LEVEL OF TECHNICAL EFFICIENCY OF THE CONSTRUCTION SECTOR IN EU COUNTRIES

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Abstract

This article deals with a quantitative assessment of the technical efficiency of the construction sector in EU countries. The construction sector is an essential part of any country's economy, yet the assessment of efficiency in this sector has been neglected. Our analysis covers a ten-year period, specifically the years between 2011 and 2020. Within this period, it is possible to observe not only long-term trends in changes in efficiency, but also changes in efficiency because of the COVID-19 pandemic. A total of five country groups were created with regard to the evolution of efficiency. The analysis shows that cyclical changes in the efficiency of the construction sector occurred in countries such as the Czech Republic, Germany, and Poland. According to the average efficiency values, the Czech Republic performs the best, while Ireland performs the worst.

Key Words

Construction sector; COVID-19; efficiency; European countries; number of enterprises.

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INTRODUCTION

The construction sector, which is an integral part of any country's economy, is an area of research in many studies. Studies are available focusing on the green technology innovation process along with the influence of state regulations. For example, according to Jaffe and Palmer (1997), tighter regulations provide a positive impetus for increased investment in innovation. Testa et al. (2011) emphasise that governments should maintain direct regulation in the field of the environment, which, if properly formulated, can have positive effects on competitive performance. Du et al. (2019) assume that the efficiency of green technology innovation reflects the efficiency of resource use. Doussoulin and Bittencourt (2022) focused on the circular economy and identified the demolition phase as the most problematic (inefficient) area.

If we exclude the area of environmental regulations, we also find current studies focusing on the evaluation of the construction sector itself. For example, Kanyilmaz et al. (2022) address the role of metal 3D printing in increasing quality and resource efficiency in the construction sector. More and more new studies are devoted to the development of the construction industry in China, as the largest construction market in the world, see for example Hou et al. (2021) or Zhang, H. et al. (2022). However, studies focusing on Europe are still scarce.

In studies by Zhang, C. et al. (2022) and Gálvez-Martos et al. (2018), attention is paid to the waste generated both during construction and demolition. However, these studies are not quantitative in nature and are not based on financial data. If we look for studies based on financial data for the European region, we will find, for example, a study by Roubalová and Viskotová (2019) or Kalantzis and Niczyporuk (2022). However, these studies focus primarily on the productivity of the construction sector (especially labour productivity) and not on efficiency itself. In everyday speech, these two terms are sometimes confused, because both productivity and efficiency deal with the ratio of outputs and inputs, but there are no links to other entities when calculating productivity. The calculation of efficiency is more complicated from a mathematical point of view, as it is necessary to take into account the production possibilities of all other units (enterprises or entire countries). Nowadays, we can find studies that use parametric or non-parametric methods to assess efficiency. However, each of these methods has different assumptions and therefore different strengths and weaknesses. Hollingsworth (2003) or Odeck and Brathen (2012) refer to the data envelopment analysis (DEA) method as the dominant method in the field of non-parametric methods (regardless of the chosen sector) and the stochastic frontier analysis method (SFA) as the main method from the parametric approaches. In the case of the SFA method (as a representative of parametric approaches), there is criticism of the need to make assumptions about the probability distribution. However, the advantage of using this method is that it can distinguish between inefficiency and noise. In contrast, the DEA method is deterministic and therefore does not allow for any randomness due to, for example, luck. However, as a representative of nonparametric methods, it does not require any assumptions about the specific probability distribution.

The efficiency of the construction sector was investigated by Křetínská and Staňková (2021), based on the DEA method. Their investigation covered the period between 2015 and 2017 and analyses were carried out for a total of 17 European countries. Their research shows that, in general, these countries succeed in increasing efficiency over time. They identified enterprises from Bulgaria as being the least efficient. On the contrary, countries such as Austria, Belgium, Denmark, the Netherlands, and Spain showed the best results. Nazarko and Chodakowska (2015) also investigated the efficiency of the construction sector in Europe, but they compiled a DEA model for the years between 2006 and 2012. Even their results show positive trends in the area of changes in efficiency over time. The results regarding the best and worst countries are also consistent, as they also identified Spain as the best and Bulgaria as the worst in terms of efficiency scores achieved.

In their later research, Nazarko and Chodakowska (2017) used both the SFA and DEA method to evaluate the efficiency of the construction sector in European countries with a detailed focus on labour efficiency. According to them, the use of both methods increases the reliability of the results. In their research, they further emphasise that efficiency has a significant link to the level of development of the given country.

Unfortunately, as already mentioned above, we currently have only a limited number of studies focusing on the evaluation of the efficiency of the European construction sector, and a large part of them are studies from around the turn of the century, see for example Brauers et al. (2013), Horta et al. (2013) or Kildienė et al. (2011). In 2020, the COVID-19 pandemic hit the economy unexpectedly and its impact on the sector's efficiency has not yet been sufficiently explored.

