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A Stochastic Frontier Analysis

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Master Thesis presented as partial requirement for obtaining the Master's degree in Information Management, specialization in Knowledge Management and Business Intelligence

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THE IMPACT OF JOURNAL EDITORS IN ACADEMIC PUBLICATIONS: A STOCHASTIC FRONTIER ANALYSIS

By

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Master Thesis presented as partial requirement for obtaining the Master's degree in Information Management, with a specialization in Knowledge Management and Business Intelligence

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ABSTRACT

Since the task of deciding whether a research work is published or not is carried out by journal editors, the composition and attributes of editorial board members are relevant variables to be investigated. In particular, when trying to understand if the scientific knowledge shared with the world is impacted by other factors instead of being judged solely by the quality and content of the research. Hence, this research analyses the composition of editorial teams from 27 journals in three main areas – Economics & Econometrics, Finance, and Business & International Management - and their influence on the efficiency of such journals.

After collecting the data required to perform this study, the composition and characteristics of editorial board members, as well as an analysis aiming to identify patterns between editors' characteristics and the context and impact of scientific publication journals were carried out. Some of the data collected about the editors and journals for the analyses were the gender, geography, affiliated institution, publisher's categories, position in those categories, H-index, and SCImago Journal Rank. The gathered data was then used to build a Stochastic Frontier Analysis (SFA) model to analyze journals' efficiency, as input. The SFA allows us to develop a multi-input single-output scenario. Primary findings suggest that the performance of research journals' is influenced by the size of the editorial board, gender, and location but not by the performance of each editor as an individual. There is an overwhelming presence of US-based, male, and academic editors among the editorial boards as well as US institutions represented by scholars. The results show that economics and finance journals tend to be more efficient than business journals and that the research industry, despite having a small margin to improve, appears to be efficient.

KEYWORDS

Editorships, Editorial Boards, Journal Impact, Journal Ranking, Stochastic Frontier Analysis

INDEX

LIST OF FIGURES

LIST OF TABLES

LIST OF APPENDIXES

LIST OF ABBREVIATIONS AND ACRONYMS

SFA	Stochastic Frontier Analysis
DEA	Data Envelopment Analysis
SJR	SCImago Journal Rank
US	United States
UK	United Kingdom
OLS	Ordinary Least Squares
MLE	Maximum Likelihood Estimation

1. INTRODUCTION

Nowadays, editors have a vast impact on academic journals since they are directly involved in the decision-making process. Hence, editorial boards of academic journals are the ones that govern the scope, mission, and context of the research publications by monitoring and deciding on what is published. Therefore, the composition of editorial boards and characteristics of its members, in particular their affiliations and individual impact, matter on the influence that a journal has, which consequently, affects its context as well as output since those are the ones who control the advances in the scientific knowledge that is shared with the world (Petersen et al., 2017).

According to Krell (2010), research has shown evidence that authors' bias, personal environments or affiliations, and strategic considerations are influential factors in the quality and relevance of references as well as the use of publication metrics to evaluate journals and research performance. Also, according to Petersen (2017), editors have a critical role in the scientific publication system, as they make the final decisions on whether to accept or reject research work. Additionally, there have been several studies done on academic journals' editorial teams and their characteristics, affiliations, and overall diversity. Some researchers studied the cooperation between authors and editors and how it affects the publications and citation impact (Zhang et al., 2021), while others studied the internal governance of research journals focusing on editorial teams of African academic journals (Mendonça et al., 2018).

Petersen et al. (2017), also showed that having editorial board members with multiple editorships and affiliated with highly reputed institutions is positively related to journal impact, whereas the duration of editors' appointments is negatively associated when analyzing editorial governance and journals' impact. It has also been shown that editors are responsible for the quality of their journals, and consequently, the higher the quality of a journal the more it can contribute to enhancing the reputation of the affiliated institutions (Wu et al., 2018). However, an efficiency analysis has not been made in this context. First, further studies on how to collect information about editorial board members are essential. Given that editors are the most accountable for a journal's quality, high-quality journals will likely also help to improve the reputation of their affiliated institution. So, due to editorial boards' variability, the journal's website might not reflect the most updated information. Therefore, through the exploration, collection, and analysis of the editor's personal information, namely name, affiliations, research field, or location, as well as journal's structure strong progress could be made on the academic journal's reputation, its members, and associated institutions (Wu et al., 2018). To accomplish this, we will use stochastic frontier analysis methods in order to research journal's efficiencies and examine if the composition of editorial teams influences a journal's output.

Thus, this thesis will focus on editorial teams of journals in three disciplines: Economics & Econometrics, Finance, and Business & International Management, as this work aims to analyze if a journal's output is affected by its editors. Consequently, it is expected that this research provides further insights on the effectiveness of members of editorial teams and if those are relevant to a journal’s rankings and influence the categories that they are a part of.

The main question leading this research is: “Does an individual editor’s reputation and composition of editorial boards influence a journal’s performance or efficiency?”. To attempt to answer the research question, the following objectives were defined:

- Overview of the composition and characteristics of editorial board members.
- Perform an analysis of the collected data about editorial teams and journals, seeking to find patterns.
- Use of indexes, rankings, and editor’s attributes to understand if there is a relation between the journal’s impact and the composition of editorial councils. And, if this phenomenon influences the scientific publication system.
- Build a Stochastic Frontier model to estimate individuals’ impact on the journal’s overall efficiency.

To accomplish this, we first conducted a literature review to acquire in-depth knowledge of the subjects present in this study and to find gaps in previous studies that can be further explored. Afterward, data about the editorial teams were collected and processed before the analysis. Following a comprehensive analysis, an SFA model was developed. Then, the results were discussed to find patterns and relations between the defined variables. Finally, conclusions were taken in order to answer the main question of this research work.

By investigating editorial board compositions of 27 journals, the results obtained will help contribute to the further exploration of some unknown editorial structures, uncover patterns relating to editorships and journal performances and comprehend the production efficiency from a journal’s perspective. This will allow arguing about journal governance and how it is their “inner works”. To do so, we propose a model that shows how much influence editorships exert on technical efficiency estimates. Thus, the justification for this study is based on the recognition that there is a lot of competition in the research industry, and that its outcomes can be easily susceptible to influences such as the efficiency of editors and journals.

This thesis is divided into several sections which are organized as follows. Section two has the literature review that addresses theoretical concepts as background for a clear understanding of the research analysis. Section three presents the methodology which references both the theoretical and practical part of the usage of all methods and models, namely from the data collection process to the development of the SF model. Section four holds the results of the descriptive and stochastic frontier analysis. Section five discusses the obtained results and compares them to prior studies, and section six concludes with a summary and comparison of the analysis of the results found, presenting some policy recommendations.

2. THEORETICAL FRAMEWORK

2.1. SCIENTOMETRICS

Scientometrics, a field of study that measures and analyzes scientific literature and a sub-field of bibliometrics, studies quantitative aspects of science and can be used to measure the research papers and academic journals impact, the understanding of scientific citations, or the publication productivity/efficiency of researchers. (Leydesdorff & Milojevic, 2012; Suresh et al., 2020). According to Hess (1997, at p. 75), Scientometrics is the "quantitative study of science, communication in science, and science policy". Since then, it has been applied to different contexts through the use of some common indicators the Science Citation Index (SCI), the H-index, the g-index, and so on (D. Hess, 1997). The most important for this research, the H-index, is a metric that represents the impact of individual authors, which can be used online with Google Scholar (GS), Web of Science, and Scopus (Osabe & Jibu, 2018)

2.2. ACADEMIC JOURNALS AND EDITORIAL GOVERNANCE

Academic journals are considered a key element for scientific research breakthroughs and for publishing the latest theories and research. In that way, ranking journals allow the readers to measure the influence of the journal or the most acknowledged among a specific discipline as well as, from a researcher's perspective, to decide which journal can be the best choice to publish. However, do these various ranking measures permit the evaluation of actual scientific impact and fairly assess performance throughout disciplines? (Michael Hall, 2011; Sasvári et al., 2019).

Such journals are composed of editorial boards that are constituted by appointed members, commonly referred to as the gatekeepers of scholarly journals. Journal editors compose the editorial boards, determining the aims and context of scholarly journals by monitoring, affecting, and even controlling the scientific knowledge advances (Petersen et al., 2017). In that way, journal scholars have significant power over a journal's subjects since they are the ones judging and taking the final decisions if a research work falls within the scope of the journal and if they are appropriate or not for publication (Xie et al., 2020).

Journal editorships have been described as the "governance set-up that shapes the selection, construction, amplification and curation of research input, output and impact" (Mendonça et al., 2018, p. 2). Considered to act as an indicator of research outputs, the number of editorships at a publishing organization can be considered in some rankings as an influence indicator (Petersen et al., 2017).

According to Xie et al. (2020, p. 2), editorship information includes “research interests, research experience, personal identity, and affiliated departments”. Hence, editor's characteristics are critical in the publication system, thus being of paramount importance for the analysis of editor’s information, such as geography, gender, background, current affiliations, and so on (Miniaci & Pezzoni, 2015). For this work’s purpose, we will consider the editor’s information as ‘‘Editormetrics’’. This methodology has been recognized to represent quantitative assessments that get the journal's editors as an empirical method for scientific analysis (Mendonça et al., 2018, p. 3). Also, it assumes that a journal’s prestige is tied to the journal's editors (Xie, Wu & Li, 2019, p. 1334).

Therefore, in this study, the focus is the analysis of cross-sectional data about the editorial teams to calculate technical efficiency estimations for the research journals industry. To accomplish this, several approaches have been applied in order to get the performance of editors as well as academic journals. To do so, we opted to use a different approach, a stochastic frontier analysis (SFA) to estimate production efficiency and performance. Also, an important fact worth mentioning about cross-sectional data, and that might represent a downfall of this type of data, is that only gives a snapshot of the producers and their efficiencies as it does not allow us to track the efficiency performance throughout a given period in time (Kumbhakar & Lovell, 2000).

