technical efficiency in the construction industry using Stochastic Frontier Analysis

(SFA) and compared it with the results of DEA in European countries. Although the models had limited compatibility, the analysis showed the most attractive countries in terms of labor costs relative to profit and turnover and emphasized that a country's level of development is a key factor in labor efficiency, although not the only one. Factors such as technology transfer, company structure, business experience, income diversification and government subsidies have a positive impact on productivity, especially for medium-sized companies.

DEA and MPI have been widely used to assess efficiency and productivity in the European construction industry, e.g., in Spain and Portugal (Kapelko et al., 2014, 2015; Procel, 2021), in Romania (Cristea et al., 2021) and in several European countries (Nazarko & Chodakowska, 2015, 2017). However, as far as the authors are aware, no assessment of the efficiency and productivity of Croatian construction companies has yet been carried out using these methodologies. While the efficiency and productivity of Croatian construction companies has not yet been analyzed using DEA/MPI methods, existing research has provided valuable insights into other critical dimensions of their performance. Studies have examined the determinants of profitability (Škuflić et al., 2018) and the impact of human resource management on perceived organizational success (Šandrk Nukić & Šuvak, 2013), as well as the main drivers of labor productivity (Nahod & Knezović, 2017). These studies provide a basic understanding of the qualitative and microeconomic factors that influence performance in the Croatian context. In this paper, the efficiency dynamics and productivity changes of large and very large Croatian construction companies are assessed to gain insight into the causes and trends of inefficiency and productivity, thereby bridging this identified gap in the literature.

3. METHODOLOGY

DEA is a widely used non-parametric method for assessing the efficiency of decision making units (DMUs) in various sectors like banking and insurance (Gržeta, Žiković & Tomas Žiković, 2023; Škrinjarić, 2016), health (Eze, Idemili & Lawani, 2024; Khalid et al., 2024), education and R&D (Almeida, 2024; Maral, 2024), real estate management (Primorac & Ignjatović, 2024), tourism (Arbula Blecich, 2024; Lado-Sestayo & Fernandez-Castro, 2019; Tekiner, 2023) and many others. In the paper, the efficiency of large and very large companies in the Croatian construction sector was evaluated over several periods of time using the window DEA analysis and their productivity using the MPI.

Window Data Envelopment Analysis (WDEA)

Traditional DEA models, such as the CCR and BCC models, evaluate the relative efficiency of DMUs within a single time period by comparing their input-output ratios. The CCR (Charnes, Cooper and Rhodes) and BCC (Banker, Charnes and Cooper) models represent two foundational approaches in Data Envelopment Analysis (DEA), differing primarily in their assumptions regarding returns to scale. The CCR model assumes constant returns to scale (CRS), meaning that changes in input levels lead to proportional changes in output levels. In contrast, the BCC model allows for variable returns to scale (VRS) and captures the effects of scale efficiency by distinguishing between pure technical efficiency and scale efficiency. Although the BCC model offers more flexibility as it does not consider constant returns, it is not more suitable in all contexts. The choice between CCR and BCC should depend on the characteristics of the production process under study. As a rule, both models are first applied and their efficiency scores compared with each other. Significant differences between the scores indicate variable returns to scale, suggesting that the BCC model is more suitable, while similar results indicate the use of the CCR model.

In DEA, the efficiency frontier (also known as the production possibility frontier or best-practice frontier) represents the benchmark of optimal performance against which the efficiency of other DMUs is evaluated. Inefficient DMUs are projected onto this frontier to assess the extent of their inefficiency. A value of 1 means that the DMU is on the efficiency frontier (fully efficient), while a value below 1 implies inefficiency and represents the potential input reduction (or output increase) required to reach the efficiency frontier. The mathematical formulation of the CCR and BCC models is presented below.

