REICE
Revista Electrónica de Investigación en Ciencias Económicas
Abriendo Camino al Conocimiento
Área de Conocimiento de Ciencias Económicas y Administrativas
Universidad Nacional Autónoma de Nicaragua, Managua (UNAN-Managua)

Vol. 12, No. 24, julio – diciembre 2024 **REICE ISSN: 2308-782X**
https://revistas.unan.edu.ni/index.php/reice
revista.reice@unan.edu.ni

Comparative Analysis of Multinational Enterprises and Domestic Companies: A Propensity Score Matching Methodology Approach

Análisis comparativo de empresas multinacionales y empresas nacionales: un enfoque basado en la metodología de emparejamiento por puntaje de propensión

Fecha de recepción: septiembre 29 de 2024
Fecha de aceptación: octubre 25 de 2024
DOI: https://doi.org/10.5377/reice.v12i24.20097

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Abstract

The study aims to employ the Propensity Score Matching (PSM) methodology to conduct a comprehensive comparative analysis of competitiveness and performance differences between publicly listed independent domestic companies (DCs) and multinational enterprises (MNEs). Utilizing data from 2010 to 2022 and encompassing companies worldwide sourced from the Orbis database, this research endeavours to offer insights into the economic performance of DCs and MNEs and consolidate results on a global scale. By creating comparable treatment and control groups of DCs and MNEs based on observable characteristics, and controlling for potential confounding variables such as company size, industry sector, number of employees, countries' economy classification, and geographical location, this approach facilitates a robust examination of the differential key performance indicators between the two groups. The findings outline the distinct characteristics and performance outcomes of DCs compared to MNEs, revealing that MNEs often outperform their local counterparts in productivity and efficiency, especially in industries marked by global competition and advanced technology. However, significant performance gaps exist across countries, influenced by factors such as global market presence, access to capital, and market conditions, with these dynamics varying over time.

***Keywords*:** Propensity Score Matching, Multinational Enterprises, Domestic Companies, Economic performance, Competitiveness.

Resumen

El estudio tiene como objetivo emplear la metodología Propensity Score Matching (PSM) para realizar un análisis comparativo integral de las diferencias de competitividad y desempeño entre las empresas nacionales independientes que cotizan en bolsa (ED) y las empresas multinacionales (EMN). Utilizando datos de 2010 a 2022 y que abarcan empresas de todo el mundo provenientes de la base de datos Orbis, esta investigación intenta ofrecer información sobre el desempeño económico de las ED y las EMN y consolidar los resultados a escala global. Al crear grupos de tratamiento y control comparables de ED y EMN basados en características observables y controlar posibles variables de confusión como el tamaño de la empresa, el sector industrial, el número de empleados, la clasificación económica de los países y la ubicación geográfica, este enfoque facilita un examen sólido de los indicadores clave de desempeño diferenciales entre los dos grupos. Los hallazgos describen las características distintivas y los resultados de desempeño de las ED en comparación con las EMN, revelando que las EMN a menudo superan a sus contrapartes locales en productividad y eficiencia, especialmente en industrias marcadas por la competencia global y la tecnología avanzada. Sin embargo, existen importantes brechas de desempeño entre países, influenciadas por factores como la presencia en el mercado global, el acceso al capital y las condiciones del mercado, y estas dinámicas varían con el tiempo.

Palabras claves: Propensity Score Matching, Empresas multinacionales, Empresas nacionales, Desempeño económico, Competitividad.

Introduction

This study aims to conduct a comparative analysis of competitiveness and performance differences between publicly listed independent domestic companies (DCs) and multinational enterprises (MNEs). By examining key performance indicators, the study seeks to consolidate and evaluate the results on a global scale.

The relationship between MNEs, DCs, ownership structure and related economic and financial performance has been the subject of extensive and ongoing debate within academic and professional circles. Scholars and practitioners have long explored how different forms of ownership, such as public versus private ownership, family ownership, or state ownership, influence a company's financial performance, strategic decisions, and overall effectiveness (Azinfar, & Shiraseb, 2016). This debate is driven by varying perspectives on how ownership affects corporate governance, risk management, and strategic orientation. Proponents of dispersed ownership argue that it enhances accountability and managerial efficiency by dispersing control among numerous shareholders (Dunning & Lundan, 2008). In contrast, advocates of concentrated ownership, such as family or state ownership, suggest that it provides stronger oversight and long-term stability (Federico, 2016).

Researchers have investigated whether ownership concentration affects managerial incentives, risk-taking behavior, and overall organizational effectiveness. Discussions also focus on how ownership structure influences long-term versus short-term performance and shapes responses to market pressures and regulatory environments. This debate is important to understanding the implications of ownership arrangements on corporate governance, strategic priorities, and economic outcomes. Empirical studies have yielded mixed results (Mikou, Lahrichi, & Achchab, 2024; Permata & Baharuddin, 2023). Some research indicates that concentrated ownership can lead to higher performance due to more effective monitoring and alignment of interests, while other studies highlight potential drawbacks, such as reduced flexibility or increased risk of managerial entrenchment. MNEs coordinate 80% of global trade, and it is estimated that they and their foreign affiliates contribute 33% of global output. Foreign affiliates generate significant value

in host countries, which supports the compensation of local production factors. These affiliates often source inputs and services from domestic suppliers (Cadestin, et al., 2018). The DCs' absorptive capacity in capitalizing on technology spillovers, competitive pressures, and productivity improvements from MNEs highlights how these factors drive their potential for growth and development (Olayinka & Loykulnanta, 2019). Consequently, the exploration of how ownership structure influences economic performance continues to be a pivotal and evolving area of research. This understanding has significant implications for both theoretical frameworks and practical applications in corporate governance, strategic management, industry dynamics, market conditions, and institutional contexts.

Based on the aforementioned discussion, the central focus of the analysis is guided by the following research question: What are the significant differences in competitiveness and performance between DCs and MNEs? What are the key drivers of competitive advantage, and which factors contribute to the performance gap between DCs and MNEs?

The originality of this study lies in its approach compared to previous research, which has typically been niche-focused and constrained by specific criteria such as periods, geographical regions, industries, and company samples. These limitations hinder the ability to draw globally representative conclusions. In contrast, this study offers a comprehensive analysis of competitiveness and performance differences between DCs and MNEs on a global scale, encompassing all geographical areas and industries. It captures the dynamic evolution of profitability and productivity indicators over time and identifies the key factors that significantly impact these metrics.