Efficiency and Productivity measurement

Coelli et al. (2005) consider two components to measure the economic efficiency of a firm, technical efficiency, and allocative efficiency describing the latter as a measure of the capacity of a firm to utilize its inputs in an optimal way given their cost. Additionally, Farrell (1957) defined technical efficiency as the ability of a firm to obtain the maximum output for a given set of inputs. It is also important to mention that firms, in the context of these work, are the academic journals while the output is the performance measures, and the input is the resources used to create the published academic research such as editorial boards characteristics. Hence, computing the aforementioned efficiency measures implicates the estimation of the unknown production frontier, that is, inputs and outputs together form a production function upon which a number of plausible assumptions in the form of mathematical axioms are suggested (Strange et al., 2021). To measure (in)efficiency, the distance between the actual output and the equivalent estimated maximum amount possible is calculated (Farrell, 1957). Therefore, the production efficiency frontier represents all "technically efficiency" input-output combinations that could exist. The frontier analysis shows the maximum production of outputs obtainable for the provided inputs, or the necessary input minimum to generate the output (Strange et al., 2021). And then, this estimated frontier is used for the benchmarking, that is when the observation being evaluated is compared against the efficient frontier by determining the distance using a distance function (Strange et al., 2021).

According to Bogetoft & Otto (2011), there are two main methodologies for benchmarking – Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). Some major differences between these techniques are the measurement errors and statistical noise incorporation in the deviation from the estimated frontier on the SFA since not all deviations from the frontier are due to technical inefficiency but from the unintentional omission of important variables from the inputs or measurement errors. This enables the efficiency analysis in circumstances where we cannot be sure that the 'output gap' between observed and optimal production is free of random (or stochastic) factors. Another distinction is the assumption of production technology, such as a parametric production function (Coelli et al., 2005).

So, as already mentioned above, in this study we will focus on the parametric approach that allows the impacts of noise and inefficiency to be separated and therefore making it less sensitive to outliers, given that the first approach (DEA) does not account for the statistical noise. Additionally, it also entails the application of econometric techniques where the efficiency is calculated relative to a frontier production function. Such analysis has demonstrated good results whenever applied to other sectors to measure production efficiency. Some examples of its usage before are enterprises, airports, container ports, and paddy farming systems efficiency or even for individual countries' industries throughout various sectors (Cullinane & Song, 2006; Hidayah et al., 2013; Oum et al., 2008; Zamanian et al., 2013).

Stochastic Frontier Analysis

Aigner, Lovell & Schmidt (1977) and Meeusen & van Den Broeck (1977) individually proposed the Stochastic Production Frontier Models, represented by the following equation. These models are known for allowing technical efficiency and acknowledging that random influences beyond the control of producers might affect the output.

$$(1) \quad y_i = f(x_i;\beta) + \varepsilon_i \; = \; f(x_i\beta) - u_i + v_i$$ [1]

The y represents the output of the model, the x_i is the vector of inputs, and the error term (ε_i) is the level of efficiency for a firm i. The u_i - random variable associated with technical inefficiency - captures the inefficiency of the model, that is, if a firm produces less than its maximum capacity according to the inputs available, while the v_i captures symmetric random influences beyond the control of the firm to account for statistical noise. So, the higher the u term, the most inefficient a firm will be (Bogetoft & Otto, 2011; Parmeter & Kumbhakar, 2014; Zamanian et al., 2013). These allow us to presume two

[1] $y > 0$; $\varepsilon_i \in [0,1]$

things: a stochastic relationship among inputs and outputs and that deviations from the estimated frontier might reflect inefficiencies or noise in the data (Bogetoft & Otto, 2011). Furthermore, the above model is called a stochastic frontier production function because the outputs are restricted from above by the random (or, stochastic) variable expressed as $f(x_i\beta) + v_i$ (Coelli et al., 2005). In fact, an SFA takes into account that the structure of the production function and the data generation process is identified beforehand but that the features of the function defined by the parameters β are unknown (Bogetoft & Otto, 2011). For example, for these unspecified parameters we can assume that the production functional form used is a Cobb-Douglas function, further explained later on:

$$(2) \quad y = \beta_0 x_1^{\beta_1} x_2^{\beta_2} \ldots x_m^{\beta_m}$$

However, as Goldberger (1968) showed in his research when the Cobb-Douglas (i.e. constant elasticity) specification is used the standard specification and approach to estimation shift attention, apparently unknowingly, from the mean to the median as a measure of central tendency. Moreover, the actual observations from the different firms are used to estimate the production function, while the estimated function is used to measure the performance of the individual firms. To estimate the values of the unknown parameters, the SFA models use statistical principles, particularly the maximum likelihood estimation (MLE), a method that estimates observations' optimum values or the best approximation of the true distribution (Bogetoft & Otto, 2011; Nishii, 1989). Given that an SFA model is normally maximum likelihood estimations, it requires the following assumptions regarding the distribution of the error terms, v_i follows a normal distribution, u_i a positive half-normal distribution or a positive truncated normal distribution and that both, v and u are independent. Such beliefs cause a left-skewed distribution of the total error terms ($\varepsilon_i = -u_i + v_i$) (Coelli et al., 2005).

Although, in the case of the u_i the half-normal distribution is the most commonly used, there are other distributional assumptions proposed for this term, such as exponential, truncated normal, or gamma distribution. However, as Cullinane & Song (2006) stated in their research, the best structure for the data can only be defined after a cautious look into the available data and the characteristics of the industry.

Production functional form used in efficiency analysis

An SFA can assume various functional forms aiming to estimate the production function. This function can be estimated using several methods that transform its parameters into linear or non-linear models. Some examples of functions that have been used are linear, linear in logarithms (Cobb-Douglas), quadratic, quadratic in logarithms (trans-log), cubic, or other higher-order exponents. These functions can also be estimated with variable transformations such as exponentials or square roots (Bogetoft & Otto, 2011).

According to Meeusen & van Den Broeck (1977), the Cobb-Douglas function is estimated by converting both sides of an equation by using ordinary least squares (OLS) logarithms. So, as a model, the left side of the equation will be the logarithm of the output and the right side the logs of the input vectors and error components. Nevertheless, non-linear functions can also be transformed into linear through the application of logarithms which will result in a log-linear function (Goldberger, 1968). Consequently, if we take the logs of both sides, and account for the same type of data to calculate a distance function in the Cobb-Douglass functional form, there is, a linear function with the variables in the log form, we have a normal linear regression model since the variables have been transformed to logarithms resulting in the following equation:

$$(3) \quad \ln y_i = \ln f(x_i;\beta) + (v_i - u_i)$$

$$\Leftrightarrow \ \ln y_i = \beta_0 + \ \beta_i \ln f(x_i) + \varepsilon_i$$

Even though, estimations with cross-sectional data require assumptions about the distributional and functional form for the production and the error components, for such type of data concealing the observations with a Cobb-Douglas production function is one way to estimate a production frontier (Ondrich & Ruggiero, 2001).

Individual (In)efficiency

Aigner et al. (1977) original model estimated the mean inefficiency of the whole group of observations did not cover the estimation of firm-specific inefficiency. As one of the aims of the SFA was to evaluate individual firms' performance as well, Jondrow et al. (1982) suggested a solution that defended that the residuals still include enough information about the inefficiency to allow the use of a conditional estimator. To do so, they proposed to estimate the "expected value of the inefficiency component conditional on the measured overall error" (Ondrich & Ruggiero, 2001, p. 2). And, then either consider the mean or mode of these distributions as the inefficiency of each observation. This proposal, filled in a considered large disadvantage of the stochastic frontier models when comparing, for example with deterministic frontiers.

$$(4) \quad E(u_i|\varepsilon_i) = \ u_i + \ \sigma_i \left[\frac{\emptyset\left(-\frac{u_i}{\sigma_i}\right)}{1-\Phi\left(-\frac{u_i}{\sigma_i}\right)}\right]$$

Where u is the expected value of the inefficiency, ε is the error term, $\emptyset$ and Φ is the density function for the standard normal distribution and cumulative density function, respectively. Additionally, $-\frac{u_i}{\sigma_i}$ represents the point where the likelihood function is calculated.

Also, on the level of firm-specific estimations, Battese & Coelli (1988, p. 4) proposed conditional efficiency as the "ratio of its mean production given its realized firm effect, to the corresponding mean production if the firm effect was zero". However, the individual inefficiencies of cross-sectional data cannot be estimated straight away as the residuals from the cross-sectional model are complex and contain both the noise and inefficiency effects.

Industry Efficiency

The efficiency average of all the firms within an industry is seen as the industry efficiency. Consequently, if we calculate the firm's average of the predicted efficiencies the result is the natural predictor of industry efficiency (Coelli et al., 2005).

In our study, could be useful to get the industry efficiency, that is, how efficient is the publishing sector, to be able to compare performance between publishers according to the research journals that they have in their portfolio and the overall efficiency of the publishing industry, that is, if given the resources available a publishing house is producing the optimal output amount. Or even, the efficiency of a segment of the market, namely, for each journal studies category.

Limitations of the SFA

As Schmidt & Sickles (1984) discusses cross-sectional stochastic frontier has three main difficulties. Firstly, in the case of the individual efficiencies even though it can be estimated, as shown before, there is no consistent estimator method. Secondly, assumptions about the distribution of technical inefficiency (e.g., half-normal) and statistical noise (e.g., normal) are necessary for the model estimation, as well as for the overall and individual (in)efficiency estimations. Lastly, assuming that inefficiency is independent of the regressors might be inaccurate. Additionally, a limitation of basic SFA models is that they only allow production function analysis, for example, in situations with one output. (Bogetoft & Otto, 2011).