CCR model (Cooper, Seiford, and Tone, 2007):

$$max \quad \theta = \mu_1 y_{10} + \ldots + \mu_S y_{S0}$$

$$\text{subject to} \quad \begin{aligned} & v_1 x_{10} + \ldots + v_R x_{R0} = 1 \\ & \mu_1 y_{1n} + \ldots + \mu_S y_{Sn} \leq v_1 x_{1n} + \\ & + \ldots + v_R x_{Rnj} \ (\mathrm{n} = 1, \ldots, \mathrm{N}) \\ & v_1, v_{2,\ldots,} v_R \geq 0 \\ & \mu_1, \mu_{2,\ldots,} \mu_S \geq 0 \end{aligned} \tag{1}$$

Here, y_{sn}, x_{rn} > 0 represent input and output values for DMU_n, where *n (n=1,...,N)* denotes the number of DMUs, *R* is the number of input variables, and *S* is the number of output variables. $(x_{1n},...,x_{Rn})$ stands for the input vector of DMU_n with the input weight vector $(v_1,...,v_R)$, while $(y_{1n},...,y_{qSn})$ stands for the output vector of DMU_n with the output weight vector $(\mu_1,...,\mu_{qS})$. The efficiency θ ranges from 0 to 1, with DMUs at the efficiency frontier having an efficiency score of 1, while inefficient DMUs have an efficiency score of less than 1.

BCC model (Cooper, Seiford, and Tone, 2007):

$$max \quad \theta = \mu_1 y_{10} + \cdots + \mu_S y_{S0} + u_0$$

$$\text{subject to} \quad \begin{aligned} & v_1 x_{10} + \cdots + v_R x_{R0} = 1 \\ & \mu_1 y_{1n} + \cdots + \mu_S y_{Sn} + u_0 \leq v_1 x_{1n} \\ & + \cdots + v_R x_{Rn} \ (\mathrm{n} = 1, \ldots, \mathrm{N}) \\ & v_1, v_{2,\ldots,} v_R \geq 0 \\ & \mu_1, \mu_{2,\ldots,} \mu_S \geq 0 \end{aligned} \tag{2}$$

$u_0 \in R$ (unrestricted in sign)

The key difference between the CCR and BCC models is that BCC includes a free variable $u_0 \in R$ to allow for VRS whereas the CCR model assumes CRS by excluding it.

Efficiency is evaluated using technical efficiency (TE), pure technical efficiency (PTE) and scale efficiency (SE) as three basic concepts to evaluate efficiency. TE, assuming constant returns to scale (CRS), measures how well resources are utilized. TE in output-oriented DEA measures a DMU's ability to proportionally increase its outputs without increasing the level of inputs. A DMU is technically efficient if it is not possible to achieve a higher level of outputs with the same inputs, meaning it lies on the efficient frontier. Pure technical efficiency is estimated under the assumption of variable returns to scale (VRS), which allows the efficiency frontier to reflect the scale-specific performance of each decision-making unit (DMU), independently of scale effects. This measure isolates scale efficiency and focuses solely on management performance in organizing inputs and the influence of external factors on the production process, especially on the outputs produced. Scale efficiency, on the other hand, provides information about the optimal production size. From a company's perspective, this indicator shows whether a DMU is operating at its optimal scale or could improve performance by adjusting its size. The TE score can be broken down into PTE and SE, which are expressed by the following relationship: TE=PTE×SE. This breakdown allows a more detailed analysis of the causes of inefficiency, distinguishing between management performance and size-related problems. Any deviation from the efficiency frontier is considered inefficiency.

A major limitation of basic DEA models is that they are unable to track efficiency fluctuations over time. To address this problem, window DEA analysis extends the conventional DEA framework by incorporating a dynamic perspective. In this approach, the same DMUs are treated as different units over multiple time periods, allowing for a more comprehensive assessment of performance trends. WDEA improves discriminatory power as it can consider a larger number of inputs and outputs.

Window DEA relies on the moving average method to show changes in efficiency over time. At each shift window, the oldest period is replaced by a new one, allowing continuous monitoring of efficiency trends. This method is particularly important for the construction sector, where project efficiency can fluctuate due to changing economic conditions, material costs and regulatory requirements. For example, this paper assesses the efficiency of construction companies over a five-year period, with a three-year window allowing for a deeper understanding of performance fluctuations.