The findings outline the distinct characteristics and performance outcomes of DCs relative to MNEs. These insights are expected to help both companies and national governments in enhancing economic growth and refining effective economic policy strategies.

The following section reviews the relevant literature, followed by the conceptual model, methodology, and findings. Conclusions and suggestions for future research conclude the study.

Literature review

The increase in competitiveness and company performance represents an ongoing challenge in international strategic management. As global markets become more interconnected and competitive, companies focus on gaining and sustaining competitive advantages in complex economic, technological, cultural factors, market conditions, and regulatory environments.

Existing studies analyze company performance based on ownership, and the results are divided according to the criteria used in the research model when examining the competitiveness indicators of MNEs and DCs.

Michel and Shaked (1986) studied the financial performance of a sample of 58 MNEs and 43 DCs for the period 1980–1982, and the results suggest that DCs are significantly less capitalized than MNEs, with higher total risk and systematic risk. The study suggests that although MNEs are larger than DCs, company size is not identified as a significant factor in explaining the performance differences between the two groups of companies analyzed.

Bellak (2001) studied the performance differences between MNEs and local counterpart companies in terms of productivity, profitability, wage levels, competencies, and growth. The results reveal that foreign ownership is not a significant explanatory factor in the performance gap. Factors such as industry, size, MNEs' attraction policies, and the provision of specific benefits better explain the performance differences.

Contrary to these conclusions, a study conducted by Aydin et al. (2007) analyzed 42 firms with foreign ownership and 259 domestic corporations listed on the Istanbul Stock Exchange in Turkey during the period 2003-2004. The study examined significant differences in financial indicators and revealed that foreign

ownership may increase company performance. Douma et al. (2006) also reveals that foreign ownership positively impacts company performance.

Greenaway et al. (2004) analyzed UK companies over five years in terms of the export behavior of domestic companies in the presence of MNEs. The study's conclusions suggest that MNEs influence the decision of domestic companies to export, increase their propensity to export, and lead to competition effects. Export spillover effects from MNEs to DCs represent an indirect channel through which MNEs can enhance the productivity of domestic companies.

Temouri et al. (2008) studied the productivity differences between MNEs and German companies by analyzing 22 manufacturing industries and 17 service industries in Germany during the period 1995-2004. The results suggest the existence of a "foreign" effect, but the determinant in the productivity gap seems to be the location (companies owned by West German firms outperform firms with East German parents) and implicitly the policies for attracting investment.

Vlachvei and Notta (2008) analyzed the determinants of performance between foreign-owned companies and domestic-owned companies for 177 large manufacturing and trading companies listed on the Athens Stock Exchange during the period 1995-2000. The results suggest that domestic-owned companies perform better when borrowed capital is efficiently utilized. Foreign-owned companies show increasing profitability related to efficient investments in sales promotion and leveraging the parent company's innovation rather than investing in research and development in the host countries. Productivity has a significant impact on the debt structure of MNEs (Valsamis, Katsaiti, & Petrakis, 2011).

Foreign direct investment is a key strategy that enables MNEs to broaden their global footprint and harness valuable resources. At the same time, developing countries gain significant advantages from the capital, technology, and expertise associated with these investments (Hansen & Rugraff, 2011). Lenggogeni (2022) studied the effect of capital expenditure and inflation variables the domestic and foreign investment in Indonesia and found that the capital expenditure variable

does not have a significant effect both on domestic and foreign investment, while the inflation variable strengthens the relationship between capital expenditures and domestic investment.

An analysis of economic performance conducted on a group of 45 MNEs and DCs in India at two different points in time (2002 and 2011) reveals similar performance levels in terms of operating profit margin, net profit margin, return on equity, and asset turnover ratio (Pai & Hiremath, 2013).

Between 1981 and 2010, MNCs and DCs in the U.S. displayed comparable patterns in their debt maturity structures, leverage adjustment rates, and choices regarding debt versus equity issuance or avoidance of debt altogether. This suggests that the financial policies of MNEs at the corporate level are not notably affected by their heightened exposure to market imperfections, such as taxes and regulations, relative to DCs (Park, Suh, & Yeung, 2013).

Other studies on foreign direct investment across different countries and industries demonstrate that MNEs outperform DCs due to their advanced management techniques. Investments in intangible assets, such as research and development, contribute to greater added value compared to what is typically observed in DCs (Rajnoha, Merková, Dobrovič, & Rózsa, 2018), (Al-Kwifi, Farha, & Zaraket, 2020). The presence of MNEs and their FDI has a significant impact on DCs by intensifying competition and boosting productivity (Hanousek, Kočenda, & Vozárová, 2020; Mihaylova, 2023; Hanousek et al., 2020; Mihaylova, 2023).

Previous studies are niche-focused, based on specific criteria such as period, territory, industries, and company samples. This limitation makes it challenging to draw globally representative conclusions.

This study provides an analysis of the competitiveness and performance differences between DCs and MNEs on a global scale, including all geographical areas and industries. It captures the dynamic evolution of profitability and

productivity indicators over time, as well as the key factors that significantly impact them.

Methodologies and Data

The study aims to conduct a comparative analysis of the differences in competitiveness and performance between MNEs and DCs. The main considerations for opting for DCs instead of all local companies (Michel & Shaked, 1986; Agmon & Lessard, 1977; Luo & Tan, 1998; Agmon & Lessard, 1977; Luo & Tan, 1998) are as follows: (1) comparable size and scale (DCs adhere to stringent financial reporting standards and disclosure requirements, ensuring transparency and comparability of financial data, making them suitable for detailed analysis and more comparable to MNEs in terms of business size and scale); (2) access to capital markets, resources and expertise (DCs, like MNEs, have access to capital markets through equity and debt financing, facilitating growth opportunities, investments in technology, and market expansion, unlike many privately held domestic companies that may face limitations in capital availability and growth prospects); (3) market-based valuation (the stock prices of DCs reflect market valuation, providing real-time indicators of market confidence and perceived performance, aligning with the market-driven metrics often used to assess MNEs; private domestic companies lack this market valuation mechanism, relying instead on internal assessments and occasional external valuations); (4) risk and return profiles (DCs face risks and challenges similar to those of MNEs, such as currency fluctuations, geopolitical risks, and global economic conditions; performance metrics, including profitability and operational efficiency, can be comparable to those of MNEs, providing a clearer understanding of competitive dynamics); (5) market orientation (both MNEs and DCs operate with a focus on market competitiveness and shareholder value; they often have sophisticated market strategies, including product diversification, market expansion, and strategic partnerships, which are less common or less visible in privately held domestic companies); (6) strategic decision making (DCs typically have independent boards of directors and shareholders, influencing strategic decisions aligned with maximizing shareholder value; this governance structure

mirrors that of MNEs, where strategic decisions are made with consideration of global market conditions and long-term growth prospects.