3. DATA AND METHODOLOGY

To accomplish the purposed research objectives, some steps of the Natural Science approach were followed, using quantitative methods. The methodology used was based on scholars' data, collected specifically for this research work, containing information about the composition and characteristics of editorial boards of several journals. In total, 3605 editors were initially recorded with 792 of those belonging to more than one journal. Moreover, 13 distinct publishers are represented among the total 27 journals considered.

Journal selection

For this study, the selection of scientific journals was done as follows. Firstly, the subjects of the academic journals aforementioned were decided on. More broad-spectrum categories were chosen to incorporate this study since they cover the overall business research developments. The objective was to identify the top-10 journals in each subject - Business, Economics, and Finance - ranked for 2020. Secondly, the disciplines were selected in Scimago Journal Ranking, and since there is no standard method to determine journal rank orders, the identification was done using Scimago which uses the SJR indicator to rank the journals, and thus ordered by this indicator. Although publication and citation patterns may vary across disciplines (Dorta-González & Dorta-González, 2013), the top-10 of each study field was extracted into a dataset. Hence, a total of 30 journals were obtained, being that only 27 remained, as three were repeated across categories. Table 1 shows the selected journals for the three disciplines, present in this work[2].

[2] The disciplines are alphabetically ordered, while the journals are ranked in decreasing order of their respective SJR within its main discipline

Table 1 - List of the 30 journals, separated by the three disciplines

Discipline	Journal
Business and International Management	Academy of Management Annals
	Academy of Management Journal
	Strategic Management Journal
	Journal of Consumer Research
	Journal of Marketing
	Journal of Business Venturing
	Journal of Marketing Research
	Marketing Science
	Journal of the Academy of Marketing Science
	Entrepreneurship Theory and Practice
Economics and Econometrics	Quarterly Journal of Economics
	Journal of Political Economy
	Journal of Finance
	American Economic Review
	Econometrica
	Review of Economic Studies
	Review of Financial Studies
	Journal of Economic Literature
	Journal of Financial Economics
	NBER Macroeconomics Annual
Finance	Journal of Finance
	Review of Financial Studies
	Journal of Financial Economics
	Foundations and Trends in Finance
	Journal of Management
	Journal of Accounting Research
	Journal of Accounting and Economics
	Accounting Review
	Journal of Financial Intermediation
	Journal of Monetary Economics

Data Collection and Sources

Intending to study the editorial teams of the journals in analysis, the names of the scholars contained on each journal's website were hand-collected and gathered to create a unique dataset combining all the scholars that perform functions in these top-ranked journals. As for the data assemblage, the first step was to define what editor's characteristics to include in the sample. Due to the fact that the editorial team's information provided on the journal's websites is essentially the name, affiliation, and geographical location an extensive search had to be conducted across several platforms such as Google Scholar, the editor's official websites, and Scopus to gather the missing information. Taking into consideration that, the labeling of job functions and responsibilities is not standardized across journals, even though most of the journal's websites contain the name and affiliations of their editors, the comparison of job functions between journals became more complex, so for this work purpose it was included only to organize the editors in the dataset.

To do so, after all the sources were combined, the data collection and composition of the dataset took several steps. The gathered data were both about the journals and editorial teams. This process was separated into two: (1) journal data and (2) journals' editorial team. Concerning the journals, after deciding upon the journals that would be considered, all the observations were confirmed manually, and the repeated ones were filtered out. Next, new variables calculated from the original ones were created to extract more information from the data. Finally, all the categories to which the journal belonged to were manually inserted and organized by importance, in the cases when there was more than one, for the study.

Table 2 - List of journal variables present in the database

Variable	Variable description
Journals' publisher	The publishing company of the journal
Journals' name	Name of the journal
Journal's H-index	H-index of the journal
Journal's SJR	Scimago Journal Ranking indicator used to rank research journals
Categories and respective positions in Scimago	Categories to which the journal belongs to
Total number of documents (3 years)	Number of papers published by the journal from 2017 to 2019
Total number of documents in 2020	Number of papers published by the journal in 2020
Total number of documents (4 years)	Sum of the previous two fields
Journal's citations (3 years)	Number of citations in 2020 received by published papers from 2017 to 2019

Concerning the editorial boards' records, these are of utmost importance to better understand the editorship structure of the journals mentioned above hence more information needed to be analyzed. As the websites only provided information about the editors' names, affiliations, and job functions, alternative sources were required to complete the data and meet our objectives. It was retrieved not only from Scimago but also from Google Scholar, Scopus, and Linked-In profiles. It is also important noticing that the journal rankings and respective positions throughout the disciplines aforementioned were collected at the same time as the editors' data to ensure consistency. Taking into account that these are values constantly changing, they are from a specific period and so it was essential to collect them in the shortest time possible. In other words, our dataset is constituted by a snapshot of the data at a certain point in time. Hence, we began by putting together the complete editors' list by combining the editorial board names from all our sources into the dataset, followed by all the qualitative information. To ensure consistency this order had to be followed because entering all the observations was a lengthy process (further explained below). Then, the quantitative information such as the individual performance measures was taken from the source and entered into the dataset. Lastly, all the information was checked manually and validated using more than one source to confirm that all the data was accurate and there were no mistakes done during the information gathering. Table 3 shows the editorships considered information and respective description.

Table 3 - List of editor's variables present in the database

Variable	**Variable description**
Editor’s name	Name of the editor the integrates the editorial board
Editor’s role	The job function of the editor within the editorial board
Editor’s gender	Gender of the editor
Editor’s country	The country where the editor is based to perform is functions
Editor’s continent	Continent where the editor is based to perform is functions
Number of affiliated institutions	Number of institutions that an editor belongs to
Types of institutions	Distinction between academic or non-academic affiliations
Institution name	Name of the affiliated institution (s)
Editor’s H-index	H-index of the editor that constitutes the main focus of analysis

So, the information about the editorial boards of the 27 academic journals considered was collected directly from each journal’s website and put into the database manually was compiled in just under a month, from August 12th to September 6th, 2021. Table 4 shows information about the variables in question and their respective sources.

Table 4 - List of variables and respective sources

Variable	Source (s)
Editor's name	Journal's website which contains their editorial boards' information
Editor's role	Journal's website
Editor's gender	Based on the first name; When the gender was not clearly identifiable, research was made on Google, or a picture of the editor was searched
Geographical location	Based on the editors' current affiliation
Affiliated institution	Journals' website and double-checked in GS and/or Scopus; In case of different information between sources, editors' profile was consulted
Editor's H-index	Google Scholar; When it was not available Scopus was consulted to further research the editor
Journal's H-index	Scimago Journal Rank
SJR	Scimago Journal Rank
Number of citations	Scimago Journal Rank
Number of documents	Scimago Journal Rank

Editor identification

Among all the variables in the analysis, two required a more strategical approach to make sure that the editors were properly identified, and thus conduct a reliable study at an authors' level. That was the case with the editor's H-index and gender. The H-index was searched in Google Scholar. While doing so, details had to be taken into consideration therefore an author disambiguation approach was adopted, to a certain extent, for this research's purpose. Empirical studies have also shown that inadequately disambiguated data can bias the outcomes of such analyses (Kim, 2019; Moed & Vriens, 1989), as a result, several approaches using techniques to handle it have been proposed (Sanyal et al., 2021; Tekles & Bornmann, 2020).

To do so, for this work the following steps were taken: (1) while searching for the editor, when there were similar names, to confirm the profile the affiliation was added to the search box to filter out results, (2) when the affiliation was not available or updated, the journals of the papers on the editors' profile and the research topics were double-checked, (3) when the editor's name was presented with only a letter of the first name and the last name on the journal's website, the name was updated accordingly to google scholar in our database, (4) when the editor was not found in Google scholar, the Scopus author finder was used to fill that value, and (5) as a last resource, if the name was not found in Scopus either, a search for one publication of that editor was done to go directly to their profile. In these cases, the editor's profiles were under variations of their names. Additionally, the names of the editors were also set according to Google Scholar because different journals have diverse ways of writing them. This was done to ensure that repeated editors throughout journals could be identified during the analysis later on.

Equally, gender was a challenging attribute to fill since there were names where the distinction between male and female names was not as clear. So, when the name allowed to clearly understand the editor's gender or there was a picture on the profile, it was filled. When that was not the case, to check their given names *GenderChecker.com* was used.

Broadly, editorial teams are composed of similar roles: editor, associate editor, editorial board, and editorial advisory board, who play a key role in shaping editorial policy and choosing the works that will be published. However, each academic journal has its own organization of editorial roles. Due to this, it is not viable to differentiate or compare scholars based on their roles. Thus, an editor's function will not be considered as a distinguisher in the analysis. It is also worth mentioning that some editors were excluded from the final list, such as Managing editors, Editorial assistants, Editorial managers, Production editors, Publications manager secretaries, Business managers, and so on since they do not take part in the decision-making process. Thereby, from a total of 3605 editors initially recorded, only 3575 made it into the final list. From the final count, 792 of them are repeated, that is, 792 editors belong to more than one journal. To make sure that the repeated authors had all the same H-index throughout the database, as mentioned previously this is a value constantly changing, when checking for the duplicates three columns were used to make sure that it was the same person. For the analysis of the data, the R software was considered.

Characterization of editorial boards

Aside from the H-Index, SJR, the total number of published documents, and citations collected from Scimago, to provide a more detailed analysis of the editorial teams per journal, the following variables were calculated by aggregation of information on an editor's level.

Table 5 - List of the calculated variables and respective description

Variable	Variable description
Editorial Board Count	Count of the number of editors per journal.
Repeated editors count	Number and proportion of editors that perform functions in more than one journal at the same time.
Average H-index	The average number of editors per journal.
Median H-index	The median number of editors per journal.
Academic editors	Number and proportion of editors affiliated with academic institutions in the total number of editors.
US editors	Number and proportion of US-based editors in the total number of editors.
Gender variety	Male and female editors count per journal.
Impact Factor (calculated a priori)	Number of citations per document from 2017 to 2019

Definition of variables

The proposed model includes one measure of editors’ impact, two of journals´ impact, and some characteristics of editors and journals considered relevant for the analysis. Based on these data, we were also able to get information about editorial teams' compositions. Hence, our variables were split into dependent (y) and independent (x) variables. The independent variables have different levels – editors' level and journals' level.