It is generally assumed that the COVID-19 pandemic has harmed most sectors, with only pharmaceutical companies having large business opportunities; see for example Mirmozaffari et al. (2022) and Devi et al. (2020). Outside the pharmaceutical and healthcare sectors, the main focus has so far been on the effects of the pandemic in areas such as tourism (see Hensler et al., 2022 or Park et al., 2022) and education (see Seow et al., 2022 or Yin et al., 2022). For the manufacturing or construction sector, detailed analyses of changes in productivity and efficiency in EU countries due to the pandemic are currently lacking.

Although it is possible to track how many businesses closed down during the pandemic, according to the results of e.g., Gaebert and Staňková (2020), a decrease in the absolute number of businesses in a given sector can be beneficial for the economy. Their research showed that if enterprises in which resources are wasted leave the market, then paradoxically the production efficiency of the entire market can benefit from their departure, if the production of these enterprises is taken over by their competitors with a more efficient transformation process.

In addition to the areas mentioned above, it can be noted that much of the research conducted to-date is micro-economically oriented. For example, the aforementioned Horta et al. (2013) conducted their analysis based only on micro data from 118 enterprises. Although they tried to generalise their results with other procedures, they did not provide a full-fledged analysis of the construction sector. In practice, these forms of micro-analysis are typically limited to a specific sub-sector of the construction industry and/or to a limited regional area, see for example Staňková and Hampel (2019) and Zubizarreta et al. (2017).

In this article, attention is paid to estimating the efficiency of the whole construction sector in selected EU countries. Efficiency is understood in this article as technical efficiency, which considers how many resources a given unit uses to achieve its output. Like Nazarko and Chodakowska (2017) or Křetínská and Staňková (2021), we will relate output (production) to factor inputs used. Since the transformation process of inputs to outputs is influenced by the available technology, the term technical efficiency is used for this area of assessment. Regarding the chosen construction sector, it can be assumed that human labour together with machinery or other equipment will have a major influence on efficiency, so we will focus on labour and capital factors in the area of inputs.

The objectives of this article are as follows:

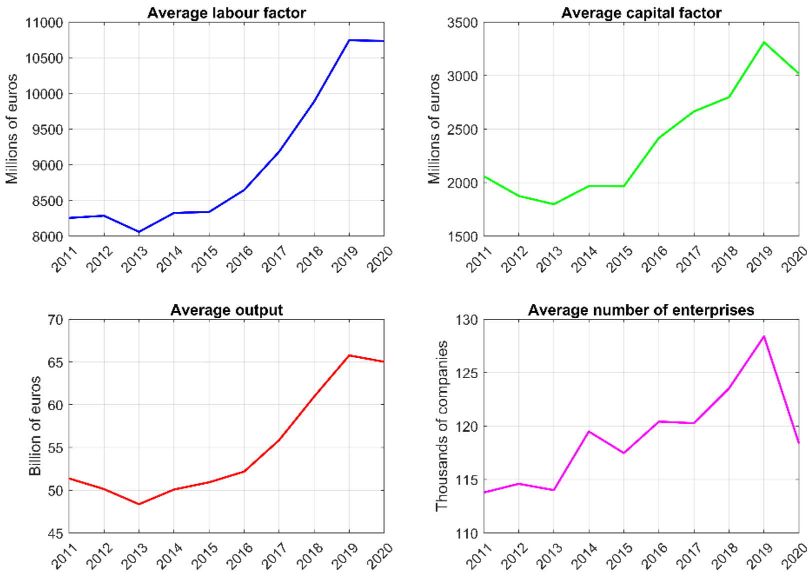
- to calculate efficiency scores of the construction sector in selected EU countries in the last decade of available data;
- to assess the evolution of efficiency over time;
- to determine whether there have been important efficiency changes in 2020 with respect to the COVID-19 pandemic;
- to divide countries into groups according to their efficiency development; and
- to test whether there is also a relationship between the number of enterprises and efficiency in the construction sector.

MATERIALS AND METHODS

The analysis is based on a two-factor Cobb-Douglas production function like in Staňková and Hampel (2021) and Varvařovská and Staňková (2021). Annual aggregated data from between 2011 and 2020 obtained from the Eurostat database were used to calculate the efficiency of the individual EU countries. The labour factor is expressed in this article in the value of total wages/salaries paid (in millions of euros) in the construction sector. Unlike the commonly used absolute number of employees, the variable we choose allowed us to capture a different "cost of work" in each country. The capital factor is understood here as gross fixed capital formation (in millions of euros) in the construction sector. Production value in millions of euros represents the output variable.