Therefore, focusing on DCs for comparative analysis with MNEs allows for the assessment of similar entities in terms of size, scale, market dynamics, competitive pressures on strategic decisions, and financial outcomes. This approach aims to provide a perspective on their competitive positioning and financial performance in the global marketplace.

To achieve these objectives, a database was sourced from the Orbis Database, spanning from 2010 to 2022, with worldwide DCs and MNEs as the selection criteria.

DCs are companies headquartered within a single country, whose shares are publicly traded on stock exchanges, and are independent entities not affiliated with multinational corporations.

MNEs are companies with operations, assets, and subsidiaries in at least two countries, ultimately owned by a parent company holding at least a 51% ownership stake, with consolidated financial statements that integrate the financial results of their controlled subsidiaries or branches.

The comparative analysis of competitiveness and performance differences between DCs and MNEs was performed using the Propensity Score Matching (PSM) methodology with Stata software. The PSM is widely used for comparing firms based in terms of the financial variables. For example, Castelo and his colleagues (2021) compared the effects on capital cost for a group of firms in Brazil that voluntarily disclosed integrated reports with a control group identified via Propensity Score Matching.

PSM represents the conditional probability of receiving the treatment based on the pre-treatment variables (Rosenbaum & Rubin, 1983). It has two significant properties: balancing pre-treatment variables given the propensity score and ensuring unconfoundedness given the propensity score.

For modelling the database, companies were assigned into two groups: treatment observations and control observations, based on the observable characteristics mentioned above. The variable D represents treatment status, with a binary value indicating whether the observation received the treatment: D=1 for DCs as treated observations and D=0 for MNEs as control observations.

A probit model was estimated for the propensity of observations being assigned to the treated group based on variables x that may affect the likelihood of this assignment. Thus, D is considered the dependent variable and x is considered the independent variable.

$$p(x) = prob(D = 1|x) = E(D|x) \quad (1)$$

The equation means the expected value of the treatment D given the covariates x. The expected value E(D|x) is used to balance or match treated and control groups to estimate the treatment effect without bias.

The confounding variable x is a factor that impacts both the selection of treatment and the outcome variables and was identified to ensure unbiased and representative model estimation (King & Nielsen, 2019). This includes company size, industry classification, region, countries' economy classification, and the corruption perceptions index.

The company size criterion was based on very large companies as defined by the Orbis database. Companies are classified as very large when they meet at least one of the following conditions: operating revenue greater than $140 million, total assets greater than $280 million, or more than 1,000 employees. For data representativeness, the criterion was conditioned by a cumulative requirement of operating revenues greater than $140 million.

Companies are categorized into industries according to the new version of the European industrial activity classification (NACE Rev 2), and the 2-digit level was considered for the analysis.

For the region criterion, all DCs and MNEs worldwide that meet the size criterion were considered.

The classification of countries' economies into income groups (low, lower-middle, upper-middle, and high-income) (The World Bank, The World by Income and Region, 2022) enables comparisons of economic performance and development across nations with similar income levels. This indicator helps identify best practices and policies effective within each income group and provides a framework for conducting comparative analysis on economic growth, development, and inequality.

The Corruption Perceptions Index offers insight into the perceived levels of public sector corruption across different countries (Transparency International, 2022). It aids multinational companies and foreign direct investors in making informed decisions regarding resource allocation. For this analysis, the index was categorized into five clusters: highly corrupt, corrupt, average, clean, and very clean. Companies were then classified accordingly to assess how corruption influences various economic outcomes, stability, and growth.

The International Tax Competitiveness Index provides insights into how a country's tax policies adhere to competitiveness and economic neutrality (Tax Foundation, 2022). While valuable for economic analysis, it primarily covers OECD countries, not worldwide jurisdictions as required for this study, and was therefore excluded from consideration as a confounding variable. Nonetheless, it remains useful for understanding how tax policies impact a country's attractiveness for investment, isolating the effects of tax policies on various economic indicators, and aiding businesses and investors in assessing the potential impact of different jurisdictions for investment and business operations.

Based on the criteria outlined above, the screening conducted from 2010 to 2022 identified a total of 15,537 companies spanning various industries, headquartered in 121 countries. To effectively apply PSM, large sample sizes are required for both treated and untreated observations. The dataset needs to include an adequate number of control observations that exhibit similar characteristics to

those of the treated observations (The World Bank, Propensity Score Matching, 2024). Specifically, there are 5,466 DCs and 10,071 MNEs in the dataset.

The outcome variable, y, is a set of variables of interest for which the treatment effect will be determined. To assess the causal effect of the treatment and determine if there is a statistically significant difference in the outcome variables between the treated and matched untreated observations, the following metrics are considered: business health indicators (net income growth rate, solvency ratio), liquidity ratios (current ratio), profitability ratios (profit margin, return on shareholders' funds, return on assets), and productivity metrics (asset turnover ratio, labor productivity, net income per employee).

The next step in PSM involves matching observations from the treated and control groups and selecting an appropriate matching method. Subsequently, the treatment effects will be determined by comparing the outcome variable y between the treated and control observations after matching.

$$y = \begin{cases} y_1 \; if \; D = 1 \\ y_0 \; if \; D = 0 \end{cases} \qquad (2)$$

Matching methods require that for each treated observation i, matches of control observations j with similar characteristics have to be found. Employing multiple matching algorithms facilitates the cross-verification of results. When treatment effects are consistent across various matching techniques, it strengthens the reliability and robustness of the findings. This approach ensures that the observed effects are not characteristic of a particular matching method but accurately reflect the underlying causal relationships.