Dependent variables

As dependent variables, we looked at two commonly used journal measures, specifically the H-index and the SCImago Journal Rank (SJR) recorded in the Scopus database. Both measures were considered the main output of the model. Moreover, was also retrieved the total number of published documents and the citations received in the selected year from the previous 3 years.

Independent variables

These will be constituted by the editor's and editorial team's characteristics. From individual observations, where each line corresponds to an editor, we have each editor: H-index, retrieved from Google Scholar; Gender; Location, composed by the country and continent that the editor is based identified through the institutional affiliation; Affiliated institutions, where only the current ones were considered; Number of affiliated institutions, by counting the affiliated institutions that the author belongs to; and Type of institution, which afterward was categorized in Academic and Non-Academic institution. Also, for each editor, there is information about the journal and publisher that he/she belongs to, and the rest of the journal's characteristics are further explained in the next paragraph. Therefore, this first set of variables is at the level of editors. From the aggregation of editors' data by journal another set of variables was created at the level of journals, namely the size of each board of editors as the count of editors with a position in that journal; the average of the editors´ H-index; percentage of gender diversity within a team; main category of the journal and how many each journal englobes. This aggregation will allow us to explore further the composition of each editorial board and enable comparison between them.

Data Analysis

The analysis of the data was divided into three main parts. We started by doing a summary analysis of the statistical properties of the variables. Afterward, we investigated specific correlations between some pairs of variables, both at the level of the editors and the level of the journals. That is, based on the results from the initial exploratory data analysis, an analysis for the more relevant variables previously mentioned regarding the editors and journals was conducted, as well as an effort to identify if there is a significant correlation between dependent and independent variables, specifically individual attributes from editorial teams with the performance of the journal. To do so, we applied linear and non-linear regressions to the data. To check the non-linearity of the data, some regression models were experimented with, such as:

- Logarithmic: $y = \log(x)$
- Quadratic: $y = x + x^2$
- Polynomial: $y = x + x^2 + \ldots + x^n$

The logarithmic transformation is often used to reduce the skewness of the data so the data can be more easily understood while quadratic functions are known to be U-shape.

Lastly, after studying more profoundly SFA approaches Kumbhakar & Lovell (2000) defended why using this analysis method could be useful: identify the individual firms that when below the threshold might need intervention and corrective measures given an SFA individual efficiency scores. And, as these scores differ across producers, due to the own characteristics of each firm, namely in this study we referred to them as editorships, the source of inefficiencies can be more easily identified. Numerous methods have been proposed over the past years to estimate efficiencies based on a frontier. In such methods, observation is considered efficient if it is situated on the cost/production frontier while inefficient observations are the ones below an expected production frontier or above the cost frontier (Cullinane & Song, 2006). Therefore, these production/cost frontier approaches are "in-line" with the economic theory of optimizing behavior (Cullinane & Song, 2006). Since our data is composed of editorships of several journals, a stochastic frontier analysis to research the editors' efficiency and if their performance affects the journal's impact was used. Additionally, to estimate the production frontier, we focused the analysis, taking into consideration our type of data, cross-sectional data, on i firms (journals in our context). So, to accomplish this it was assumed that the Cobb-Douglas log-linear function had a proper structure for our model.

4. RESULTS

4.1. EXPLORATORY DATA ANALYSIS

4.1.1. Editors level

Overall, 3573 editorships were collected: 2382 from Business journals, 859 journals from Finance journals, and 332 from Economics journals[3]. Additionally, most of these journals overlap in some categories[4] so there is not a strict division - one editor can belong to more than one journal category. From this count, 2781 editors work only in one journal, and therefore, the remaining 792 editors belong to two or more journals simultaneously. Moreover, two editors had missing values in the H-index attribute so during the data preprocessing these records were removed given that the main scope of this study is the research on the performances of editors and journals. Respecting the categories is noticeable that the number of editors varies significantly between categories, where the most represented discipline among editors is Business, a phenomenon that could be further studied later in this work to understand why this happens (Figure 1).

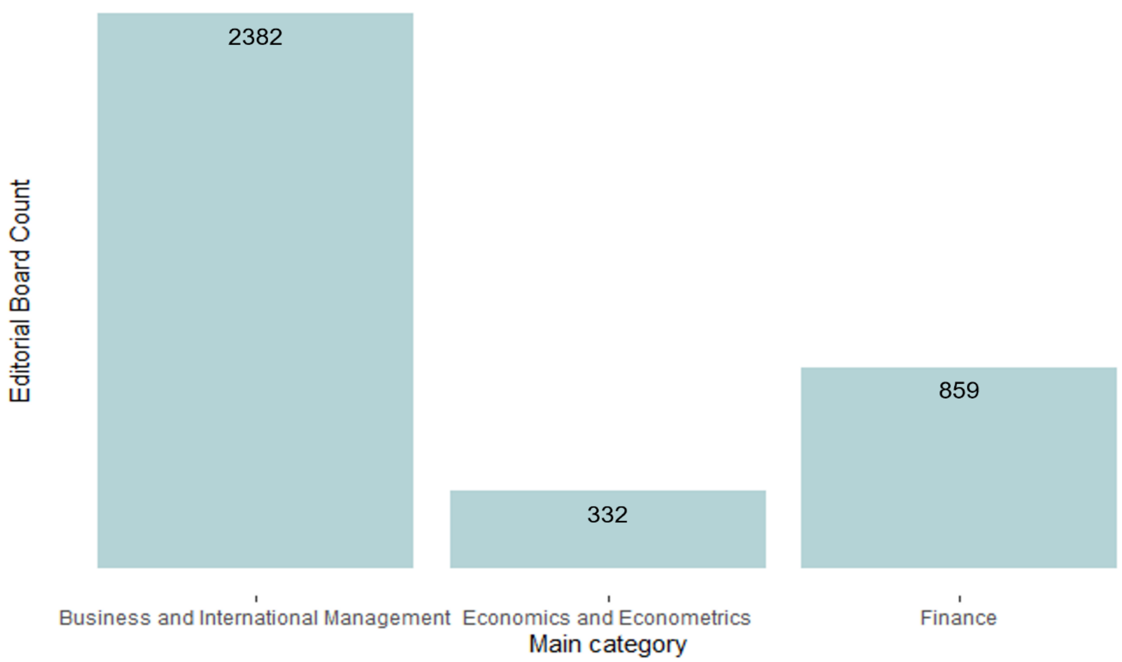


Figure 1 - Count of editors per journal category

[3] See Appendix 1 with the editor count of each journal.
[4] See Appendix 2 with the categories that each journal belongs to.

The three journals with the biggest editorial boards are the Strategic Management Journal, Journal of Management, and Academy of Management Journal, with 440, 354, and 348 editors, respectively. Two of them belong to a business category and the other to Finance. On the other hand, the three journals with the smallest editorial boards have 3, 13, and 15 editors - Foundations and Trends in Finance, Academy of Management Annals, and NBER Macroeconomics Annual, respectively.

4.1.2. Journals level

Concerning the 27 journals assembled from three disciplines, there are other categories present - Strategy and Management, Management of Technology and Innovation, Organizational Behavior and Human Resource Management, Accounting, Marketing, and Anthropology – to which the journals also belong.

Table 6 - List of repeated journals and positions on the disciplines they belong too

Journal	Discipline	Position	Discipline	Position
Journal of Finance	Finance	1	Economics	3
Review of Financial Studies	Finance	2	Economics	7
Journal of Financial Economics	Finance	3	Economics	9

Thus, for analysis purposes, the main category was defined for each journal based on its position in the discipline. The highest position was chosen as the main category. Furthermore, the 3 repeated journals are the top-3 ranking journals in Accounting, a category present in the database as well. From the journals observed, 8 of them are published by academic publishing houses. Thus, 3 out of 13 publishers present in our sample are directly connected to academic institutions. Moreover, all of the publishers are based in the United States (US) except two of them, established in the Netherlands and the United Kingdom (UK).

Table 7 - List of publishers of the collected journals

Country	Continent	Publisher	Number of journals	Type of publisher
United States	North America	Academic Press Inc.	1	Commercial[5]
United States	North America	Academy of Management	2	Academic
United States	North America	American Accounting Commercial	1	Association
United States	North America	American Economic Association	2	Association
United States	North America	American Marketing Association	2	Association
Netherlands	Western Europe	Elsevier	5	Commercial
United States	North America	Institute for Operations Research and the Management Sciences	1	Academic
United States	North America	Now Publishers Inc	1	Commercial
United Kingdom	Western Europe	Oxford University Press	5	Academic
United States	North America	SAGE Publications Inc.	1	Commercial
United States	North America	Springer New York	1	Commercial
United States	North America	University of Chicago Press	2	Academic
United States	North America	Wiley-Blackwell	6	Commercial

Additionally, looking broadly at some journal indicators[6] – Nº documents, and Citations – in Figure 2 is possible to understand that the journals with the highest numbers of published documents and citations do not necessarily have the highest performance. In terms of published articles and citations the *American Economic Review*, the *Journal of Management*, and the *Strategic Management Journal*. Confirming the initial assumption, the ones with the highest SJR are not the previously mention but the *Quarterly Journal of Economics*, the *Journal of Political Economy*, and the *Academy of Management Annals*. Even though all are situated in the middle of the plot, they present a medium number of published documents and citations compared to the others, suggesting that the SJR is not strictly moved by these two variables.

