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EFFICIENCY BASED ON SMART COMPANY PERFORMANCES: BOD ANALYTICS IN URBAN AGENDA CONTEXT

Abstract: Modern conditions characterized by the fourth industrial revolution emphasized the crucial role of intangible assets in the success of companies. Tangible and intangible assets of companies within cities make a significant part of the development of competitive knowledge-based cities. However, development trends in recent decades have shifted the focus from tangible assets to intangible assets such as knowledge, innovation and intellectual property. In modern conditions, intangible assets are becoming an important strategic resource necessary for the improvement of the competitive advantage of companies within any industry. There is evidence of the influence of intangible assets on improving company performance and creating corporate value. The development of the knowledge-based economy has additionally encouraged companies to efficiently use soft capital such as human capital and knowledge since economic development in modern conditions is driven by soft capital. Therefore, the aim of this paper is to evaluate the efficiency of intangible asset management within the high-tech industry companies of ten European cities (Amsterdam, Barcelona, Berlin, Brussels, Dublin, Lisbon, London, Oslo, Paris and Zurich). The sample consists of data for 2775 high-tech companies within stated cities related to the number of patents, the number of trademarks, annual fixed asset growth rate, annual intangible asset growth rate, share of intangible asset in total asset, annual current asset growth rate and current ratio for the last year available in the Amadeus database. Efficiency evaluation was performed by creating a composite index using the Benefit of Doubt approach. The results of the efficiency analysis indicate that a large part of the companies in the sample achieves relatively low levels of efficiency. Differences in average efficiency between companies in the analysed cities were assessed using one-way ANOVA. The results indicate that the average efficiency of high-tech companies operating in Dublin is significantly better than the average efficiency of high-tech companies in other analysed European cities. In addition, high-tech companies operating in Berlin are, on average, more efficient than high-tech companies operating in Paris and London. There are no statistically significant differences between the average efficiencies of high-tech companies in other analysed European cities.
Keywords: Efficiency, Benefit of Doubt, Intangible Assets, High-tech Companies, Innovation

1. INTRODUCTION

The modern competitive environment imposes constant competition on market participants for different resources. In order to be successful in market competition, companies and especially high-tech companies, are required to present themselves to potential investors in such a way that they can show in an unequivocally sustainable and credible way that they are able to follow a business model that can contribute to intangible assets in order to increase company values above pure book value (Lange & Markovic, 2020). Although the importance of tangible assets for companies is indisputable, in modern conditions, intangible assets are a very important factor when evaluating business success. Categorization of intangible assets is a complex task, as there is no generally accepted definition of intangible assets. Corrado et al. (2005) grouped the various items that make up intangible assets into three basic categories: (i) computerized information (software, databases), (ii) innovative property (patent, license, general knowledge) and (iii) economic competence (brand and other knowledge embedded in human and structural resources specific to the firm). Dreger et al. (2011) state that intangible assets consist of elements such as education and knowledge embodied in the workforce and accumulated as human capital as well as other intangible assets (intellectual property rights such as patents, copyrights, brand names or trade secrets such as customer and supplier relationships). Companies that can successfully transform intangible assets into tangible results can gain a significant competitive advantage (Vodák, 2011). The knowledge that represents intangible assets is the bearer of the modern economy and is an essential part of the company's value. Intangible assets of the company, that is, its intellectual capital is organized knowledge on the basis of which it is possible to improve business and increase the value of the company. It is a mixture of structural and human capital and includes the results of people's knowledge and abilities, that is, patents and protected technology (Vodák, 2011) that enables companies to obtain a competitive advantage.

Contemporary literature, when considering the competitive advantages of companies, mainly focuses on the concept of dynamic capabilities, which defines the company's ability to build, integrate, and reconfigure internal and external competencies to adapt to a dynamic environment (Teece et al., 1997). The essence of the concept of dynamic capabilities is in the innovative potential of the company. Innovation and innovation capabilities are the central entities of dynamic capabilities (Strønen et al., 2017). Thus, according to this understanding, innovation is defined as the most important driver of a company's growth (Bagna et al., 2021). In addition, the basic principle of a resource-based approach is that competitive advantage relies on the ability of enterprises to develop and implement valuable, rare, unique and irreplaceable resources and capabilities (Thornhill & Gellatly, 2005). Consequently, innovation is the key to the creation of the intangible assets of companies, such as intellectual property based on research and development, and the basis for gaining a competitive advantage that can further create a number of positive effects on the economic environment.