Unfortunately, one of the EU countries, Malta, did not have the necessary data available. Therefore, only 26 Member States were included in the analysis (i.e., excluding Malta). The development of average values (for the whole dataset) in the monitored period is shown in Figure 1. In addition to the variables entering directly into the efficiency assessment, this figure also plots the variable of the average number of enterprises, which, according to the results in Gaebert and Staňková (2020), may be related to the efficiency results.

Figure 1: The development of the average values of the variables used (labour, capital, and output) in contrast to the development of the average number of enterprises in the construction sector



The average values of the labour factor, capital, output, and number of enterprises for the whole sector show a similar development over time. The European construction sector, like other sectors, was hit by the economic crisis in 2009. Due to the relatively high level of uncertainty, the recession lasted until 2013. The construction sector only began to recover after 2013. Continuous growth in all three variables was then disrupted by the COVID-19 pandemic in 2019. After 2019, there was a large drop in the average number of enterprises in the sector. The closure of so many enterprises was also reflected in a decline in the average values of capital and output. Thanks to the efforts of individual European governments, there was no significant decline in the average values of the labour factor. However, the question remains whether, in an effort to maintain employment, governments contributed to maintaining the competitiveness of the construction sector or reduced its efficiency.

The SFA method was chosen for efficiency estimation because of its valuable property of distinguishing inefficiency from noise. Due to the macroeconomic nature of the data, SFA panel models were estimated following Greene (2005):

$$\ln y_{it} = \alpha_i + \ln f(x_i;\beta) + \varepsilon_i,$$
$$\varepsilon_i = v_{it} - u_{it},$$

where α_i is a constant related to unit i, $i = 1, \dots, I$, y_{it} is the observed output scalar of each unit in period t, $t = 1, \dots, T$, x_i is a vector of inputs, $f(x_i; \beta)$ represents the production frontier (based on specific production function), β is a vector of technology parameters. The composed error term ε_i includes both units' inefficiency u_{it} and standard error term v_{it}. Furthermore, it is worth noting that all distributional assumptions for building an empirical model according to Greene (2005) are met in our case.

Greene's models (Greene, 2005) can be estimated on the basis of both fixed and random effects. Furthermore, for the SFA method, it is necessary to choose an assumption regarding the estimation of (in)efficiency either based on the ideas of Jondrow et al. (1982) or on the Battese and Coelli (1988) procedure. Given the chosen period, it can be assumed that it will be necessary to also capture in the model the increase in production possibilities due to technological progress. Similar to Staňková and Hampel (2021), an artificial time variable was added to the model to capture this increase. Last but not least, it was necessary to choose one of the common probability distributions for inefficiency. The distribution functions of exponential and half-normal are most often used in practice.

Technical efficiency (TE) of the i-th unit can be derived based on level of inefficiency as:

$$TE_i = \exp(-u_i).$$

As will be seen, in this analysis, the final choice was to focus on the random effect panel model based on a JLMS estimator based on the conditional mean:

$$E(\exp(-u_i)|\varepsilon_i),$$

with an exponential probability distribution of inefficiency:

$$\hat{E}(u) = \hat{\sigma}_u = \sqrt{\frac{RSS}{I-(K+1)}},$$

where the mean value of the inefficiency $\hat{E}(u)$ is calculated based on the magnitude of the deviations $\hat{\sigma}_u$, which are derived using the residual sum of squares RSS. I in this equation represents the sample size and K indicates the number of model parameters that need to be estimated. Furthermore, it was found that there was a significant increase in production possibilities over the period due to technological progress, so a variable representing efficiency growth over time was added to the model like in Staňková and Hampel (2021).

Given the scope of the analysis, another analytical tool was used to form homogeneous groups of countries according to their obtained efficiency. In an unconventional way, we clustered countries based on the efficiency values in each year using cluster analysis. In the event that the obtained time series of country-specific efficiencies were not stationary, the process of station-arising the time series through differencing as in Nchor et al. (2015) was undertaken.

Cluster analysis allows for different settings (both for calculating distances between objects and between clusters). In the case of calculating the distance between clusters, we use Ward's method, which is very popular in practice, see for example Zámková et al. (2021). This is a variability minimisation algorithm that considers the inner square distance. In calculating the distance between clusters, we used a technique that focuses on correlations, specifically the value of one minus the sample correlation between points (treated as sequences of values). Technical details on cluster analysis can be found in Everitt et al. (2011).

Correlation analysis was used to test whether there is a link between efficiency and the number of enterprises in the construction sector, as has been shown for example in the pharmaceutical industry by Gaebert and Staňková (2020). In the case of correlation analysis, assumptions regarding normality and stationarity must be met. The normal probability distribution was verified using the Shapiro–Wilk and Jarque-Bera test like in Stehlík et al. (2023). The aggregated values in Figure 1 show that the stationarity assumption is likely to be violated. In this case, the analysis would have to be performed on differenced time series of efficiency and number of enterprises.