[5] Elsevier is the parent company.
[6] See Table 12 with all the values of the performance indicators for each journal in Ch. 4.2

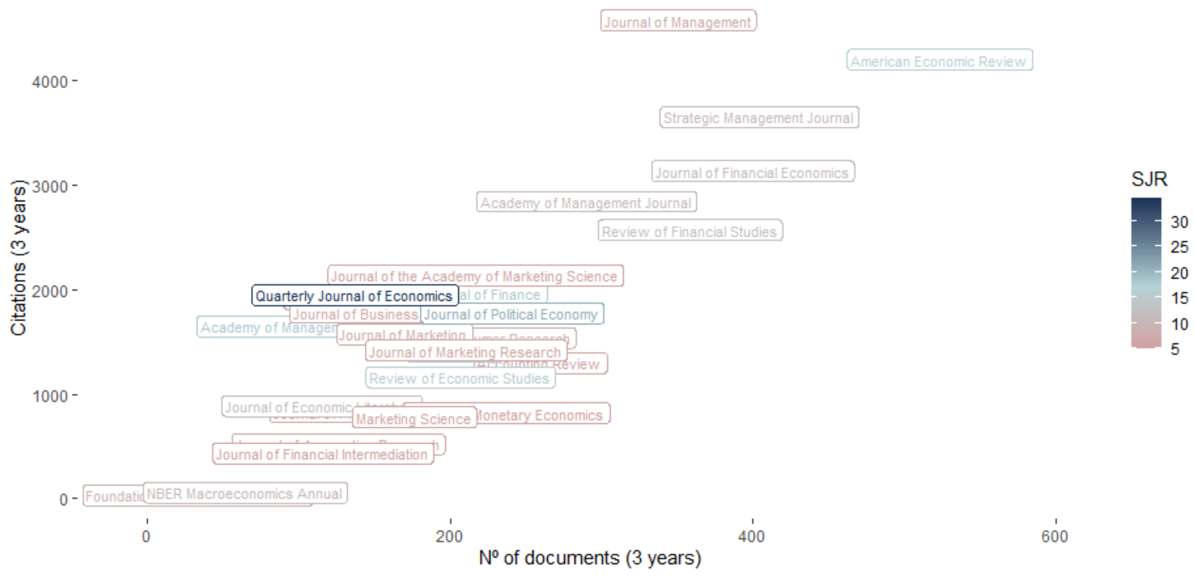


Figure 2 - Nº of documents, Citations, and SJR per journal for all categories

On the contrary, when examining these variables with the H-index (Figure 3) of the journals the previous conclusions differ. In general, it is noticeable that the higher the documents and citations, the higher the H-index. This shows that both variables move the H-index which makes sense since it is a measure of productivity and citation impact (journal's number of articles (h) that have received at least h citations).

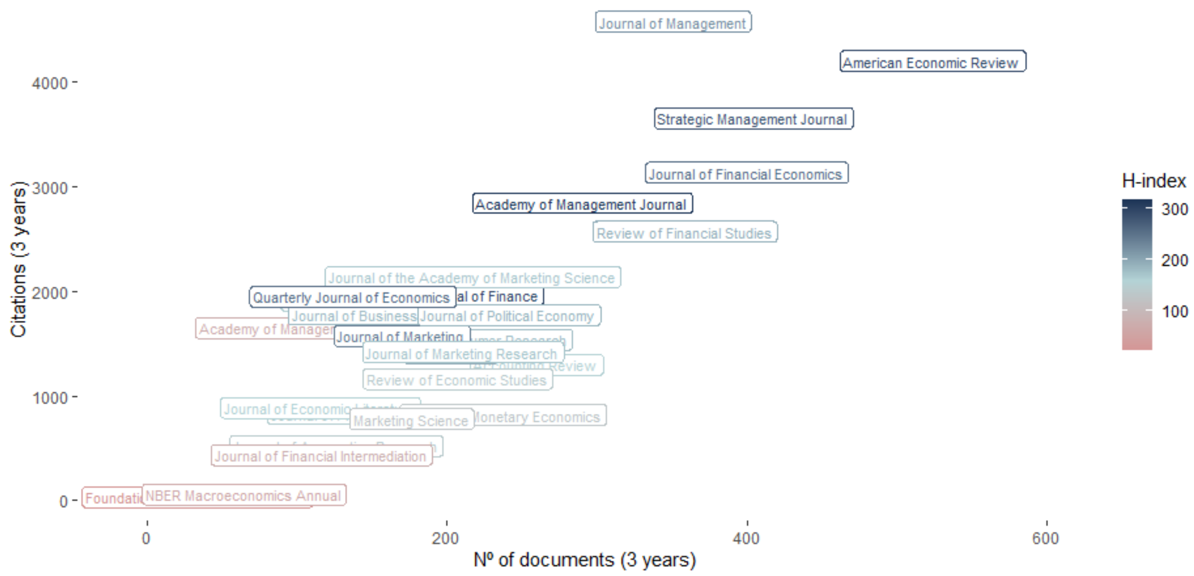


Figure 3 - Nº of documents, Citations, and Journal H-index per journal for all categories

Geography

Editors' geographical location was studied to better understand the patterns of scholarly research. A total of 37 countries are represented by editors in the journals analyzed.

Table 8 - List of countries per continent present on the dataset

Europe	North America	Central and South America	Asia	Oceania	Africa
Austria (6)	Canada (169)	Brazil (6)	China (76)	Australia (62)	South Africa (1)
Belgium (18)	United States (2478)	Chile (2)	India (7)	New Zealand (5)	
Czech Republic (2)		Colombia (1)	Israel (15)		
Denmark (13)		Mexico (1)	Japan (4)		
Finland (14)			Russia (2)		
France (70)			Saudi Arabia (1)		
Germany (82)			Singapore (70)		
Hungary (3)			South Korea (9)		
Ireland (5)			Taiwan (6)		
Italy (35)			Turkey (3)		
Netherlands (75)			United Arab Emirates (1)		
Norway (9)					
Portugal (5)					
Spain (39)					
Sweden (18)					
Switzerland (46)					
United Kingdom (216)					
655	**2646**	**10**	**194**	**67**	**1**

As we can see in Table 8, Europe has the highest number of countries represented, followed by Asia, while North America only has 2 countries. However, the most represented countries are the US (69%), the UK (6%), Canada, and Germany with less than 5% each. This shows that there is no proportion in terms of editors count and the number of countries within a continent. Hence, while European editors are spread through several countries North Americans are concentrated in the US (2477) and Canada (169). These results show that the US alone has a major influence on Business, Economics, and Finance studies, on the contrary, for example, Africa with only one based editor (see Appendix 3).

Africa, Asia, Eurasia[7], Central Europe, Western Europe, North Europe, South Europe, North America, Americas[8], and Oceania were the regions into which the countries were divided into. These divisions are crucial to study the location of editors in a high-level detail, especially to make a distinction within Europe, and between North America and Central & South America.

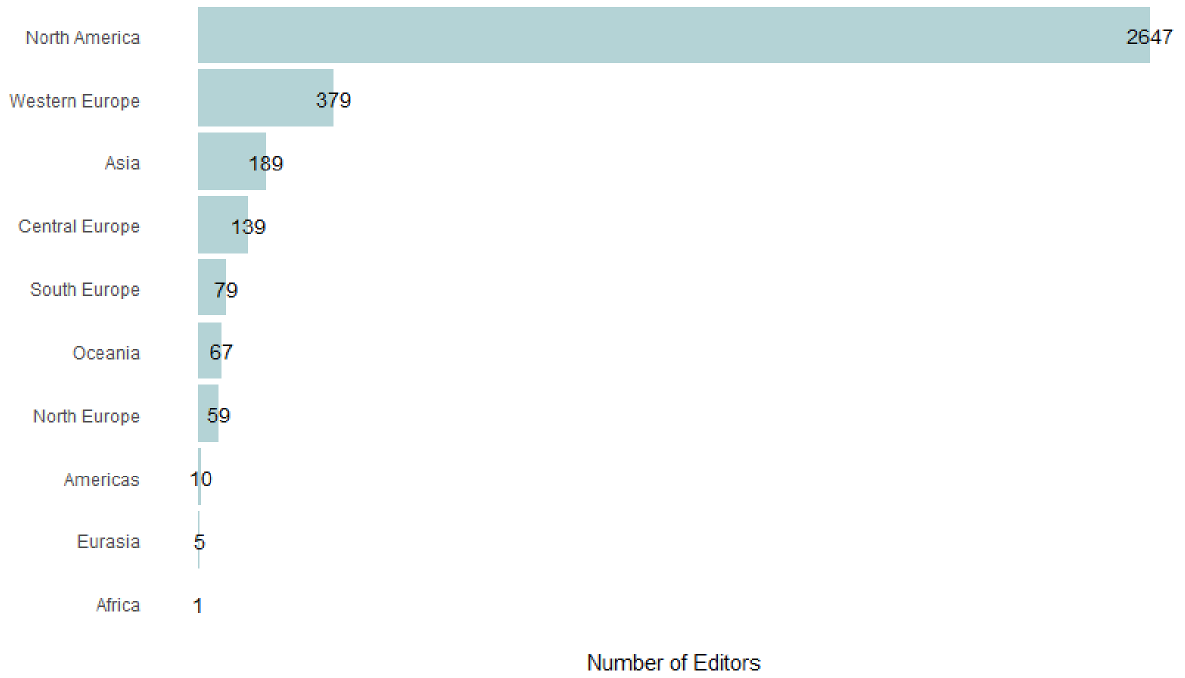


Figure 4 - Number of editors by region

So, in total the great majority of editors are based in North America (2646), representing 74% of the total scholarly population, followed by Western Europe, with 10.89% of the editors. The regions more underrepresented are Africa, Eurasia, and the Americas with only 1, 5, and 10 editors, respectively. Together, they correspond to no more than 0.41% of the editorial population. Looking at the geographical distribution of the scholarly journals, more than half are based in North America while the rest are situated in Western Europe (Table 9).