According to research, more than 70% of the balance sheets of companies in the United States are intangible assets (Hasprová et al., 2019), while this percentage is higher when it comes to high-tech companies. High-tech companies base their business mainly on intangible assets, in other words, on the knowledge and skills of their employees and intellectual property rights. Given the fierce market competition in the high-tech sectors, companies lagging in product innovation would be quickly put out of business (Yu et al., 2021). High-tech industries are characterized by a high degree of international technological and economic competition as they achieve high added value and have a significant impact on other industries (Wang et al., 2020).

With the purpose of comparison with other companies in order to identify the best practices, it is necessary to measure the quality of intangible assets. However, having in mind the nature of intangible assets, it can be concluded that their measurement is difficult. Quantification of intangible assets is generally performed by the number of patents or the amount of investment in research and development. Nevertheless, observing individual measures of intangible assets can give an incomplete picture of their quality and the success of companies. Therefore, the paper aims to create a methodological approach for measuring the efficiency of intangible assets of high-tech companies. The sample consists of 2775 high-tech industry companies in ten European cities (Amsterdam, Barcelona, Berlin, Brussels, Dublin, Lisbon, London, Oslo, Paris and Zurich) and contains data related to the number of patents, the number of trademarks, annual fixed asset growth rate, annual intangible asset growth rate, share of intangible asset in total asset, annual current asset growth rate and current ratio for the last year available in the Amadeus database. The evaluation of the intangible management efficiency of European high-tech companies is performed by creating a composite index using the Benefit of Doubt (BoD) approach.

2. LITERATURE REVIEW

Smart growth and development of companies refer to growth and development based on knowledge and innovation, that is, based on intangible assets. There is ample evidence in the literature on the positive impact of intangible assets on economic performance, both on macroeconomic and microeconomic levels. Observed at the macroeconomic level, numerous studies indicate that there is a positive link between regional economic development and the level of knowledge and innovation, while at the microeconomic level, the economic literature indicates that intangible capital is a vital factor in innovation and future economic growth (Rico & Cabrer-Borrás, 2020). Due to the accelerated transformation of developed economies into knowledge-based economies, intangible capital is becoming vital for their future competitiveness (Roth & Thum, 2022).

In the European context, intangible assets are considered a key determinant in growth policy (Peiró-Palomino, 2016). Intangible assets are particularly important in creating knowledge, improving efficiency and productivity, and ultimately fostering economic growth and regional well-being (Melachroinos & Spence, 2014). Corrado et al. (2012) indicate that intangible capital significantly contributes to economic growth in the United States and Europe, especially given that there are significant investments in intangible assets in these regions. Jona Lasinio and Manzocchi (2012) have shown that intangible capital accumulation has strongly contributed to labour productivity growth in the best performing European economies/regions. Furthermore, they have found that intangible capital accumulation is associated with spill over effects. Roth and Thum (2022) have investigated data on intangible capital investment by business using a panel analysis between 1998 and 2005 in an EU country sample and discovered a positive and significant relationship between intangible capital investment and labour productivity growth. Ökten et al. (2019) observed the effect of investing in national brands and increasing brand values of the country and have discovered that the effects were negative in the short-term, but positive in the long-term concerning the country's economic growth. Jona Lasinio and Meliciani (2018) showed that intangible capital is as important as fixed/tangible capital in many advanced countries, and its importance is growing over time. Their results indicate that there is a positive correlation between intangible assets, global value chain participation and productivity growth.