The methods addressed in this study, as defined and analyzed by various researchers based on the matching algorithms employed (Caliendo & Kopeinig, 2008), (Harris & Horst, 2019), (Austin, 2011), (Baser, 2007) (Caliendo & Kopeinig, 2008; Harris & Horst, 2019; Austin, 2011; Baser, 2007), are as follows: Nearest Neighbor matching method, Radius, Kernel and Stratification.

Nearest Neighbor matching method is a technique used to pair each treated observation with the closest untreated observation based on their propensity scores. This method aims to identify the nearest match (neighbor) for each treated observation by comparing propensity scores, thereby creating a control group that closely resembles the treated group in terms of observable characteristics. The process begins with estimating the propensity scores for all observations using logistic regression. The method identifies the nearest control observation for each treated observation by finding the one with the most similar propensity score, where "nearest" is defined as the smallest absolute difference in propensity scores. This results in matched pairs, where each treated observation is paired with its closest control counterpart. The matching procedure can be expressed as follows: for each treated observation i, the algorithm selects a control observation j with the closest x.

$$min \, || \, p_i - \, p_j \, || \qquad (3)$$

The matching method used is Nearest Neighbor with replacement, allowing each control observation to be matched with several treated observations (Heinrich, Maffioli, & Vazquez, 2010). This approach does not limit the number of matches for any given observation, as long as the observations are sufficiently similar.

After matching the treatment effect is estimated by comparing the outcomes between the treated observations and their matched controls.

The Radius Matching method, also known as the Caliper Matching method, pairs treated and control observations based on their propensity scores within a specified distance or radius. As with other matching methods, the first step involves estimating the propensity scores for all observations using logistic regression. The model predicts the likelihood of receiving the treatment based on pre-treatment characteristics.

Matches are formed using the radius criterion, which considers all cases within a specified radius (defined for the dataset by a propensity score deviation of 0.1) as potential matches for constructing the control group. Each treated

observation i is matched with control observations j that fall within the specified radius.

$$|| p_i - p_j || < r \quad (4)$$

If a control observation's propensity score falls within the specified radius of a treated observation's score, they are matched together. If no control observation is within the specified radius for a given treated observation, that treated observation may not receive a match. By using the specified radius, this method reduces the likelihood of matching treated and control observations that are too dissimilar. This helps improve the quality of matches, reduce selection bias, and achieve balance between treated and control groups across observed covariates (Caliendo & Kopeinig, 2008).

After matching the outcome of interest is analyzed for the matched pairs to estimate the treatment effect.

Kernel matching method is a non-parametric matching method used in PSM to estimate the treatment effect. Unlike Nearest Neighbor and Radius matching, which rely on identifying specific matches for each treated observation, Kernel matching uses a weighted average of all control observations based on their distance from the treated observation's propensity score to construct the counterfactual outcome for each treated observation (Heinrich, Maffioli, & Vazquez, 2010). The closer a control observation's propensity score is to the treated observation's score, the higher the weight it receives.

Each treated observation i is matched with several control observations, with weights inversely proportional to the distance between treated and control observations. When matching based on propensity scores, the weights are defined as:

$$w(i,j) = \frac{K(\frac{pj-pi}{h})}{\sum_{j=1}^{no} K(\frac{pj-pi}{h})} \quad (5)$$

where wij is the weight assigned to control observation j for treated observation i, K is the Kernel function, pi and pj are the propensity scores for the treated and control observations, and h is the bandwidth parameter controlling the weights' spread.

The treatment effect is estimated by comparing the average outcomes of the treated observations with their constructed counterfactual outcomes. This involves calculating the difference between the actual outcomes of the treated observations and the weighted average outcomes of the matched control observations. Kernel matching tends to use more information from the control group compared to methods like Nearest Neighbor, leading to potentially more stable and efficient estimates of the treatment effect (Morgan & Harding, 2006).

Stratification matching, also known as interval matching or subclassification, is a technique used to estimate the treatment effect by dividing the data into strata or intervals. Within each interval, the treatment effect is calculated by taking the mean difference in outcomes between treated and control observations (Caliendo & Kopeinig, 2008).

The overall treatment effect is obtained by combining the treatment effects estimated within each stratum. This involves calculating a weighted average of the stratum-specific treatment effects, where the weights are proportional to the number of observations in each stratum.

As outlined above, combining results from these methods offers a perspective on analyzing competitiveness and performance differences between DCs and MNEs.

In conducting the analysis, the average treatment effect (ATE) was determined, representing the difference between the outcomes of treated and control observations.

$$\Delta = y_1 - y_{01}$$

$$ATE = E(\Delta) = E(y_1 \mid x, D = 1) - E(y_0 \mid x, D = 0) \quad (6)$$

To assess whether there were significant differences in the means of covariates between the treated and control groups, a t-test was conducted to compare the outcomes for both groups (Rosenbaum & Rubin, 1985). Subsequently, the Average Treatment Effect on the Treated (ATT) was calculated, which represents the difference between the outcomes observed for the treated group and the outcomes those same observations would have experienced if they had not been treated.

$$ATT = E(\Delta|D=1) = E(y_1 \mid x, D=1) - E(y_0 \mid x, D=1) \quad (7)$$

where the second term is a counterfactual which is not observable and has to be estimated based on the propensity score method.

After matching propensity scores using each method, the outcomes of the treated and control observations are compared.

$$ATT = E(\Delta|p(x), D=1) = E(y_1 \mid p(x), D=1) - E(y_0 \mid p(x), D=0) \quad (8)$$

Empirical estimation assumes that each treated observation i is matched with j control observations, and their outcomes y_0 are weighed by $w_{\mathrm{i,j}}$.

$$\mathrm{ATT} = \frac{1}{n_1} \sum_{i\epsilon\{D=1\}} [y_{1,\mathrm{i}} - \sum_j w(i,j) y_{0,\mathrm{j}}] \quad (9)$$

For each year from 2010 to 2022, the ATT was calculated for indicators of competitiveness and profitability. The results were then compared across the different propensity score matching techniques. Additionally, sensitivity analysis was conducted to evaluate the robustness of the findings across various model specifications and matching algorithms.