[7] Eurasia comprises the countries situated on the border of Europe and Asia (Turkey and Russia)
[8] Americas: Englobes Central and South America

Table 9 - Journal's geographical distribution per region

Region	Number of Editors	% of total editors	Number of Journals	% of total journals
Africa	1	0.03%	-	-
Asia	189	5.29%	-	-
Eurasia	5	0.13%	-	-
Central Europe	139	3.89%	-	-
Western Europe	379	10.89%	14	46.7%
North Europe	59	1.65%	-	-
South Europe	78	2.18%	-	-
North America	2646	74.05%	16	53.3%
Americas	10	0.28%	-	-
Oceania	67	1.88%	-	-

Similarly, Western Europe is the region with the second-highest number of academics. This allows us to conclude that within the European regions considered the western zone produces more academic research, which could be explained by the fact that it´s where the European journals are all based. Therefore, is evident that the most developed nations have an almost absolute representation, comprising 90% of the editorial population. The same can be concluded at the journal level, where all the journals are based either in the US, UK, or Netherlands. Additionally, there is one country that deserved further study due to its high geographical representativeness. US-based editors are the most represented ones, thus a comparison between these and the rest of the geographical locations was done to further investigate the impact of this singularity on the individual's H-index. According to the boxplot below, even though the median is similar which indicates that there is no apparent difference in the editor's H-index in terms of based location, the US-based editors have a few editors with higher H-index values. This can be seen by the values above the upper whisker. One possible explanation for this could be that these outliers are editors that belong to high prestigious institutions and therefore they have a higher influence.

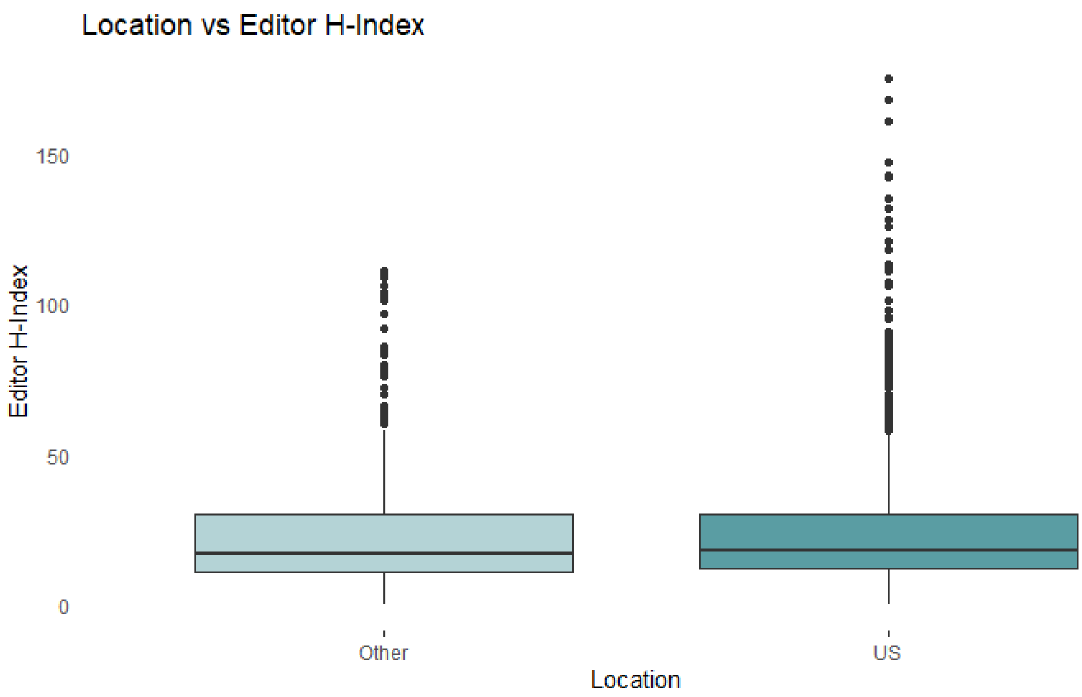


Figure 5 - Editor's H-index by location (US vs Non-US)

Gender

Taking into consideration the whole data, the results show that out of 3573 editors only 1086 are women, which is about 30% of the total scholarly population. When analyzed against the editor´s H-index is visible that male editors have higher averages throughout all categories (see Appendix 4).

A One-Way ANOVA test was done for each gender and category, both categorical variables, with the H-index (numerical variable). Given that, the F-statistic is used to understand if the means between two populations are significantly different, from the ANOVA tests we were able to check that the gender is statistically significant[9] while the category variable is not since it surpasses the alpha level of significance (.05). This was also confirmed by the F value[10] for the gender being larger than the F critical values[11] which shows strong evidence that we can reject the null hypothesis, meaning that the data from the different populations have different means, being likely that our results did not happen by chance. While the F value for the categories is equal to the critical value, we cannot reject the null hypothesis, which says that there is no significant difference in the population means. Thus, our data give strong evidence that there is a significant difference in the editor's H-index within genders but

[9] p-value(gender) = < 2.2^{-16}; p-value(category) = .007
[10] F value(gender) = 107.62 ; F value (category) = 4.919
[11] F critical value(gender) = 68.065 ; F critical value (category) = 4.918

belonging to a different journal category does not significantly impact this measure. Figure 6 interpretation confirms these results which indicate that male editors have a higher individual impact.

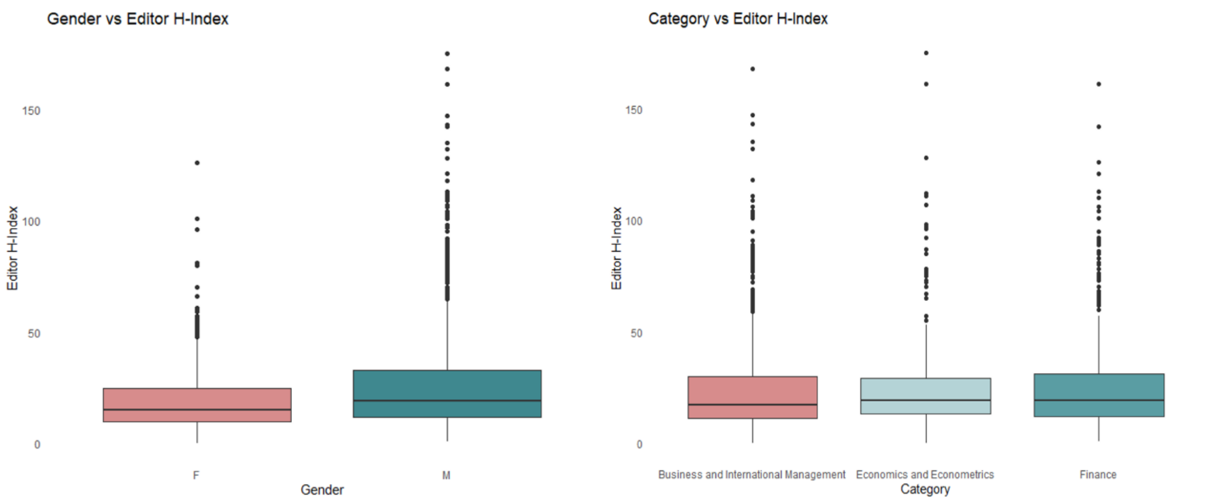


Figure 6 - Editor's H-index by gender (Female vs Male) and by category (Business, Economics, and Finance)

From, a geographical perspective more developed countries have a higher percentage of females on editorial boards when compared to the undeveloped ones. Additionally, countries like Turkey, Russia, Saudi Arabia, or even Colombia, in our sample, have the highest proportion of women. This could be due to the fact that the number of editors from this region is only 5, and thus, might not be a representative sample (refer to Appendix 3 for further details).

On the region level, we can see North Europe with 33.9% of female editors, closely followed by North America (31.4%) and Western Europe (31.1%) with similar ratios. The less diversified regions in terms of gender are Africa, Central, and South America, with 0% and 10% of female representation, respectively, in editorial boards.

Table 10 - Editors and Gender distribution per region

Region	Editorial Board count	Males	Females	% Females
Africa	1	1	0	0.0%
Asia	189	140	49	25.9%
Eurasia	5	1	4	80.0%
North Europe	59	39	20	33.9%
South Europe	78	60	18	23.1%
Central Europe	139	113	26	18.7%
Western Europe	379	261	118	31.1%
North America	2646	1814	832	31.4%
Americas	10	9	1	10.0%
Oceania	67	49	18	26.9%
Total	3573	2487	1086	30.4%

Overall, in this study male authors surpass the number of women in editorial board positions by a proportion of 3 to 1, there is, for every three men in an editorial board position there is one woman. Equally, the gender distribution from a journal's point of view reveals that only two journals can be considered to have a somewhat even gender distribution, the *Academy of Management Annals* with 53.8% of females and the *Journal of Consumer Research* with 45%. Both of them are Business studies´ journals. Contrariwise, the journals with less diversified boards are the *Foundations and Trends in Finance* (0%), *Journal of Financial Economics* (7.5%), and *Journal of Political Economy* (8.3%). Despite that, contradicting what has been already stated in this chapter we have the *Journal of Economic Literature* with an astonishing percentage of females (70%). Curiously, the most and less diversified journals collected, from a gender perspective, belong to either Finance and/or Economics studies.

Table 11 - Editors and Gender distribution per journal

Journal	Editorial Board count	Males	Females	Females %
Academy of Management Annals	13	6	7	53.8
Academy of Management Journal	348	217	131	37.6
Accounting Review	219	148	71	32.4
American Economic Review	90	71	19	21.1
Econometrica	66	53	13	19.7
Entrepreneurship Theory and Practice	243	158	85	35.0
Foundations and Trends in Finance	3	3	0	0.0
Journal of Accounting Research	24	18	6	25.0
Journal of Accounting and Economics	50	37	13	26.0
Journal of Business Venturing	237	174	63	26.6
Journal of Consumer Research	231	127	104	45.0
Journal of Economic Literature	27	8	19	70.4
Journal of Finance	43	37	6	14.0
Journal of Financial Economics	40	37	3	7.5
Journal of Financial Intermediation	47	36	11	23.4
Journal of Management	354	255	99	28.0
Journal of Marketing	277	172	105	37.9
Journal of Marketing Research	205	129	76	37.1
Journal of Monetary Economics	47	41	6	12.8
Journal of Political Economy	24	22	2	8.3
Journal of the Academy of Marketing Science	231	156	75	32.5
Marketing Science	157	123	34	21.7
NBER Macroeconomics Annual	15	13	2	13.3
Quarterly Journal of Economics	34	26	8	23.5
Review of Economic Studies	76	60	16	21.1
Review of Financial Studies	32	21	11	34.4
Strategic Management Journal	440	339	101	23.0

Business studies journals have around 30% of female editors in editorial positions, which is a proportion slightly higher than the one that Economics or Finance studies journals have (see Appendix 5).