During a given time period t $(t = 1,\dots T)$, a set of DMUs n $(n=1,\dots,N)$ utilizes r inputs ($r=1,\dots,R$) to produce s outputs ($s=1,\dots,S$). The input and output quantities for each DMU_n at time t are represented by DMU_n^t. The methodological foundation of window DEA was introduced by Charnes, Cooper, and Golany (1984) and the corresponding input and output vectors (X_n^t) (Y_n^t) are expressed following the operational notation of Asmild et al. (2004).

$$X_n^t = \begin{bmatrix} x_n^{1t} \\ \vdots \\ x_n^{Rt} \end{bmatrix} \qquad Y_n^t = \begin{bmatrix} y_n^{1t} \\ \vdots \\ y_n^{St} \end{bmatrix} \tag{3}$$

Assuming the window begins at the time k $(1 \le k \le T)$ and has a length of w $(1 \le w \le T - k+1)$, the input (X_{kw}) and output (Y_{kw}) matrices for each window (kw) are constructed using the same notation and are defined as in Asmild et al. (2004).

$$X_{kw} = \begin{bmatrix} x_1^k & x_2^k & \dots & x_N^k \\ x_1^{k+1} & x_2^{k+1} & \dots & x_N^{k+1} \\ \vdots & \vdots & \ddots & \vdots \\ x_1^{k+w} & x_2^{k+w} & \dots & x_N^{k+w} \end{bmatrix},$$

$$Y_{kw} = \begin{bmatrix} y_1^k & y_2^k & \dots & y_N^k \\ y_1^{k+1} & y_2^{k+1} & \dots & y_N^{k+1} \\ \vdots & \vdots & \ddots & \vdots \\ y_1^{k+w} & y_2^{k+w} & \dots & y_N^{k+w} \end{bmatrix} \tag{4}$$

The results of the DEA window analysis are obtained by substituting the inputs and outputs of DMU_n^t into the CCR (1) and BCC (2) models. Based on this, the output-oriented WDEA approach for evaluating the efficiency (E_{nkw}) of a DMU_N^t under the assumption of CRS and VRS is presented as follows, following the methodology proposed by Charnes, Cooper, and Golany (1984):

WDEA (output oriented and CRS)

$$\begin{gathered} E_{nkw} = max\ \theta_{nkw}^t \\ subject\ to\quad X_{kw}\lambda \le X_n^{t'} \\ Y_{kw}\lambda \ge Y_n^{t'}\theta_{nkw}^t \\ \lambda \ge 0 \end{gathered} \tag{5}$$

WDEA (output oriented and VRS)

$$\begin{gathered} E_{nkw} = max\ \ \theta_{nkw}^t \\ subject\ to\quad X_{kw}\lambda \le X_n^{t'} \\ Y_{kw}\lambda \ge Y_n^{t'}\theta_{nkw}^t \\ \sum \lambda = 1 \\ \lambda \ge 0 \end{gathered} \tag{6}$$

Where E_{nkw} denotes the efficiency score of DMU n in window w at time t, and θ_{nkw}^t represents the output expansion factor (efficiency score). The matrices X_{kw} and Y_{kw} contain the inputs and outputs, respectively, of all DMUs in the window w, while $X_n^{t'}$ and $Y_n^{t'}$ are the input and output vectors of DMU n at the specific time t′ under evaluation. The vector λ consists of intensity variables that weight the peer DMUs in projecting inefficient DMUs onto the efficient frontier.

Malmquist Productivity Index

MPI is a sophisticated tool for measuring changes in productivity over time, especially in the context of comparing the performance of different DMUs such as companies, industries or economies.

The MPI breaks down productivity changes into components related to technological changes (TC) and technical efficiency changes (TEC) when comparing the efficiency frontier from one period to the next (MPI=TEC*TC). The TEC measures the change in a DMU's efficiency in converting inputs into outputs over time and reflects the extent to which a DMU is catching up to the best practice frontier, i.e., the most efficient production possible with the available technology. The TC component captures shifts at the production frontier itself, indicating advances or regressions in technology, and shows whether the production technology has improved or deteriorated over time.