Results and discussion

A significant challenge in international strategic management is enhancing the competitiveness and performance of companies. MNEs often outperform DCs when expanding internationally (Morck & Yeung, 1991). Figure 1 indicates that throughout the analyzed period, MNEs consistently achieved significantly higher revenue and net income compared to DCs. This advantage is largely due to their ability to

leverage national differences in market structures, product life cycles, access to advanced technologies, and other critical resources. These factors provide MNEs with competitive advantages, such as economies of scale, diversified risk, and access to a broader talent pool, ultimately leading to superior performance and growth opportunities.

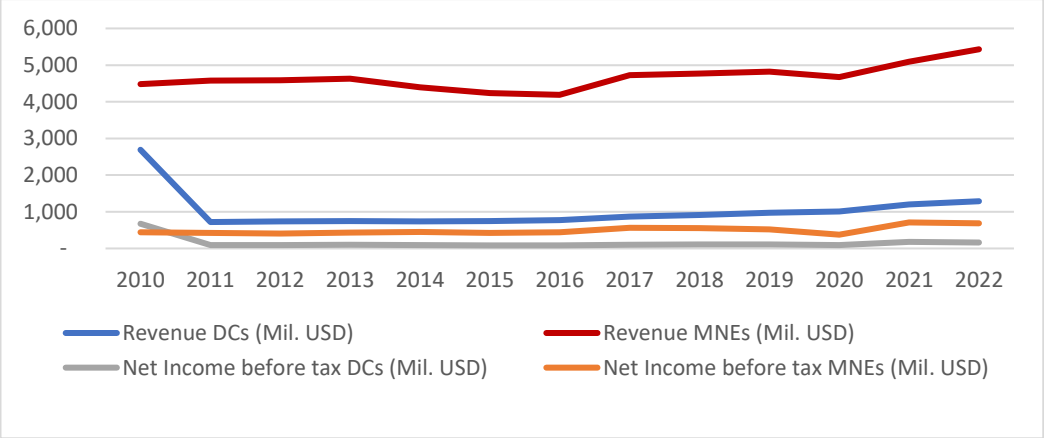

Figure 1. Long-term trends in revenue and net income before tax (in Million USD)
Source: Author's graphical representation and own data processing and analysis.

On the other hand, DCs often possess a deeper understanding of the local market, culture, consumer behavior, and preferences. This in-depth market knowledge enables them to tailor their products and services more effectively to meet local demands. Additionally, from an operational flexibility perspective, being more localized allows them to adapt more quickly to changes in the market or business environment. This agility is essential for responding to new opportunities or threats (Luo & Tan, 1998).

Although MNEs report significantly higher revenue and net income compared to DCs, their net income growth rate is lower due to a significantly larger reporting base. Table 1 indicates that the estimated ATT for the net income growth rate shows that DCs exhibit a relatively constant growth trend. However, in recent years, MNEs have surpassed the net income growth rate of DCs by approximately 3,4% to 6,4%. Significant differences were observed between 2018 and 2019 in the energy and

financial industries, as well as in healthcare and technology. Companies with significant growth rates are regionally found in Europe and South America. The results are consistent with studies conducted across different periods, geographic areas, and industries (Bellak, 2001) (Greenaway, Sousa, & Wakelin, 2004) (Pai & Hiremath, 2013) (Al-Kwifi, Farha, & Zaraket, 2020) (Bellak, 2001; Greenaway et al., 2004; Pai & Hiremath, 2013; Al-Kwifi et al., 2020). These empirical findings indicate that, in addition to company size, industry sector, and geographical location, the most critical explanatory variables are company-specific advantages. These include global market presence, access to capital, and differences in technological and managerial expertise, all interconnected.

Table 1. ATT for net income growth rate (%)

Estimation method	2011/2010	2013/2012	2016/2015	2019/2018	2022/2021
T-test	2.369	2.617	3.736*	15.224***	-6.350*
	(0.2292)	(0.2626)	(0.3307)	(0.3487)	(0.3392)
Regression with dummy	3.986*	2.524	1.194	11.355***	-9.013**
	(0.2495)	(0.2859)	(0.3602)	(0.3794)	(0.369)
ATT Nearest Neighbor Matching method	-0.734	-2.920	-1.234	13.575	-5.957
	(0.3056)	(0.3225)	(0.4407)	0.2677)	(0.4523)
ATT Radius Matching method	2.594	2.406	3.287	14.254	-6.449
	(0.2316)	(0.2686)	(0.3324)	(0.3570)	(0.3481)
ATT Kernel Matching method	2.005	1.533	-1.610	12.303	-3.445
	(0.2708)	(0.2895)	(0.4922)	(0.2826)	(0.3488)
ATT Stratification Matching method	1.330	2.658	-2.782	13.321	-5.683
	(0.2756)	(0.141)	(0.2955)	(0.3659)	(0.4131)

Notes: PSM results with standard errors in parenthesis. *, **, and *** denote statistical significance at 10, 5, and 1 percent level.

Liquidity refers to a company's ability to meet its short-term liabilities. Liquidity ratios do not directly address solvency issues, but poor liquidity over the long term can negatively impact a company's solvency. The current ratio, calculated as the ratio between current assets and current liabilities, suggests that a higher current ratio indicates a higher level of liquidity, as it shows that the company has more current assets relative to its current liabilities. However, maintaining a high level of

unused cash can ultimately reduce profitability. This demonstrates the trade-off between liquidity and profitability (Utami, 2017).

It is observed that ATT for the current ratio shows relatively close results across the analyzed companies, with DCs slightly outperforming MNEs in recent years, with values ranging between 0.2 and 0.4 (Table 2). The highest values are recorded in healthcare and technology, in Asia, America, and Europe. These results suggest that MNEs rely on debt financing (Hansson, Olofsdotter, & Thede, 2016) which is consistent with the profit margin results as will be seen in the following sections.