Institutions

In general, regarding the institutions, there were 497 institutions represented, of which 450 were universities and 27 other organizations. When looking into the top-15 of most strongly represented affiliations all of them were universities[12].

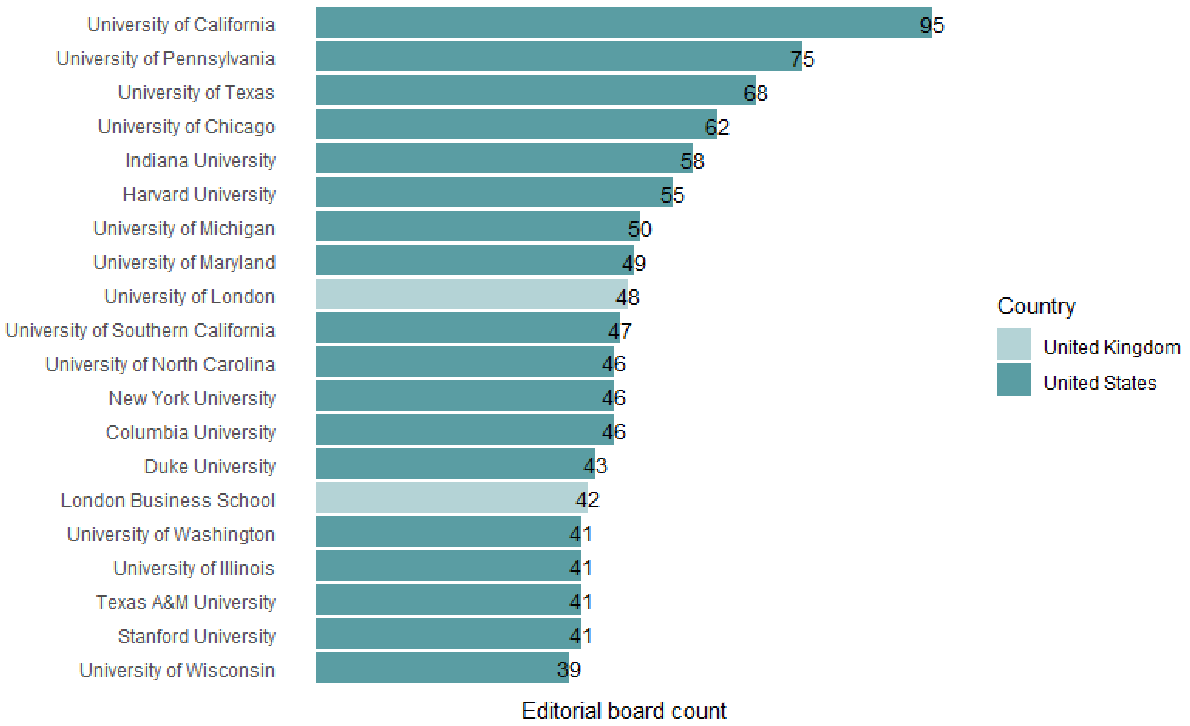


Figure 7 - Ranking of top-15 most represented affiliations by editors

Among the academic institutions represented above, is clear that US-based universities lead the chart, followed by the UK with two universities represented. When analyzing the top universities per category, in the Finance and Business studies journals top-3 affiliations there is just US-based universities, while in Economics studies´ in second place is a UK-based university[13]. Affiliated institutions were further investigated to understand if there was any relation with other editorships.

[12] See to Appendix 6.

[13] Top-3 universities: Finance journals: University of Pennsylvania (26), University of Chicago (23), and Indiana University (20). Business journals: University of Texas (49), University of California (44), and University of Maryland (39). Economics journal: University of California (36), University of London (29), and University of Chicago (24).

On an editor's level, they can be divided into Academic vs Non-academic editors. Since an editor can have more than one affiliation, we considered all editors that belong to academia as Academic editors even if the same is also part of another Non-academic institution.

Therefore, to study in dept the affiliations of editorial boards, editors' were categorized into Academic and Non-academic based on their affiliations, where academics were considered the ones that work or research in a university and the non-academics are the authors that do not associate with any type of teaching institution. Considering the editors' institutional affiliations, the great majority of members of editorial boards, 3542 out of 3573 editors, are a part of academia representing 99% of the total editorial records[14]. The remainder of non-academic editors is associated with several other institutions such as central banks, think tanks, research organizations, multinationals, etc. Figure 8 below shows the top-10 non-academic affiliations[15].

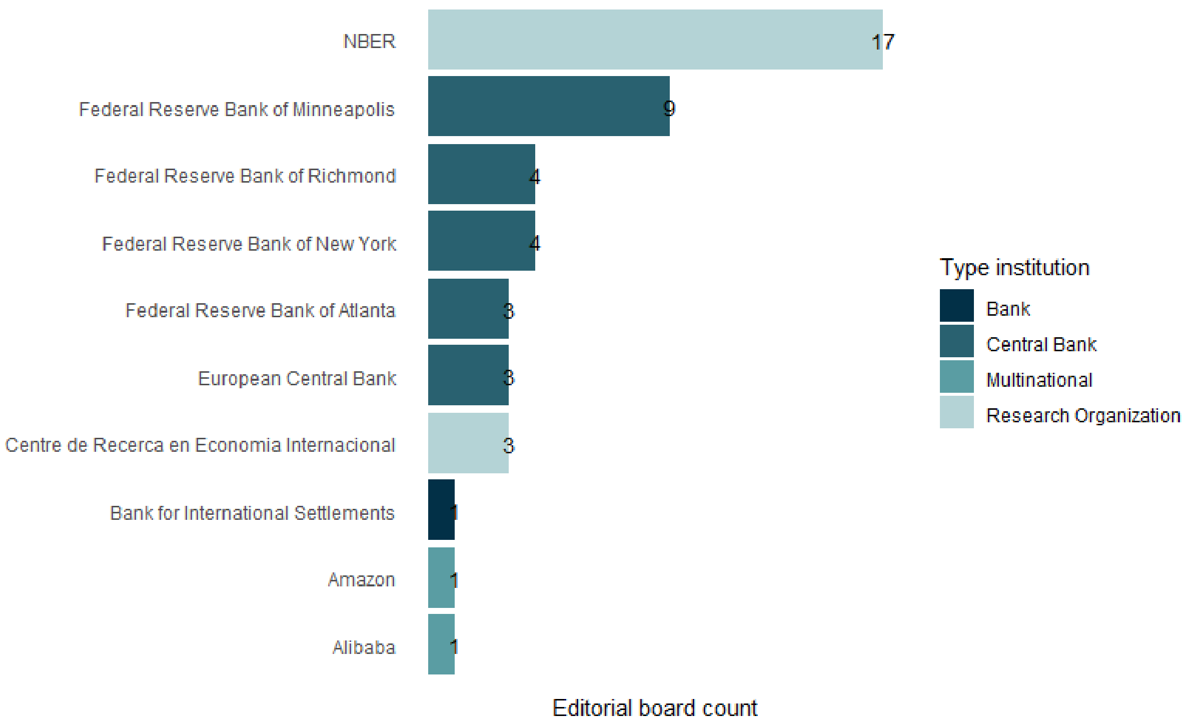


Figure 8 - Ranking of top-10 most represented non-university institutions by editors

[14] Academic editors: 3542 (99.1%); Non-Academic editors: 31 (0.9%)
[15] See Appendix 7.

4.2. EDITORSHIPS VS PERFORMANCE

In this segment, editors' and journals' scientific performance was analyzed against other individual editorships, to investigate if any connection or pattern existed. The measure used for the editors' performance was the H-index. To measure the journal's performance, the H-index, SJR, number of published documents and citations, and the Impact Factor were used. It is also worth mentioning that the Impact Factor (IF), a method to measure a journal's relevance by doing the average of the number of citations per published document, was calculated a priori using data from the three years before the selected year.

$$IF = Citations / Nº\ Documents$$

The skewness of the various variables was checked[16]. Taking into account that, the Editor's H-index is right-skewed, or positively skewed, to attempt to lower the impact of outliers, instead of using the average the median was used. Similarly, the SJR presents the same skewness.

Accordingly, the median H-index of all the academic scholars present in the data was 18. When the same calculation was performed for each journal (Table 12), the journals with the highest editors´ H-index median were the *NBER Macroeconomics Annual*, followed by the *Journal of Financial Economics*, and *Foundations and Trends in Finance*. In terms of category, finance journals have the highest recognized editors, followed by economics[17]. Furthermore, the median H-index for the repeated editors is 20 which suggests that editors with a higher ranking might hold more positions in different journals. The journal with the highest median editors' H-index has a much lower journal H-index. When compared to other journals' performances, the opposite happens for *Accounting review*, which has a significant H-index and the lowest editors' median H-index. The SJR does not follow this pattern. For example, when studying the *Quarterly Journal of Economics*, has the highest SJR even though had fewer papers published than others but still managed to have a fair number of citations and consequently the second highest IF.

[16] See Appendix 8 and Appendix 9.