MPI, initially proposed by Färe et al. (1994), is defined as a DEA-based linear programming model.

$$M(x^t, y^t, x^{t+1}, y^{t+1} = \\ = \left[\frac{D^t(x^{t+1}, y^{t+1}}{D^t(x^t, y^t)} \cdot \frac{D^{t+1}(x^{t+1}, y^{t+1}}{D^{t+1}(x^t, y^t)}\right]^{\frac{1}{2}} \quad (5)$$

In the given equation, x denotes the input vector, and y represents the output vector. The term (x^t, y^t) is expressed as a function of distance results, while M signifies the total productivity change between periods t and t+1

In the literature, productivity is described as the result of efficiency changes (catch up) and technological changes (frontier shift). A decrease in productivity compared to the previous period is indicated by an MPI value below 1, while a value above 1 indicates an increase in productivity between periods.

The MPI provides a comprehensive analysis by breaking down productivity changes in both TEC and TC, allowing a clearer view of performance factors. It enables comparisons across different time periods and shows growth or decline in efficiency. By differentiating between efficiency gains and technological advances, it also helps to identify areas for improvement. This makes it a valuable tool for assessing and improving performance in different sectors.

4. DATA AND VARIABLE SELECTION

The model is based on accounting data and uses three input and one output. The selection of variables is based on previous studies and the availability of data. In this paper, the production function of construction companies is defined as the use of labor and capital (fixed assets and materials) to generate operating revenues (turnover). While profit maximization remains a key business objective, modern management recognizes that companies, especially large construction companies, often pursue multiple performance objectives simultaneously (Freeman, 2010). Therefore, maximizing operating revenues is as important as maximizing profits. Capital is defined by the book value of tangible fixed assets (fixtures and fittings) and the cost of materials (intermediate goods). Labor is represented by the cost of employees.

The data on inputs and outputs are collected from the Bureau van Dijk's (BvD) Orbis Europe database for the five-year period (2019-2023). The data are collected for large and very large companies classified under NACE Rev. 2 code 4120 – Construction of residential and non-residential buildings, which ensures the homogeneity of the sample. Companies on Orbis Europe are categorized as very large or large if they fulfill at least one of the criteria specified for the respective category.

The construction companies selected for the study were required to operate continuously throughout the observation period and to have complete data. After excluding companies with incomplete data on the selected inputs or outputs that were unsuitable for the analysis, the final number of DMUs was 64. Summary statistics for the input and output variables used in the DEA of Croatian construction companies for the period from 2019 to 2023 are shown in the table below.

When selecting the inputs and outputs for performing the DEA, it is important that all input and output variables have non-negative values. This requirement arises from the mathematical structure of DEA models, which rely on linear programming techniques that assume non-negativity to ensure meaningful and interpretable efficiency scores (Cooper, Seiford and Tone, 2007).

Finally, when conducting the analysis, it is crucial to determine the orientation of the model, i.e., minimizing inputs or maximizing outputs. This decision depends on the objective of the DMU under consideration. In capital-intensive sectors such as construction, where fixed assets and skilled labor represent significant sunk costs, output-oriented efficiency better reflects management's priorities for two main reasons. First, construction firms compete for market share through growth in operating revenues, as contract awards are highly dependent on demonstrated capacity utilization (Grimsey & Lewis, 2004). Second, input factors (equipment, skilled labor) are often rigid in the short to medium term due to long-term equipment leases, unionized labor contracts, and project-based fixed cost structures. On the other hand, oper-

Table 1: Size Classification for Large and Very Large Companies (Bureau van Dijk's (BvD) Orbis Europe)

Very Large	Operating revenue ≥ 100 million EUR (130 million USD)	Total assets ≥ 200 million EUR (260 million USD)	Employees ≥ 1,000	Listed
Large	Operating revenue ≥ 10 million EUR (13 million USD)	Total assets ≥ 20 million EUR (26 million USD)	Employees ≥ 150	Not very large