Numerous studies at the microeconomic level examine the impact of intangible assets as a whole, or some part of intangible assets, on the efficiency, productivity and growth of firms. Intangible assets have positive effects on the company's profitability and value and are an indicator of future financial results (Manikas et al., 2019). Thornhill and Gellatly (2005) indicate that the growth of SMEs is positively related to investments in intangibles, regardless of whether the investments are financed from debt or equity. Chen et al. (2016) have discovered that intangible capital contributes systematically to labour productivity growth and its output elasticity is found to be significantly higher in ICT-intensive industries than in those that use little ICT. Niebel et al. (2017) have investigated the importance of investment in intangible assets for labour productivity growth and discovered that the contribution of intangibles to labour productivity growth is higher in manufacturing than in services. Seo and Kim (2020) have discovered that the investment in intangible assets has a positive effect on a firm's profitability and value and state that managers should strategically utilize intangible assets and adopt investment in intangible assets to accomplish their managerial goals. Sallah and Caesar (2020) have found evidence of the positive effect of intangible assets on the growth of women's entrepreneurship. Manikas et al. (2019) have discovered that the value of intangible assets ins positively associated with the stock of younger capital assets and the flow of capital assets based on a sample of 1390 manufacturing firms. Bontempi and Mairesse (2015) have found that intangible capital has a stimulating effect on the productivity of Italian firms. Greenhalgh and Longland (2005) have investigated the effects of R&D expenditures, patents and trademark registration on productivity and discovered that trademark activity is correlated with permanent productivity gains. Greenhalgh and Rogers (2012) have discovered that firms that are trademark active (that had applied for a trademark in the previous year) have significantly higher productivity and improved productivity growth compared to non-trade markers. Rico and Cabrer-Borrás (2020) have analysed a panel of companies from the seventeen Spanish regions over the period between 2006 and 2015 and discovered that there is a positive effect of intangible capital on companies' productivity and evidence of a spill over effect.
Intangible assets and the quality of managing intangible assets are particularly important in the business of high-tech companies. The high-tech industry has developed significantly in recent decades in Europe. The importance of the high-tech industry is particularly pronounced in the knowledge-based economy, where the high-tech industry is one of the most important industries (Hong et al., 2016). Innovation and competitiveness have turned out to be the most important features of successful companies in high-tech markets in recent years (Haschka & Herwartz, 2020). Namely, due to the rapid progress of technology, the high-tech market is developing fast and it is necessary for high-tech companies to continuously develop their innovative potential in order not to fall out of market competition. Given that the survival and success of high-tech companies in market competition depend on strong innovation capacities, these companies must make efforts to protect their technological assets and improve their innovation processes (Ortiz-Villajos & Sotoca, 2018). In other words, high-tech companies protect their business by investing in intangible assets. Specifically, high-tech companies can monopolize their ideas through patents. In this manner, a high-tech company can protect its idea, prevent competitors from applying the idea, limit the ability of rivals to use similar ideas, and ultimately defend its market position (Haschka & Herwartz, 2020). High-tech companies are a key element in creating intangible assets, as their business is largely knowledge-based. Such companies have an important role in endorsing scientific and technological research, collecting scientific and technological resources, and eventually play a role directly or indirectly in the transformation of the economy (Liu et al., 2020). Bearing in mind the importance of intangible assets, improving the innovation capacity and quality of intangible assets of high-tech companies is becoming an important goal at both micro and macro levels, given that the high-tech industry is one of the most innovation-oriented industries, and improving their capabilities would greatly contribute to industry growth and stimulate the economy of the whole country (Yu et al., 2021). In order to achieve sustainable development of the high-tech companies, managers should be provided with a methodological tool to assess its efficiency in order to identify its strengths and weaknesses and make rational plans for its future development (An et al., 2020).

3. DATA, METHODOLOGY AND RESULTS

In order to assess the efficiency of intangible asset management within the high-tech industry companies of ten European cities were analysed. The sample consists of data for 2775 high-tech companies in cities Amsterdam, Barcelona, Berlin, Brussels, Dublin, Lisbon, London, Oslo, Paris and Zurich. The definition of high-tech companies is based on their research and development efforts. Yu et al. (2021) identify several criteria by which companies can be classified as high-tech: (i) the company's business activity largely depends on innovation in technology and science, (ii) companies whose share of research and development costs is more than 5% of revenue from sales, (iii) companies with a higher share of resource investment in innovative research and development activities. Data are obtained from the Amadeus database and described in Table 1.