Table 2. ATT for current ratio

Estimation method	2010	2013	2016	2019	2022
T-test	0.017*	0.015*	0.197***	0.225***	0.239***
	(0.057)	(0.053)	(0.045)	(0.036)	(0.048)
Regression with dummy	0.166***	0.212***	0.355***	0.356***	0.367***
	(0.061)	(0.057)	(0.048)	(0.039)	(0.052)
ATT Nearest Neighbor Matching method	0.110	0.204	0.410	0.465	0.409
	(0.076)	(0.054)	(0.060)	(0.039)	(0.065)
ATT Radius Matching method	0.014	0.016	0.195	0.220	0.235
	(0.062)	(0.058)	(0.049)	(0.041)	(0.053)
ATT Kernel Matching method	-0.046	0.076	0.290	0.347	0.290
	(0.047)	(0.076)	(0.039)	(0.027)	(0.064)
ATT Stratification Matching method	0.000	0.116	0.329	0.390	0.322
	(0.076)	(0.052)	(0.046)	(0.029)	(0.054)

Notes: PSM results with standard errors in parenthesis. *, **, and *** denote statistical significance at 10, 5, and 1 percent level.

Comparing the solvency ratios of DCs and MNEs to understand the financial dynamics and risk profiles of these two types of companies reveals that MNEs, due to their diversified operations and access to global capital, exhibit higher solvency ratios compared to DCs. Table 3 shows that this trend continues until 2016, after which the results become linear. Companies operating in the healthcare and technology sectors have the highest solvency ratios, predominantly located in Asia and Australia.

Table 3. ATT for solvency ratio (%)

Estimation method	2010	2013	2016	2019	2022
T-test	-3.413***	-3.431***	0.169	1.329***	0.687*
	(0.408)	(0.406)	(0.405)	(0.398)	(0.411)
Regression with dummy	-3.164***	-3.231***	-0.023	1.236***	0.856**
	(0.428)	(0.425)	(0.418)	(0.410)	(0.423)
ATT Nearest Neighbor Matching method	-0.916	-0.900	0.607	2.135	3.287
	(0.343)	(0.363)	(0.384)	(0.532)	(0.485)
ATT Radius Matching method	-3.505	-3.587	-0.165	0.965	0.339
	(0.428)	(0.428)	(0.430)	(0.419)	(0.428)
ATT Kernel Matching method	-3.372	-3.325	0.211	1.892	1.141
	(0.273)	(0.544)	(0.636)	(1.892)	(0.549)
ATT Stratification Matching method	-2.809	-2.746	0.817	2.548	1.655
	(0.433)	(0.490)	(0.475)	(0.273)	(0.496)

Notes: PSM results with standard errors in parenthesis. *, **, and *** denote statistical significance at 10, 5, and 1 percent level.

The profit margin, defined as the percentage of profit before tax relative to operating revenue, shows a trend consistent with the net income growth rate, reflecting a similar trajectory. Until 2016, healthcare companies reported higher net margins compared to those in other industries, particularly in America. Throughout the analysis period, companies in the Financials sector consistently exhibit significant margins. The disparity between the profit margins of DCs and MNEs diminishes notably after 2017, with MNEs demonstrating increasingly higher margins in recent years (Table 4). Profitability differences between companies can be attributed to accounting, managerial, and economic factors. In terms of accounting, MNEs' motivation to minimize their tax burden may result in lower performance. As previously shown, the fact that MNEs rely on debt financing may lead to a reduction in their taxable profits (Hansson, Olofsdotter, & Thede, 2016). Economically, higher capital intensity, which significantly boosts labor productivity, can lead to increased profit margins. If the opportunity costs of using internally generated funds are lower than those of externally sourced funds, managers may be willing to accept lower profitability when utilizing reinvested profits (Bellak, 2001). Related to firm size,

market share has been recognized as a significant determinant of profitability (Mataloni, 2000).

Table 4. ATT for profit margin (%)

Estimation method	2010	2013	2016	2019	2022
T-test	35.381***	27.206***	12.154***	3.438*	0.525*
	(0.5426)	(0.4930)	(0.3441)	(0.2256)	(0.2287)
Regression with dummy	41.18***	35.34***	14.135***	3.928*	-0.747*
	(0.5547)	(0.5365)	(0.3745)	0.2454)	(0.2491)
ATT Nearest Neighbor Matching method	36.433	29.242	8.632	5.313	3.448
	(0.4589)	(0.3291)	(0.5541)	(0.3032)	(0.1759)
ATT Radius Matching method	37.356	27.098	12.922	3.233	-0.685
	(0.6657)	(0.5913)	(0.4088)	(0.2652)	(0.2559)
ATT Kernel Matching method	36.998	30.502	12.966	6.197	3.679
	(0.6450)	(0.6890)	(0.3760)	(0.3370)	(0.1759)
ATT Stratification Matching method	36.281	30.133	10.863	5.269	3.181
	(0.6490)	(0.5724)	(0.3233)	(0.2545)	(0.2285)

Notes: PSM results with standard errors in parenthesis. *, **, and *** denote statistical significance at 10, 5, and 1 percent level.

Return on shareholders' funds, calculated as the ratio between profit before tax and shareholders' funds, reveals that the dynamics of this indicator are consistent with those observed in the profit margin, following the same trend

Table ***5***. Companies in the Energy, Industrial, and Financials sectors in Europe and South America record the highest values for this indicator. The findings are consistent with previous findings across developed, developing, and transition economies (Aydin, Sayim, & Yalama, 2007), (Valsamis, Katsaiti, & Petrakis, 2011) (Aydin et al., 2007; Valsamis et al., 2011).

Table 5. ATT for Return on Shareholders' funds (%)

Estimation method	2010	2013	2016	2019	2022
T-test	3.817***	4.416***	1.803**	0.535*	-4.204***
	(0.877)	(0.831)	(0.838)	(0.725)	(0.826)
Regression with dummy	4.105***	3.177***	1.018*	0.263*	-4.497***
	(0.897)	(0.904)	(0.912)	(0.789)	(0.898)
ATT Nearest Neighbor Matching method	4.339	4.719	2.050	1.286	-2.650
	(0.750)	(0.896)	(0.872)	(0.831)	(0.988)
ATT Radius Matching method	5.817	6.141	3.026	4.633	-2.291
	(0.5739)	(0.1258)	(0.1214)	(0.1321)	(0.1328)
ATT Kernel Matching method	4.842	4.117	2.450	2.078	-1.930
	(0.1098)	(0.919)	(0.771)	(0.810)	(0.1369)
ATT Stratification Matching method	4.468	4.505	2.775	2.156	-2.055
	(0.913)	(0.1028)	(0.918)	(0.1009)	(0.1098)

Notes: PSM results with standard errors in parenthesis. *, **, and *** denote statistical significance at 10, 5, and 1 percent level.