Source: Bureau van Dijk, 2023

Table 2: Summary Statistics for Croatian Construction Companies for the Period from 2019 to 2023 (in Thousands EUR)

	Tangible fixed assets	Costs of employees	Material costs	Operating revenue (Turnover)
Max	24,582.00	17,684.96	152,072.20	196,018.60
Min	52.07	70.26	186.92	1,114.58
Average	2,725.71	1,608.69	15,593.40	19,709.06
SD	4,042.05	2,308.31	23,757.30	29,496.61

Source: Author

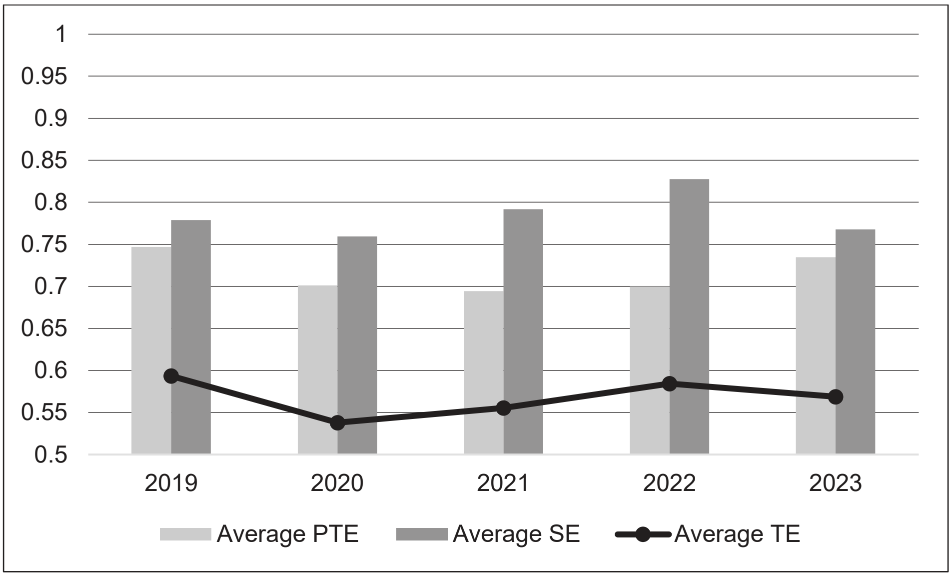
ating revenue (turnover) corresponds to what managers can most directly influence through bidding strategies, project portfolio optimization and operational efficiency improvements. The output-oriented DEA model therefore answers the more policy-relevant question: by how much could revenues increase with current resource utilization? This approach is particularly suitable for analyzing large companies where economies of scale play an important role.

A fundamental requirement for the application of DEA analysis is the fulfilment of the isotonicity condition (Wang, Nguyen and Tran, 2015), which states that input and output variables must be positively correlated, meaning that output increases as input increases. The correlations of all variables are consistently positive and strong across all observed years, so that the isotonicity condition for the data is fulfilled.

The WDEA overcomes the limitation of the standard DEA rule, which states that the number of DMUs should be at least three to four times the total number of selected inputs and outputs. By considering the same DMUs as different units over different time periods (Cooper, Seiford and Tone, 2007) the WDEA allows the inclusion of a larger number of inputs and outputs. Asmild et al. (2004) emphasize that the time window should be carefully balanced, i.e., it must be small enough to allow a fair comparison of DMUs over time and at the same time large enough to ensure a sufficient sample size; however, there is no strict theoretical basis for selecting an optimal window size (Cullinane et al., 2004).