Table 1: Description of the variables of the BOD model

Variable	Description
Number of patents	The total number of patent applications published by the issuing patent office
Number of trademarks	The total number of registered trademark applications
Annual fixed asset growth rate	Year-over-year percentage change in fixed assets
Annual intangible asset growth rate	Year-over-year percentage change in intangible assets

Share of intangible assets in total	Percentage share of intangible assets in total assets
Annual current asset growth rate	Year-over-year percentage change in current assets
Current ratio	The ratio between current assets and current liabilities

Source: Authors' preview.

Evaluation of intangible asset management efficiency was performed by creating a composite index using BoD approach. The creation of a composite index using the BoD approach has been proposed by Cherchye et al. (2007), while the BoD approach was initially presented in Melyn and Moesen (1991). BoD approach represents a variant of a Data Envelopment Analysis (DEA) approach. The standard DEA model consists of n decision making units (DMUs), which use s different inputs to produce t different outputs, where x_{ij} and y_{rj} represent the input quantities used and the output quantities produced in the j^{th} DMU (André et al., 2010). Depending on the nature of the return-to-scale, there are two different models: model with the constant return-to-scale (Charnes et al., 1978) and model with the variable return-to-scale (Banker et al., 1984). In the general case, the efficiency of the DMUs in the model with the constant return-to-scale is defined as the ratio of the weighted sum of outputs to the weighted sum of inputs. The mathematical model can be formed as (Jemric & Vujcic, 2002):

$$\max_{u} z_0 = \sum_{r=1}^{s} u_r y_{r0} \quad (1)$$

s.t.

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, j = 1,2 \dots, n \quad (2)$$

$$\sum_{i=1}^{m} v_i x_{i0} = 1 \quad (3)$$

$$u_r \geq 0, r = 1,2 \dots s \quad (4)$$

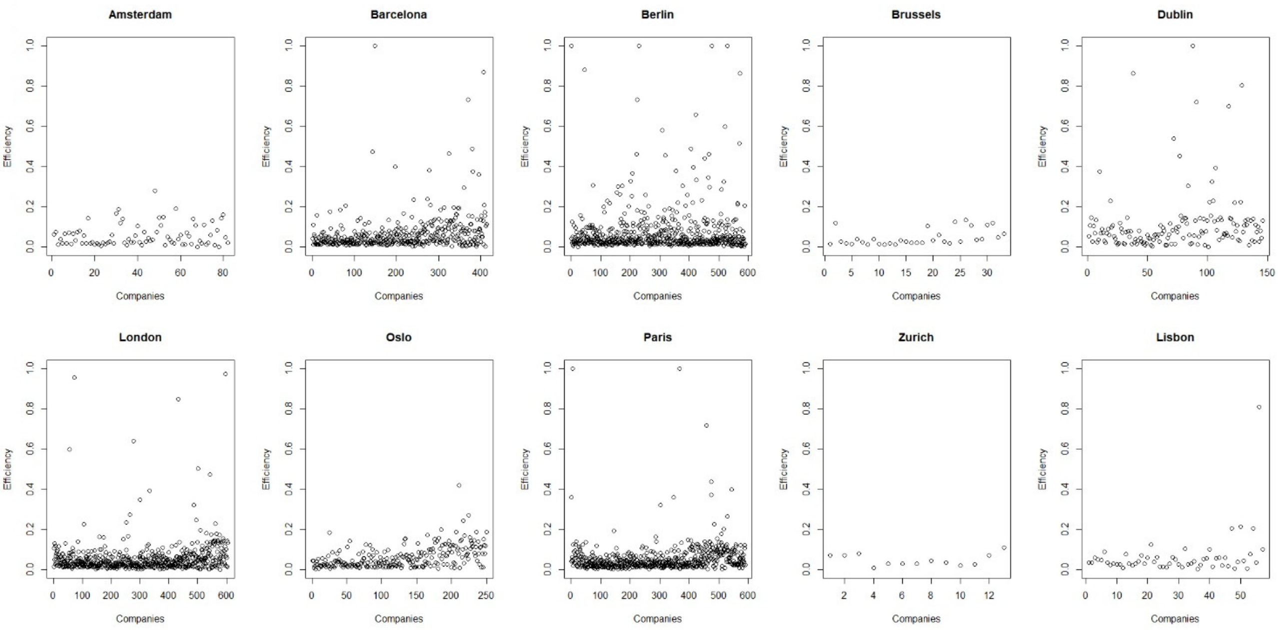
$$v_i \geq 0, i = 1,2 \dots m \quad (5)$$