Panel SFA models were estimated in Stata (version 17 SE), and comparison of the results and graphical outputs was made in MATLAB (version 2023a).

RESULTS

First, attention is given to the estimated efficiency score itself. Subsequently, a cluster analysis is described using the obtained efficiency score. The last part of the results is devoted to examining the possible link between the number of enterprises and the efficiency of the sector.

Efficiency Evaluation Results

In this section, we present the results of the SFA model based on random effects through estimation following the procedure of Jondrow et al. (1982), since in this setting all the estimated model parameters were statistically significant. According to this model, the level of efficiency in the construction sector is relatively high. The numerical results of the efficiency of individual countries are shown in Table 1. In terms of the average efficiency values over the whole period under review, Czech enterprises are doing the best, with France coming in second place. By contrast, Ireland achieved the worst average results overall. The second worst country is Latvia. A positive finding about the construction sector in the EU countries is that even in these worst countries the average efficiency has not fallen below 60%.

Based on the results of the efficiency estimates, the initial impacts of the COVID-19 pandemic can also be observed. In Table 1, it can be seen that 19 EU countries experienced a decline in efficiency level in 2020. For Denmark, Germany, Italy, Poland, and Romania, the efficiency scores in 2020 are higher than in 2019, but in absolute terms the increase is between 0.1 and 6 percentage points, which can be considered an insignificant change. Only Belgium (less than 10 percentage points) and Bulgaria (almost 29 percentage points) show a significant increase in efficiency.

According to the European Construction Industry Federation (FIEC) reports (FIEC, 2021a), the Belgian construction industry has largely differentiated itself from other EU countries, as even in 2020 the Belgian construction industry was able to maintain its production capacity. Even in this period, the outlook in terms of employment was positive, as employment in this sector was expected to grow in 2021. The FIEC (2021b) reports for Bulgaria also reveal positive efficiency results in 2020, as they show that since 2017, housebuilding in Bulgaria has experienced a huge boom (roughly double the volume compared to previous years). Although the number of new building permits issued declined slightly in 2020, the demand for housebuilding here was so high compared with previous years that long-term contracts sustained production in this sector.

Table 1: Results of the efficiency scores in each period together with the average result and the derived country ranking

Country	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Average	Rank
Austria	0.933	0.934	0.917	0.901	0.909	0.905	0.903	0.894	0.871	0.825	**0.899**	**5**
Belgium	0.827	0.726	0.737	0.769	0.867	0.942	0.921	0.822	0.869	0.965	**0.845**	**13**
Bulgaria	0.928	0.939	0.898	0.938	0.977	0.583	0.651	0.708	0.648	0.935	**0.821**	**15**
Croatia	0.943	0.911	0.917	0.936	0.963	0.918	0.879	0.853	0.899	0.809	**0.903**	**3**
Cyprus	0.584	0.563	0.636	0.653	0.702	0.829	0.890	0.940	0.947	0.865	**0.761**	**19**
Czech Rep.	0.936	0.868	0.893	0.939	0.957	0.899	0.928	0.944	0.938	0.899	**0.920**	**1**
Denmark	0.830	0.847	0.798	0.819	0.879	0.888	0.889	0.920	0.924	0.945	**0.874**	**10**
Estonia	0.897	0.938	0.912	0.899	0.783	0.798	0.936	0.893	0.827	0.775	**0.866**	**11**
Finland	0.869	0.872	0.854	0.866	0.893	0.920	0.941	0.916	0.914	0.912	**0.896**	**6**
France	0.918	0.938	0.925	0.902	0.913	0.915	0.894	0.896	0.930	0.847	**0.908**	**2**
Germany	0.890	0.877	0.874	0.883	0.880	0.874	0.888	0.934	0.902	0.935	**0.894**	**7**
Greece	0.517	0.698	0.727	0.945	0.974	0.776	0.925	0.790	0.790	0.641	**0.778**	**18**
Hungary	0.554	0.474	0.618	0.821	0.815	0.616	0.769	0.951	0.964	0.893	**0.747**	**21**
Ireland	0.613	0.359	0.540	0.507	0.535	0.650	0.630	0.713	0.747	0.734	**0.603**	**25**
Italy	0.905	0.869	0.852	0.812	0.743	0.680	0.666	0.671	0.668	0.679	**0.754**	**20**
Latvia	0.922	0.914	0.885	0.648	0.584	0.354	0.464	0.503	0.417	0.346	**0.604**	**24**
Lithuania	0.796	0.727	0.724	0.872	0.754	0.575	0.585	0.656	0.440	0.431	**0.656**	**23**
Luxembourg	0.835	0.863	0.824	0.873	0.916	0.941	0.940	0.948	0.953	0.900	**0.899**	**5**
Netherlands	0.748	0.664	0.659	0.713	0.757	0.817	0.946	0.952	0.962	0.956	**0.817**	**17**
Poland	0.775	0.610	0.697	0.936	0.905	0.830	0.888	0.933	0.930	0.937	**0.844**	**14**
Portugal	0.976	0.932	0.881	0.793	0.820	0.730	0.812	0.853	0.851	0.806	**0.845**	**12**