The analysis covers the period from 2019 to 2023, using a three-year window to track the dynamics of DMU efficiency through moving averages. The three-year window was selected to balance methodological rigor and practical considerations: it provides sufficient data stability while remaining sensitive to temporal efficiency changes, as recommended in DEA literature (Asmild et al., 2004). A three-period window is

Figure 1: TE, PTE and SE Dynamics (2019 to 2023) – Construction Sector Average



Source: Authors

commonly used in many papers (Charnes, Clark, Cooper and Golany, 1984). This intermediate duration avoids the excessive volatility of shorter windows (1-2 years) while preventing the smoothing effect of longer windows (4-5 years). In construction, short time windows (1–2 years) tend to amplify short-term shocks (e.g., seasonality, input price spikes, tendering cycles), leading to excessive volatility in efficiency scores that does not necessarily reflect underlying performance. Conversely, longer time windows (4–5 years) excessively smooth cyclical dynamics and can hide significant changes from year to year. Windows are: Window 1 (2019, 2020, 2021), Window 2 (2020, 2021, 2022) and Window 3 (2021, 2022, 2023). With a five-year analysis period and a three-year time window the study exceeds the DMU limit in terms of the number of inputs and outputs. The total number of DMUs in our sample is 320, calculated as n*k, where *n* represents the number of DMUs and *k* the number of time periods (Cooper, Seiford and Tone, 2007).

5. RESULTS AND DISCUSSION

This section first presents the results of TE and of PTE and SE as its components. The results of MPI, TEC and TC are then presented.

Figure 1 shows the results of TE, PTE and SE for large and very large Croatian companies operating in the construction sector from 2019 to 2023.

The TE, which is also referred to as overall efficiency, indicates a relatively low efficiency of the companies analyzed. Looking at the development of TE, a decline can be observed from 2019 to 2020, which is attributable to the effects of the COVID-19 crisis. Although this decline is noticeable, it is not as sharp as in some other sectors, e.g., tourism (Arbula Blecich et al., 2025). Nevertheless, the downward trend in the construction industry has not continued in the years following the pandemic. The analysis of the causes of inefficiency leads to the conclusion that the greater source of inefficiency in all observed years is management and other exogenous factors, as the PTE shows. Although the main cause of inefficiency remains unchanged in 2023, it is noticeable that the gap between PTE and SE has narrowed. The results of MPI, TEC and TC are shown in the following table.

Table 3: MPI, TEC and TC for Croatian Construction Companies

	MPI	TEC	TC
2019 → 2020	1.0313	1.1863	0.8811
2020 → 2021	1.0334	0.9945	1.0668
2021 → 2022	1.1134	0.8909	1.2906
2022 → 2023	1.1141	1.1965	0.9689
Geo. Average	1.0731	1.0671	1.0519
Max	1.9211	1.6107	1.3685
Min	0.8541	0.8578	0.8433
SD	0.1466	0.1352	0.0676

Source: Authors

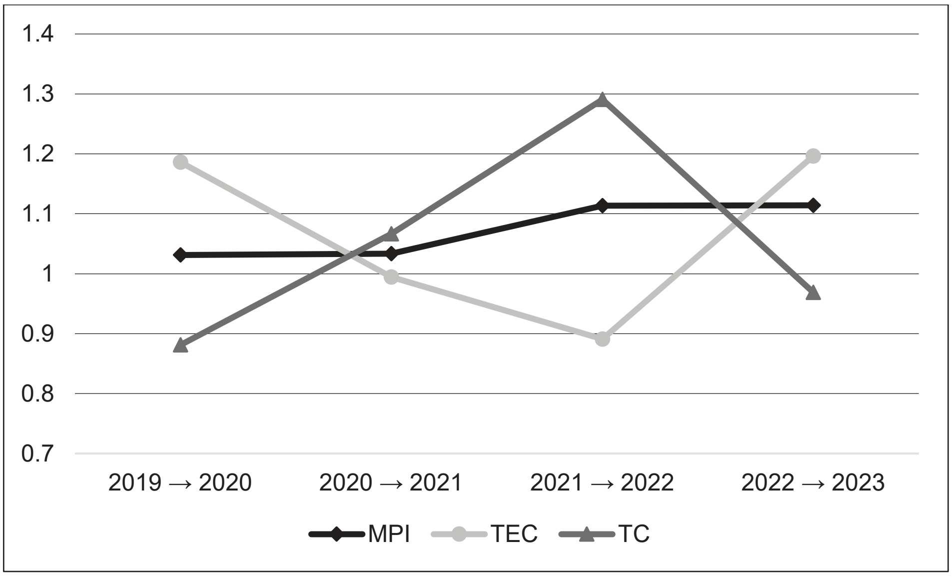
As shown in Table 3 and Figure 2, the lowest average MPI value for large and very large construction companies in Croatia is 0.8541 while the highest average value is 1.9211. It is clear that the observed construction companies in Croatia have a geometric average of 1.0731, which means an average increase in MPI of 7.31%. The increase in productivity is approximately equally driven by improvements in technical efficiency (6.71%) and technological change (5.19%). An analysis of productivity changes over the observation period shows that productivity increased in all years, with the strongest increase between 2022 and 2023 (11.41%) and the lowest between 2019 and 2020 (3.13%). From 2019 to 2020, productivity increased mainly due to changes in technical efficiency, as technological change decreased by 11.89% due to the pandemic. The average productivity changes across the entire sample are shown more clearly in Figure 2.