Return on assets is a key metric for evaluating a company's efficiency in generating profit from its total assets. MNEs report a higher return on assets compared to DCs in the early period of the analyzed interval. In recent years, DCs have outpaced MNEs by margins ranging from 0.4% to 1.15% (

Table *6*). A higher return on assets indicates superior performance, demonstrating the company's effectiveness in leveraging its assets to generate income and achieve profitability. Companies in the Technology sector, predominantly located in South America and Europe, exhibit the highest return on assets. The main explanatory variables stem from the likelihood that companies are significantly

influenced by technology spillovers, industry composition, and competition (Bellak, 2001).

Table 6. ATT for return on assets (%)

Estimation method	2010	2013	2016	2019	2022
T-test	-1.812*	-1.270*	0.2590*	-0.094*	-0.026*
	(0.937)	(0.816)	(0.194)	(0.24)	(0.632)
Regression with dummy	-3.206***	-2.430***	-0.661***	-0.481*	0.128*
	(0.1019)	(0.888)	(0.21)	(0.261)	(0.687)
ATT Nearest Neighbor Matching method	-2.366	-1.742	0.468	0.878	1.151
	(0.1268)	(0.140)	(0.261)	(0.323)	(0.852)
ATT Radius Matching method	0.547	0.429	0.758	0.871	-0.145
	(0.718)	(0.691)	(0.545)	(0.271)	(0.459)
ATT Kernel Matching method	-2.682	-2.047	0.170	0.390	0.438
	(0.1748)	(0.1381)	(0.187)	(0.409)	(0.547)
ATT Stratification Matching method	-2.623	-1.984	0.323	0.455	0.553
	(0.1022)	(0.1192)	(0.139)	(0.312)	(0.325)

Notes: PSM results with standard errors in parenthesis. *, **, and *** denote statistical significance at 10, 5, and 1 percent level.

Labor productivity, defined as the ratio between total output and total input, respectively the ratio between turnover and the number of employees, indicates that productivity differences between DCs and MNEs are significant, especially in terms of productivity, wages, skills, and factor intensity. Structural factors such as industry, company size, and market share are the most relevant in explaining these differences (Bellak, 2001).

Turnover for MNEs is up to six times higher, and their number of employees is up to four times greater compared to DCs. This leads to a significantly higher

output-per-input ratio for MNEs over DCs. From a territorial perspective, America scores the highest, with the energy sector achieving by far the best productivity scores.

The results presented in Table 7 suggest that DCs can benefit from the presence of MNEs through intensified competition. This imitation effect can lead to increased productivity, technological advancements, reduced production costs, and improved efficiency. These factors are intended to contribute to competitive policies among governments to attract MNEs, thereby enhancing DCs' exports and positively impacting their market share (Greenaway, Sousa, & Wakelin, 2004). Additionally, productivity has a significant impact on the debt structure of MNEs (Valsamis, Katsaiti, & Petrakis, 2011).

Table 7. ATT for labor productivity (in Million USD)

Estimation method	2010	2013	2016	2019	2022
T-test	-3.055*	0.621*	-0.110*	-0.285*	-0.523*
	(0.2314)	(2.593)	(0.291)	(0.370)	(0.455)
Regression with dummy	-2.806*	0.914*	0.251*	-0.022*	-0.315*
	(0.2521)	(0.2823)	(0.317)	(0.403)	(0.495)
ATT Nearest Neighbor Matching method	-1.989	0.975	0.350	0.314	0.185
	(0.656)	(2.734)	(0.274)	(0.248)	(0.270)
ATT Radius Matching method	-2.133	1.679	-0.088	-0.254	-0.407
	(0.762)	(0.2937)	(0.280)	(0.332)	(0.403)
ATT Kernel Matching method	-1.715	1.409	0.130	-0.010	-0.348
	(0.1281)	(0.2780)	(0.224)	(0.267)	(0.353)
ATT Stratification Matching method	-4.613	1.645	0.321	0.275	0.100
	(0.3127)	(0.3584)	(0.227)	(0.243)	(0.290)

Notes: PSM results with standard errors in parenthesis. *, **, and *** denote statistical significance at 10, 5, and 1 percent level.

The asset turnover ratio, defined as the ratio between turnover and total assets measures how efficiently a company's assets support sales. This ratio has a significant impact on profit growth.

In the first part of the analyzed period, DCs recorded a significantly higher asset turnover ratio, particularly in the Industrial and Technology sectors. However, after 2015, the differences diminished significantly (Table 8. ATT for Asset turnover ratio

Estimation method	2010	2013	2016	2019	2022
T-test	7.741***	9.642***	0.226***	0.029*	-0.022*
	(0.2704)	(0.3021)	(0.082)	(0.016)	(0.015)
Regression with dummy	6.064**	8.945***	0.347***	0.082***	0.032*
	(0.2945)	(0.3291)	(0.089)	(0.017)	(0.016)
ATT Nearest Neighbor Matching method	7.830	9.742	0.348	0.146	0.093
	(0.3426)	(0.3088)	(0.140)	(0.020)	(0.015)
ATT Radius Matching method	7.719	9.623	0.218	0.019	-0.031
	(0.3669)	(0.4099)	(0.111)	(0.018)	(0.016)
ATT Kernel Matching method	7.709	9.632	0.265	0.063	0.011
	(0.2525)	(0.501)	(0.112)	(0.024)	(0.014)
ATT Stratification Matching method	7.761	9.683	0.297	0.099	0.046
	(0.2346)	(0.3421)	(0.111)	(0.019)	(0.018)

Notes: PSM results with standard errors in parenthesis. *, **, and *** denote statistical significance at 10, 5, and 1 percent level.

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As previously mentioned, the turnover of MNEs compared to DCs is up to six times higher, and total assets for MNEs are up to four times larger than those of DCs. This suggests that MNEs' investment in assets leads to increasing revenue, and their asset management positively impacts profit growth. Balancing asset management effectiveness is very important. If investment in assets is too high, the cost of capital increases, negatively affecting profit. Conversely, if assets are kept too low, profitable sales will be diluted (Utami, 2017).