Romania	0.954	0.953	0.965	0.885	0.790	0.633	0.556	0.446	0.378	0.437	**0.700**	**22**
Slovakia	0.754	0.678	0.560	0.764	0.959	0.854	0.923	0.932	0.935	0.835	**0.820**	**16**
Slovenia	0.938	0.952	0.952	0.965	0.911	0.765	0.885	0.933	0.858	0.769	**0.893**	**8**
Spain	0.949	0.863	0.807	0.880	0.920	0.894	0.891	0.939	0.912	0.858	**0.891**	**9**
Sweden	0.879	0.856	0.840	0.857	0.907	0.908	0.946	0.938	0.943	0.928	**0.900**	**4**

The Clusters Created

Based on the results in Table 1, it was possible to make an initial division of countries into a group of those whose efficiency increased between 2011 and 2020 and into a group of countries where efficiency, on the contrary, decreased, see Table 2. Using this criterion, we divide the countries into two groups of almost equal size. The largest increase was recorded in countries such as Hungary and Cyprus, on the other hand, the largest decrease was in countries such as Latvia and Romania.

Table 2: Division of countries into two groups according to their overall change in efficiency

Efficiency level	Country
Increased	Belgium, Bulgaria, Cyprus, Denmark, Finland, Germany, Greece, Hungary, Luxembourg, Netherlands, Poland, Slovakia, Sweden
Decreased	Austria, Croatia, Czech Republic, Estonia, France, Ireland, Italy, Latvia, Lithuania, Portugal, Romania, Slovenia, Spain

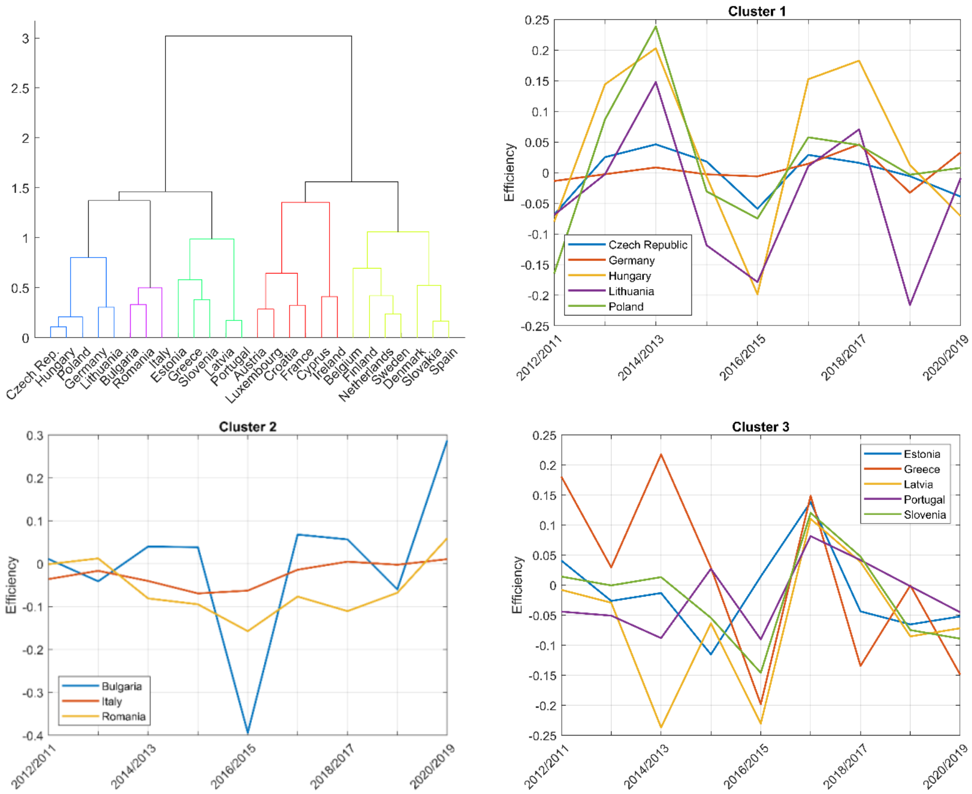
If we were to focus on the average results for the entire period under review, the Czech Republic achieves the best results (efficiency at the level of 92%), but it has a specific development of efficiency. In absolute terms, this country recorded the smallest drop in efficiency between 2011 and 2020 and, unlike other countries, it shows a relatively constant trend with a hint of a cyclical element with a period of 4 years. This can be influenced by the economic cycle or even the political situation (frequency of elections). As average values are strongly influenced by differences in trends, countries needed to be further differentiated according to developments in efficiency changes.