The discussion of these results can be enriched by placing them in the broader context of the specific challenges and opportunities of the Croatian construction industry. The identified low technical efficiency (TE) and its primary cause in management and exogenous factors (as indicated by the PTE) suggest that the potential for improvement lies not only in the introduction of technologies, but also in the optimization of internal processes and human resource management. The focus on tangible inputs and outputs in the efficiency analysis can be complemented usefully by findings on the management of human capital. The findings of Šandrk Nukić & Šuvak (2013) suggest that investment in employee training and knowledge management systems, important intangible resources, could be crucial influencing factors that are not fully captured by conventional DEA models. Furthermore, the labor productivity factors identified by Nahod & Knezović (2017), such as work discipline and job satisfaction, are essentially an expression of how efficiently human resources are deployed on the construction site and thus represent a crucial link between qualitatively measured strategic HR practices and the operational efficiency targeted by quantitative models.

The observed productivity growth driven by both TEC and TC is consistent with the findings of Omotayo et al. (2024), Pan and Zhang (2023), Gamil et al. (2020), Ghosh et al. (2021), Woodhead, Stephenson & Morrey (2018) and Regona et al. (2022) and underlines the importance of investing in technological progress. However, the role of human capital, knowledge management and labor motivation (Šandrk Nukić & Šuvak, 2013; Nahod & Knezović, 2017) suggests that the productivity growth captured by the MPI is not only related to macroeconomic conditions or technology adoption, but essentially to the effective development, management and motivation of human resources in the specific national and sectoral context. The emphasis on economic factors such as salary in Croatia (Nahod & Knezović, 2017) is consistent with the finding that a country's level of development influences labor efficiency and highlights the need for management strategies that address the fundamental motivation of workers.

The slow adoption of technological innovations, including automation, AI and IoT, has limited the sector's ability to fully realize the potential for productivity gains. A notable example is the application of BIM in the construction of the Sydney

Figure 2: Dynamics of MPI, TEC and TC for Croatian Construction Companies (2019 to 2023)



Source: Authors

Metro, Australia's largest public transport project, which demonstrates how digitalization can optimize workflows and resource management on major transport projects (Lại et al., 2023). In this sense, targeted policy interventions in the form of subsidies for the introduction of BIM and pilot programs for AI-driven project management tools are crucial to boost the sector's sluggish technological progress. Alongside digital transformation, sustainability also remains a priority. Circular economy principles are gaining traction as an effective means of reducing waste and improving resource efficiency (Guerra et al., 2021). The Sydney Metro project also demonstrates that the use of advanced technologies can contribute to sustainable growth by increasing efficiency, minimizing resource waste and promoting a data-driven approach to construction (Succar, 2009). In Croatia, by combining technological improvements with sustainable practices, both productivity challenges and environmental goals could be achieved.