Where u_r and v_i represent the weighting coefficients of output and input, respectively. The model calculates the weighting coefficients so that the analysed DMU is evaluated as best as possible (Terzi & Pierini, 2015). From this formulation of the linear programming model, it can be concluded that the set of weighting coefficients (one for each DMU) is endogenously determined in such a way as to maximize their efficiency under given constraints (Greco et al., 2019).

When constructing composite indices using BoD approach, the standard DEA model is modified to create a model that contains only outputs (Hermans et al., 2008). In other words, all indicators are treated as outputs, while inputs are not taken into account. Thus, the denominator of the coefficient consists of weighted inputs of decision-making units that contain a dummy variable equal to one, while the numerator is a weighted set of indicators that form the total composite index (Yang et al., 2018).

The essence of this approach is in gaining flexible weights that vary between the DMUs and over time. Determination of weight coefficients is done on the basis of the data of DMUs. In particular, the basic idea is that a good relative performance of a DMU in one particular dimension indicates that this DMU considers the dimension in question to be relatively important, while, conversely, the DMU attributes less importance to those dimensions in which it is relatively weak in relation to other DMUs in the sample (Cherchye et al., 2007). Such a data-oriented differential weighting approach is justified since there is a lot of uncertainty and lack of consensus on the appropriate weighting scheme when constructing composite indices. Another benefit of the BoD approach is that it allows indicators to be weighed in situations where objective knowledge of the true relative importance of indicators is lacking or information is limited, as the BoD approach derives a set of optimal weights for each DMU from the observed value indicators themselves (Verbunt & Rogge, 2018). More specifically, the BoD approach defines weighting coefficients for each DMU so that the impact of the indicator according to which the DMU shows relative strengths is maximized and the impact of the indicator according to which the DMU shows relative weaknesses is minimized in the composite index. This feature of the BoD approach is also one of the main reasons for the attractiveness of this approach. The application of DEA in evaluation of the efficiency of high-tech companies has become particularly popular in recent years (Yu et al., 2021; Wang et al., 2021; Li et al., 2017; Han et al., 2017; Zhang et al., 2019; Chiu et al., 2012; Lin et al., 2021; Chen et al., 2022).

The results of the efficiency analysis indicate that a large part of the companies in the sample achieves relatively low levels of efficiency (Picture 1). The results indicate that the average efficiency of the high-tech companies in the sample is 0.0665 (Table 2).



Picture 1: Efficiency of high-tech companies
Source: Authors' preview

A more detailed analysis of the efficiency of high-tech companies by cities was performed based on the average values of the achieved efficiency.

Table 2: Descriptive statistics of efficiency of high-tech companies in the sample and by city

Companies in the sample	2775				
Min	0.0004				
Average	0.0665				
Max	1.0000				
City	**Amsterdam**	**Barcelona**	**Berlin**	**Brussels**	**Dublin**
Number of companies	82	413	588	33	146
Min	0.0004	0.0020	0.0006	0.0110	0.0015
Average	0.0574	0.0675	0.0777	0.0467	0.1144
Max	0.2789	1.0000	1.0000	0.1334	1.0000
City	**Lisbon**	**London**	**Oslo**	**Paris**	**Zurich**
Number of companies	57	604	250	588	13
Min	0.0037	0.00109	0.0045	0.0024	0.0100
Average	0.0651	0.05734	0.0628	0.0567	0.0490
Max	0.8074	0.97010	0.4203	1.0000	0.0112

Source: Authors' preview.