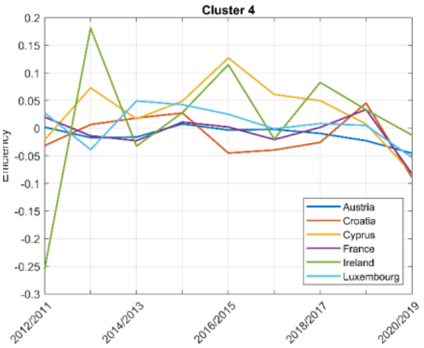
Due to the scope of the analysis, we incorporated the method of cluster analysis into this process, which enables the division of countries into several clusters. In order to really evaluate the development of efficiency and thereby emphasise changes, a cluster analysis was performed on differentiated efficiency values (mainly to minimise the effects of non-stationarity). A total of five clusters were created. The resulting dendrogram along with the evolution of efficiency (differentiated efficiency values) are included in Figure 2.

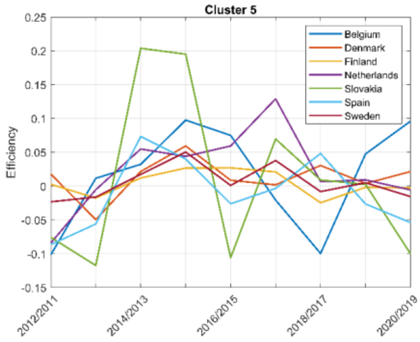
The first cluster (blue in the dendrogram) is made up of five countries. These are mainly Central European countries together with one Baltic country. These countries are not only connected by geographical proximity, but from the point of view of the efficiency trend, a certain cyclicality can be seen in the results. Although it is difficult to fully examine the cyclical component in such a short period of time, two recurring fluctuations are evident from Figure 2. These changes are most significant in Hungary. With respect to the scale, the Czech Republic has the smallest fluctuations.

The first cluster contains three of the four V4 countries. Only Slovakia is included in the fifth (yellow) cluster. However, in terms of the evolution of efficiency, this country also has fluctuations in common with the countries of the first cluster. However, since Slovakia did not have such significant fluctuations as e.g., Poland in the second half of the period under review, it was placed into the fifth cluster together with Belgium, Denmark, Finland, the Netherlands, Spain, and Sweden.

Figure 2: Dendrogram and the evolution of country efficiency in each cluster







Countries in the second cluster (purple on the dendrogram) had relatively high efficiency scores (over 90%) in 2011. However, during the period under review, Bulgaria, Italy, and Romania experienced a systematic decline in efficiency scores, which peaked in 2015 (in the case of Romania, there was also a decline in 2019). However, from this point onwards, there are signs of a positive trend in the efficiency score. Nevertheless, the difference between the maximum and minimum measured efficiency scores over the whole period under review is e.g., almost 59 percentage points in the case of Romania. Major changes would be needed for these countries to reach their 2011 levels of efficiency.

The third cluster (green on the dendrogram) connects the efficiency trends of the countries, especially in the second half of the period under review. Estonia, Greece, Latvia, Lithuania, Portugal, and Slovenia have almost identical trends in differentiated efficiency values between 2015 and 2020. According to reports from the European Commission, the construction sector in these countries did not fare well around 2015. However, in 2017, there was a recovery in these countries. In the case of Greece, for example, this was due in no small part to the efforts of the government itself (European Commission, 2018). However, as we can see by the evolution of efficiency after 2017, these “injections” did not help the construction sector in the long run.

The last so far unmentioned cluster 4 (red on the dendrogram) brings together Austria, Croatia, Cyprus, France, Ireland, and Luxembourg. Perhaps the most dramatic efficiency development in this group is Ireland, which saw a significant drop in efficiency after 2011. It was not until the second half of the period under review that Ireland reached a similar level of efficiency to the other countries in this cluster. In this case, Ireland was helped by Strategy 2020, which the government introduced in 2014 (European Commission, 2014). A set of 75 policies were intended to fix the most serious problems in the Irish construction industry, which as we can see actually helped to increase the efficiency of the construction sector in this country. Even so, the country still lags far behind other EU countries.

If we want to generalise the level of efficiency over the whole period for each cluster, we find that countries in the fourth and fifth clusters generally perform the best, see Table 3. On the other hand, countries in the third and second clusters perform the worst.