Finally, the adoption of advanced technologies in construction offers significant potential to increase productivity and operational efficiency, but also poses critical challenges to the preparation of the labor force (Hajirasouli et al., 2025). Digital transformation is radically changing labor dynamics in construction, creating new job requirements and increasing the importance of technological skills. This transition requires a coordinated approach between construction companies, academic organizations and regulators to create comprehensive support frameworks that enable seamless technological integration while promoting equitable development of the sector. Measures to strengthen vocational training by modernizing curricula, incentivizing upskilling programs and facilitating the recruitment of foreign workers are crucial to ensure that the potential productivity gains from technological change and efficiency gains are sustainable and comprehensive.

6. CONCLUSION

The analysis of efficiency and productivity trends in the Croatian construction sector from 2019 to 2023 reveals both challenges and opportunities for improvement. The results demonstrate relatively low TE among large and very large construction companies, with a notable decline during the COVID-19 pandemic and only a partial recovery by 2023. This inefficiency is primarily attributed to management practices and exogenous factors, as evidenced by the PTE scores. However, the MPI shows an encouraging average productivity growth of 7.31%, driven almost equally by improvements in technical efficiency (6.71%) and technological advancements (5.19%). The strongest productivity surge occurred between 2022 and 2023 (11.41%), highlighting the sector's potential for recovery and growth when external conditions stabilize.

The limitations of this paper arise from the unavailability of non-accounting data, which restricts the analysis to financial and operational metrics. Future research should consider the inclusion of macroeconomic factors and examine how these relate to the observed levels of efficiency and productivity. Longitudinal studies on the effects of technology adoption and management reforms, potentially incorporating qualitative insights into human resource practices, would further enrich the understanding of the drivers behind these trends.

To conclude, the Croatian construction sector should proactively address digitalization, sustainability, and labor market challenges. By utilizing technologies such as BIM and AI, while incorporating circular economy principles, the industry can achieve both productivity gains and better stewardship of the environment. However, these technological advancements must be accompanied by strategic labor market interventions to address factors such as workforce skills, training, and motivation. Such comprehensive efforts, combining technological adoption, environmental responsibility, and workforce development with targeted policy support, will be crucial for enhancing productivity and ensuring long-term growth in both domestic and international markets.

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Analiza učinkovitosti i produktivnosti hrvatskog građevinskog sektora: trendovi i izazovi

Sažetak

Hrvatska građevinska poduzeća još uvijek se suočavaju s neučinkovitošću i sporim usvajanjem digitalnih alata. Stoga je razumijevanje uzroka neučinkovitosti i slabe produktivnosti ključno za osiguranje održivosti i konkurentnosti sektora. U radu se analiziraju trendovi učinkovitosti i produktivnosti u hrvatskom građevinskom sektoru u razdoblju od 2019. do 2023. godine s fokusom na velika i vrlo velika građevinska poduzeća primjenom DEA analize prozora i Malmquistovog indeksa produktivnosti (MPI). Pored navedenog analiziraju se i ključni izazovi koji utječu na njihovu izvedbu. Rezultati pokazuju da ukupna učinkovitost ostaje relativno niska, ali stabilna, uz blago poboljšanje u 2023. godini. Glavni uzroci neučinkovitosti su upravljačke prakse i vanjski faktori, a ne (ne)optimalna veličina proizvodnje. S druge strane, produktivnost je općenito porasla, posebno između 2022. i 2023. godine, prvenstveno zahvaljujući poboljšanjima u tehničkoj učinkovitosti, a ne tehnološkim inovacijama. Ovi rezultati naglašavaju potrebu za većim ulaganjima u digitalne alate i inovacije kako bi se povećala učinkovitost i rast produktivnosti u sektoru na dugi rok. Istraživanje pruža vrijedne informacije za donositelje politika, industrijske lidere i istraživače, ističući važnost ostvarivanja dugotrajne učinkovitosti, bržeg usvajanja novih tehnologija te rješavanje problema nedostatne radne snage, kako bi se osigurala konkurentnosti građevinskog sektora na domaćem i međunarodnom tržištu.

Ključne riječi: građevinski sektor, window DEA, Malmquistov indeks produktivnosti, učinkovitost, produktivnost, računovodstveni podaci