Table 8. ATT for Asset turnover ratio

Estimation method	2010	2013	2016	2019	2022
T-test	7.741***	9.642***	0.226***	0.029*	-0.022*
	(0.2704)	(0.3021)	(0.082)	(0.016)	(0.015)
Regression with dummy	6.064**	8.945***	0.347***	0.082***	0.032*
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Notes: PSM results with standard errors in parenthesis. *, **, and *** denote statistical significance at 10, 5, and 1 percent level.

Net income per employee, calculated as the ratio between net income and the number of employees, provides insight into a company's efficiency in utilizing its human resources to generate profit. During the analyzed period, fluctuations are observed, but the overall trend shows that MNEs consistently achieve higher results compared to DCs (Table 9). It is also observed that the recent years are characterized by a decrease in the existing performance gap (Mihaylova, 2023).

The findings are explained by the fact that the net income for MNEs is up to five times higher than that of DCs, while the number of employees is up to four times greater. Companies in the healthcare, technology, and financial sectors stand out from other industries based on their results. These results allow companies to benchmark themselves against industry standards or competitors, serving as a measure of productivity by indicating how much profit is generated per employee.

MNEs exhibit greater flexibility, allowing them to downsize more readily during economic downturns compared to DCs. Conversely, they also contribute more significantly to job creation during economic upturns, which leads to higher productivity (Blanchard, Dhyne, Fuss, & Mathieu, 2013).

The main factors that explain this dynamic are company size (larger companies may benefit from economies of scale, potentially leading to higher net income per employee); operational efficiency (efficient processes, automation, and a skilled workforce may contribute to higher net income per employee); cost structure (companies with lower operational costs and higher revenue generation capabilities

tend to have a higher net income per employee); market conditions (economic conditions, market demand, and the competitive landscape may also impact this metric).

Table 9. ATT for net income per employee (in Million USD)

Estimation method	2010	2013	2016	2019	2022
T-test	-0.187*	-0.142*	-0.095*	0.130*	-0.103*
	(0.123)	(0.121)	(0.115)	(0.083)	(0.139)
Regression with dummy	-0.148*	-0.091*	-0.024*	0.207**	-0.084*
	(0.134)	(0.132)	(0.126)	(0.091)	(0.151)
ATT Nearest Neighbor Matching method	-0.097	-0.049	-0.027	0.176	0.002
	(0.076)	(0.091)	(0.033)	(0.068)	(0.061)
ATT Radius Matching method	-0.140	-0.098	-0.095	0.117	-0.076
	(0.096)	(0.096)	(0.092)	(0.073)	(0.115)
ATT Kernel Matching method	-0.066	-0.02	-0.021	0.176	-0.060
	(0.030)	(0.050)	(0.050)	(0.038)	(0.082)
ATT Stratification Matching method	-0.251	-0.206	-0.019	0.165	0.001
	(0.109)	(0.155)	(0.054)	(0.035)	(0.079)

Notes: PSM results with standard errors in parenthesis. *, **, and *** denote statistical significance at 10, 5, and 1 percent level.

Conclusion

The study examines the comparative analysis of competitiveness and performance differences between DCs and MNEs using PSM methodology. Unlike other studies that have focused on either specific countries, regional analyses, particular industries, or even a selection of companies, this study aims to analyze these indicators on a global scale for greater representativeness. Utilizing the Orbis database, which covers 121 countries from 2010 to 2022, the paper analyzes profitability and productivity indicators as outcome variables between DCs (treated observations) and MNEs (control observations). To ensure unbiased and representative model estimation, confounding variables that may impact both the treatment selection and outcome variables were identified. These include company size, industry classification, regional factors, countries' economic classification, and the corruption perceptions index.

The differences observed in the outcome variables suggest that the treatment has a causal effect, providing insights into the impact of the intervention on the outcome of interest. To enhance the robustness of the PSM results, multiple matching algorithms were employed, including Nearest Neighbor Matching, Radius Matching, Kernel Matching, and Stratification Matching methods.

The analysis highlights the drivers of competitive advantage and the performance gap between DCs and MNEs, leading to the following conclusions.

During the analyzed period, MNEs consistently achieved significantly higher revenue and net income compared to DCs. Competitive advantages such as economies of scale, diversified risk, and access to broader resources contribute to superior performance and growth opportunities for MNEs. Meanwhile, DCs are distinguished by their adaptability and agility, enabling them to respond effectively to opportunities and threats.

The net income growth rate analysis reveals that DCs outperformed MNEs in the initial stages of the period. However, recent years have seen a significant shift, with MNEs showing markedly superior performance. Key factors driving this change include company-specific advantages such as a global market presence, greater access to capital, and disparities in technological and managerial expertise.

Liquidity and solvency indicators show that, in recent years, DCs have slightly outperformed MNEs. The profit margin and return on shareholders' funds exhibit a similar trend to the net income growth rate, with the gap narrowing significantly in recent years. The differences in profitability between companies can be attributed to both accounting factors (such as MNEs' tendency to reduce taxable profits, which may lead to lower reported performance) and economic factors (such as higher capital intensity, which substantially enhances efficiency and productivity).

In recent years, DCs have slightly outpaced MNEs in terms of return on assets. Explanatory factors include the influence of technology spillovers, industry composition, and competitive dynamics.

Productivity indicators position MNEs significantly ahead of DCs in terms of labor productivity and net income per employee. Key factors explaining this trend include company size, operational efficiency, cost structure, and market conditions. The recent narrowing of performance gaps between DCs and MNEs can be attributed to the benefits that DCs derive from the presence of MNEs. The imitation effect can lead to increased productivity, technological advancements, enhanced absorptive capacity, and improved efficiency for DCs. Productivity is also a key factor in determining the debt structure of MNEs.

In terms of limitations, while the study investigates competitiveness and performance differences between DCs and MNEs using four PSM methods to enhance the robustness of the results, future research should address challenges such as temporal changes in the economic environment and industry conditions. Additionally, external economic shocks, such as financial crises or global pandemics, which can disproportionately impact the performance of DCs and MNEs, should be considered.

Acknowledgement

This paper was co-financed by The Bucharest University of Economic Studies during the PhD program.

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