The average efficiency of high-tech companies operating in Dublin (0.11436), Berlin (0.07765) and Barcelona (0.06749) is higher than the average efficiency of all analysed high-tech companies, while the average efficiency of high-tech companies in other cities is below the average efficiency of all analysed high-tech companies. The lowest average efficiency of high-tech companies was achieved by high-tech companies operating in Brussels (0.04668). Furthermore, the results of the efficiency analysis indicate that all analysed high-tech companies that operate in Amsterdam, Brussels, Lisbon, London, Oslo and Zurich have been inefficient.

Testing of statistical significance of observed differences in average efficiency between companies in the analysed cities was performed using one-way ANOVA. There was a statistically significant difference between efficiency of high-tech companies operating within analyzed cities ($F(9, 2764) = 6.242$, p =0.001).The results of the post hoc test are presented in Table 3.

Table 3: Results of the post-hoc test

	Amsterdam	Barcelona	Berlin	Brussels	Dublin	Lisbon	London	Oslo	Paris
Zurich	-0.0084	-0.0185	-0.0286	0.0023	-0.0653*	-0.0161	-0.0083	-0.0138	-0.0077
Paris	-0.0007	-0.0108	-0.0209*	0.0100	-0.0576*	-0.0084	-0.0006	-0.0061	
Oslo	0.0054	-0.0047	-0.0149	0.0161	-0.0516*	-0.0023	0.0054		
London	-0.0001	-0.0101	-0.0203*	0.0107	-0.0570*	-0.0078			
Lisbon	0.0077	-0.0024	-0.0125	0.0185	-0.0492*				
Dublin	0.0570*	0.0469*	0.0367*	0.0677*					
Brussels	-0.0107	-0.0208	-0.0310						
Berlin	0.0202	0.0102							
Barcelona	0.0101								

* Results are significant at 0.01 level

Note: The value in the table cell represents the difference between the average efficiency of the city in the row of the table and the average efficiency of the city in the column of the table.
Source: Authors' preview.

The results indicate that the average efficiency of high-tech companies operating in Dublin is significantly higher than the average efficiency of high-tech companies in other analysed European cities. In addition, high-tech companies operating in Berlin are, on average, more efficient than high-tech companies operating in Paris and London. There are no statistically significant differences between the average efficiencies of high-tech companies in other analysed European cities.

4. CONCLUSION

The modern competitive environment has changed significantly, especially having in mind the development of modern technology. Consequently, the nature of competitiveness has changed, which companies no longer achieve based on the possession of tangible assets. This is especially important when it comes to highly technologically advanced companies that base their business mainly on intangible assets. The management of modern high-tech companies takes place in a complicated competitive environment, and it is necessary to provide an adequate information base and methodological tool for decision-making and evaluation. A methodological tool based on the application of mathematical and statistical techniques can make it easier for managers of high-tech companies to assess various aspects of business, identify areas for improvement, monitor the company's progress in achieving defined goals and compare with companies within the industry.

Therefore, the main goal of this paper was to create a methodological tool based on the BoD approach that allows the creation of composite efficiency indices based on which it is possible to assess the success of high-tech companies in the management of intangible assets. High-tech companies within ten European cities were analysed and the results indicate that a large percentage of companies achieve low efficiency, which indicates the need for them to reconsider the way of managing intangible assets.

The contribution of the paper is twofold. From the methodological aspect, the contribution of the paper is reflected in the creation of a composite index for quantifying the efficiency of intangible asset management. From a theoretical point of view, the paper contributes to the modern literature related to measuring the efficiency of high-tech companies.

Further research in this area can be directed towards including more periods in the analysis, in order to determine the trend of efficiency of intangible asset management. Moreover, it is possible to examine the determinants of the efficiency of high-tech companies.

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