Table 3: Average efficiency results for each country cluster, including the derived ranking

Year	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
2011	0.790	0.929	0.850	0.804	0.836
2012	0.711	0.920	0.887	0.761	0.786
2013	0.761	0.905	0.871	0.793	0.751
2014	0.890	0.878	0.850	0.795	0.810
2015	0.862	0.836	0.814	0.823	0.883
2016	0.759	0.632	0.684	0.860	0.889
2017	0.812	0.624	0.804	0.856	0.922
2018	0.884	0.608	0.794	0.874	0.917
2019	0.835	0.565	0.749	0.891	0.923
2020	0.819	0.684	0.667	0.830	0.914
Average	**0.812**	**0.758**	**0.797**	**0.829**	**0.863**
Rank	**3**	**5**	**4**	**2**	**1**

Comparison of Efficiency with the Number of Enterprises

Correlation analysis was used to determine whether there is a link between the number of enterprises and country efficiency. Since both time series were non-stationary so as not to bias the results, the analysis was also performed on differenced time series. The results of both Shapiro–Wilk and Jarque-Bera tests at a significance level of 5% showed that the assumption of a normal probability distribution was met (all p-values were greater than 0.05) and therefore the Pearson correlation coefficient was calculated. The calculated correlation coefficients for each country are given in Table 4.

Table 4: Correlation coefficient values between the number of enterprises and the level of efficiency for each country.

Cluster No.	Country	Coefficient	Cluster No.	Country	Coefficient
1	Czech Rep.	-0.053	4	Austria	-0.481
	Germany	-0.036		Croatia	-0.123
	Hungary	0.054		Cyprus	-0.266
	Lithuania	0.362		France	-0.054
	Poland	0.010		Ireland	0.052
2	Bulgaria	0.212		Luxembourg	-0.012
	Italy	0.032	5	Belgium	0.361
	Romania	0.359		Denmark	0.320
3	Estonia	0.200		Finland	-0.314
	Greece	-0.389		Netherlands	-0.351

	Latvia	-0.240		Slovakia	0.438
	Portugal	0.447		Spain	0.839
	Slovenia	-0.535		Sweden	0.254

Within the first cluster, it can be seen that Lithuania differs from the other countries not only in terms of geographical area, but also in the size of the correlation coefficient. For all other countries in this cluster, the value of the correlation coefficient is almost zero, indicating the independence between efficiency and the number of enterprises. In the case of Lithuania, we are in an interval typically indicating weak dependence. Even in the case of the second cluster, the correlation results are not at the same level, as the correlation coefficient of Italy is also almost zero, but Bulgaria and Romania show a weak dependence.

In the case of the third cluster, we can generally speak of a week/moderate dependence, but Greece, Latvia, and Slovenia show a negative dependence, and Estonia and Portugal show a positive dependence. In the fourth cluster, the calculated correlation coefficient is negative for all countries except Ireland. However, in the case of Ireland, as in the case of, say, France, the number is so close to zero that it is possible to speak of independence. The fifth cluster as a whole contains the strongest correlations, but there are also countries with both positive and negative correlations.

For countries where the correlation coefficient values are negative, the same situation occurred as in the German pharmaceutical industry in the study by Gaebert and Staňková (2020). In this case, the exit of enterprises from the market is paradoxically positively related to the efficiency of the sector as a whole. Therefore, in the case of countries such as Slovenia, Greece, the Netherlands, Finland, and Latvia, enterprises that would otherwise operate inefficiently in the market are being priced out of the market.

A different situation can be expected for countries where positive dependencies have been identified. The strongest positive dependence (of 0.839) was identified in the case of Spain (despite the low number of degrees of freedom, this is the only statistically significant relationship in this case). Although Spain shows neither a clear upward nor a clear downward trend (either in efficiency or in the number of enterprises), partial increases/decreases in the number of enterprises do indeed follow increases/decreases in efficiency. So here, generally speaking, the arrival of new enterprises can make the sector more efficient. Conversely, if enterprises leave the sector, this will be reflected in reduced efficiency.

DISCUSSION

As already mentioned, there are currently no comprehensive studies examining the efficiency of the construction sector in European countries in recent years. Therefore, the validity of our results can only be supported by studies conducted on older years, which also typically cover a smaller geographical area. Probably the closest comparison can be made with the study by Křetínská and Staňková (2021), although their study was conducted using a completely different method (data envelopment analysis) for only a few European countries between 2015 and 2017. Unfortunately, their model did not enable a clear-cut determination of the best country, but in both studies, developed countries such as Austria, France, and Germany are among the most effective representatives between 2015 and 2017. Similarities can also be found in the results of the worst performing enterprises. When for the years between 2015 and 2017, according to our results, Latvia ranked the worst with an average efficiency of around 47%, in the study by Křetínská and Staňková (2021), Latvia has an efficiency of around 50%. Given the similar results of two quite different methods, they can be considered sufficiently robust.

Our analysis found that despite the efforts of the European Union, the level of efficiency varies between Member States. Countries such as the Czech Republic and France have an average efficiency of over 90%, while Hungary and Italy are at 60%. Moreover, the correlation analysis between the number of enterprises and the efficiency scores showed that different principles are established in different countries. In countries where a negative correlation has been shown, there is a situation where there are still enterprises in the market that are not operating efficiently and the market would benefit from them leaving, as has happened in the pharmaceutical industry since Gaebert and Staňková (2020). Here, therefore, governments should encourage the transition (either of enterprises or of employees) to other sectors. It is well known that a large part of the workforce in this sector is regarded as unskilled labour or low-wage labour, see for example Soundararajan (2019). Therefore, there is scope to retrain these workers by retraining them to work in other related fields (for example, manufacturing). From an enterprise perspective, focus should then be on removing barriers to entering individual markets to make it easier for them to transfer their activities.

However, within countries where a positive link has been identified, it is advisable to support enterprises and their employees in the sector. Here, on the other hand, the findings on wage levels and employee productivity could be used. Higher productivity may then be positively reflected in higher efficiency. There has been a large amount of research on the link between wage levels and labour productivity. Here we can use the wage efficiency theory by Yellen (1984), which states that an increase in wages leads to an increase in the productivity of the worker. Based on these ideas, it is possible to increase labour productivity and consequently the efficiency of the sector as a whole, while maintaining (or even increasing) the number of enterprises in the sector. But as recent results, such as Kubicová and Blašková (2021), show, income levels alone are not the only determinant of individuals' actual well-being.

By including data from 2020, the analysis was able to uncover efficiency drops due to the COVID-19 pandemic. The COVID-19 pandemic completely disrupted the natural processes in the market, as there were government regulations that enterprises could not influence in any way. In an effort to fight against a brand-new challenge, the governments of individual countries put various measures in place. What they had in common, however, is that they implemented measures in an attempt to protect their citizens at the expense of the economy. Everyone assumed that in 2020, which we can describe as the beginning of the pandemic in Europe, the economy would be disrupted, but no one could say in advance how large it would be and what impact it would have on the efficiency of individual sectors. With the passage of time, however, we have macroeconomic data available that will help us quantify the effects of the pandemic.

In the case of the construction sector, according to the European Construction Industry Federation (FIEC, 2022), the COVID-19 pandemic provoked an unprecedented economic crisis. Based on their reports, we can measure the impact, for example, by a 5.9% decline in EU GDP in 2020. Based on our results, we can conclude that the pandemic caused an average drop in efficiency of more than 2 percentage points in the EU construction sector. The main problem can be identified as the lack of manpower, as demonstrated by reports from Germany, where roughly 25% of construction enterprises reported this problem. Another large problem is the price of input materials. However, this problem is not only related to the COVID-19 pandemic but is further exacerbated by the ongoing war in Ukraine. There has been a disruption to established supply chains, leading to price increases, which combined with energy growth has had a significant impact on business costs.

However, as mentioned above, not all EU countries saw a decline in efficiency in 2020. For example, Bulgaria, saw a significant increase in efficiency. Unfortunately, even our study cannot fully analyse the impact of the COVID-19 pandemic. Future research will also need to conduct analyses (with a time lag) to see how individual enterprises in the countries concerned have coped with this situation. According to the European Commission report (2019), this sector was already undergoing significant changes before the pandemic. Enterprises in this sector have to adapt to new trends in smart materials with an emphasis on environmental aspects or intelligent systems and smart technologies for building operation management. However, despite these modernisations, the construction sector and its efficiency are still heavily dependent on the skills of its employees.

CONCLUSION

This article focused on a quantitative assessment of the efficiency of the construction sector in EU countries. Our analysis covers the period between 2011 and 2020. The results of our analysis show that despite the efforts of the European Union, there are still significant differences in efficiency at the level of individual countries. The efficiency of the best ranked countries (such as the Czech Republic or France) is around 90%, while countries such as Ireland are around 30 percentage points less efficient. In terms of the evolution of efficiency, it was found that in some countries (Czech Republic, Germany, Hungary, Lithuania, Poland, and possibly also Slovakia) there is a hint of a cyclical component. Efficiency here therefore corresponds to other factors (e.g., the economic cycle or political elections).

Attention was also paid to the correlation between sector efficiency and the number of enterprises in the sector. It was found that for some countries there are negative correlations, while for others there are positive correlations. On the basis of this finding, it can be concluded that individual countries have to choose different strategies to improve their efficiency levels.

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