[17] Median Editors H-index(Business) = 182; Median Editors H-index(Economics) = 199; Median Editors H-index(Finance) = 224;

Table 12 – Summary Editormetrics per journal

Journal	Median Editors H-index	Journal H-index	SJR	Nº documents (3 years)	Citations (3 years)	IF (Cits/ doc)
Academy of Management Annals	26.0	73	18.32	76	1648	21.68
Academy of Management Journal	18.0	318	11.19	261	2839	10.88
Accounting Review	13.0	156	5.68	242	1296	5.36
American Economic Review	19.0	297	16.94	499	4193	8.4
Econometrica	17.5	199	16.7	190	1407	7.41
Entrepreneurship Theory and Practice	19.0	155	5.37	139	1911	13.75
Foundations and Trends in Finance	38.0	21	9.23	3	33	11
Journal of Accounting Research	17.0	141	6.77	98	522	5.33
Journal of Accounting and Economics	18.0	151	6.61	130	825	6.35
Journal of Business Venturing	18.0	182	7.11	134	1777	13.26
Journal of Consumer Research	17.0	179	8.92	188	1537	8.18
Journal of Economic Literature	15.0	160	11.77	89	887	9.97
Journal of Finance	22.0	299	18.15	206	1966	9.54
Journal of Financial Economics	39.0	256	11.67	373	3129	8.39
Journal of Financial Intermediation	23.0	77	5.45	87	436	5.01
Journal of Management	20.0	224	7.49	330	4569	13.85
Journal of Marketing	23.0	243	7.8	152	1572	10.34
Journal of Marketing Research	15.0	171	6.32	184	1416	7.7
Journal of Monetary Economics	23.0	130	4.99	210	819	3.9
Journal of Political Economy	32.5	186	21.03	217	1773	8.17
Journal of the Academy of Marketing Science	21.0	170	5.51	178	2134	11.99
Marketing Science	16.0	127	5.94	160	779	4.87
NBER Macroeconomics Annual	47.0	61	10.54	38	60	1.58
Quarterly Journal of Economics	29.5	259	34.57	110	1945	17.68
Review of Economic Studies	15.0	141	15.64	182	1162	6.38
Review of Financial Studies	16.0	190	12.8	334	2565	7.68
Strategic Management Journal	14.0	286	11.04	378	3648	9.65

Next, to search for patterns between the editors´ and journals´ performances, correlation coefficients, using both Pearson and Spearman were calculated among the most relevant variables. While the Pearson correlation only checks correlations for linear relationships between two variables, the Spearman coefficient – a non-parametric (no assumption about variables' frequency distribution) test applied to measure the degree of association between both variables - also works with non-linear correlations as well. In Table 13[18], we can see both correlation coefficients. The use of both methods already gave us an initial understanding of the linearity or non-linearity of the data.

[18] Table 13 is organized as followed - Pearson (Spearman). When there is only one value it means that the correlation coefficient is the same or the difference is irrelevant.

Table 13 - Correlations between editorships and journals performance measures

	Editor H-index	**Gender**	**US-based**	**Number of affiliations**	**Journal H-index**	**Journal SJR**
Editor H-index	1	0.17 (0.164)	0.04	0.08	0.01	-0.008 (0.02)
Gender		1	-0.021	0.03	0.005	0.007 (0.02)
US-based			1	-0.02	-0.02	-0.03 (-0.015)
Number of affiliations				1	-0.05	-0.06 (0.06)
Journal H-index					1	0.47 (0.73)
Journal SJR						1

A positive relation was discovered between the journal H-index and the journal SJR which makes sense since they are both journals' impact measures. This shows, that the higher an H-index of a journal is, the higher the SJR will be as well. Nevertheless, no more relations were found between the remnant variables. Similarly, the correlation coefficients on a journal's level were checked. Additionally, the Pearson and Spearman methods were both used to investigate if they would make a difference.

Table 14 - Correlations between journal-level indicators (Pearson and Spearman correlations)

	Editorial Board Count	Median Editor H-index	% Academic editors	% Males	% US editors	Journal H-index	Journal SJR	Nº Docs (3 years)	Citations (3 years)	Impact Factor
Editorial Board Count	1	-0.45	0.26	-0.25	-0.43	**0.45**	-0.37	0.37	**0.53**	0.18
Median Editor H-index	-0.43	1	0.05	**0.52**	0.31	-0.28	0.26	-0.27	-0.2	0.01
% Academic editors	0.05	0.14	1	-0.05	0.03	0.28	0.09	0.13	0.25	0.26
% Males	-0.37	0.42	-0.08	1	0.02	-0.03	0.1	0.12	-0.05	-0.36
% US editors	**-0.57**	0.2	0.08	0.11	1	-0.06	-0.02	-0.02	-0.15	-0.25
Journal H-index	0.45	-0.09	0.09	-0.08	-0.19	1	0.34	**0.72**	**0.76**	0.19
Journal SJR	-0.39	0.19	0.01	0.16	0.005	0.45	1	0.07	0.2	**0.42**
Nº Docs (3 years)	**0.46**	-0.28	-0.003	0.12	-0.1	**0.7**	0.16	1	**0.86**	-0.07
Citations (3 years)	**0.47**	-0.01	0.09	-0.18	-0.23	**0.83**	0.35	**0.71**	1	**0.38**
Impact Factor	0.23	0.21	0.16	-0.39	**-0.44**	0.39	0.3	-0.03	**0.6**	1

Pearson Spearman

From Table 14, there are some pairs worth mentioning.

- Editorial Board Count and Editor H-index; Editorial Board Count and % US editors: present a negative moderate relation, so we can assume that as the size of the board increases the Editor's H-index, and the percentage of US-based editors decreases.
- Editorial Board Count and Journal H-index/SJR; Editorial Board Count and Nº of documents published; Editorial Board Count and Citations: present a positive moderate relation, so the bigger the editorial board, the more the published articles, and citations a journal will have, and the higher the H-index of the journal
- Median Editor H-index and % of Males have a positive moderate relation suggesting that as the percentage of males increases throughout the journals, the editors' median H-index increases as well
- Nº Docs/Citations and Journal H-index: despite all being used as performance measures, this positive strong relation indicates that the higher the number of published papers and citations, the higher the H-index of a journal will be.
- Impact Factor and Journal SJR; Impact Factor and % US editors: the IF shows a moderate relation with both of these variables, one positive and the other negative, respectively. So, it seems that when the IF increases, the SJR increases as well. On the other hand, when the US-based editor's percentage increases, the impact of a journal decreases.
- Citations and Impact Factor: in this specific situation the results between Pearson and Spearman statistical outcomes are farther away which suggests that the relation between these two variables might not be as linear.

Given that between the Editorial Board Count and Journal H-index/SJR, there was a moderate relation, and the data points seem a bit randomly distributed[19], an analysis by category was done. Figure 9 shows significant correlation differences between categories.

[19] See Appendix 10.

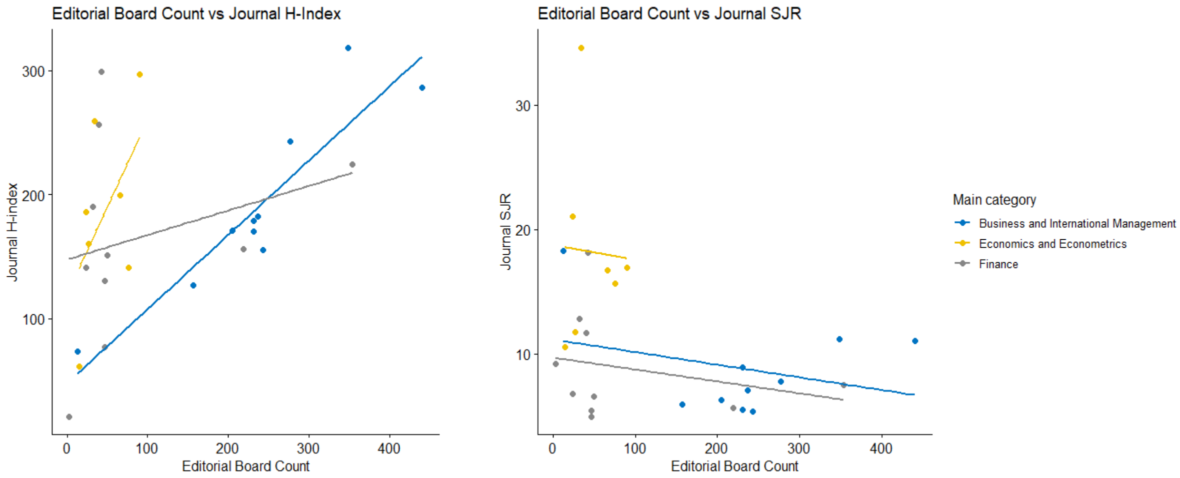


Figure 9 - Editorial Board count vs Journal H-index (left) and Journal SJR (right)

While relating to the Journal H-index, Business & International Management journals have a strong correlation (0.92 / 0.85), Economics & Econometrics a moderate relation (0.53 / 0.57), and lastly, Finance is the category with the weaker one (0.24 / 0.27)[20]. This shows that, for example, when the business journals´ editorial board size increases, the H-index also increases, interpreted as 85% of the Journal H-index increases are explained by the increase of editorial board size. On the other hand, finance journals´ do not appear to have a linear association in that sense showing no impact between these two attributes. Regarding the SJR, is visible that the opposite happens since some r coefficients[21] are negative.

Lastly, the IF was crossed against the other two journals' performance measures for each category. Figure 10, shows that business journals H-index and IF have a negative relation (-0.2) while the economics (0.7) and finance (0.5) journals show a moderate positive relation. Regarding the IF and SJR, economics journals have a very strong positive relation (0.9) whereas the business (0.6) and finance (0.4) show more moderate relations.

[20] Correlation coefficients organized as followed: (Pearson / Spearman)
[21] Business and International Management journals (-0.29 / 0.15), Economics and Econometrics journals (-0.04 / 0.29), and Finance journals (-0.25 / -0.46)

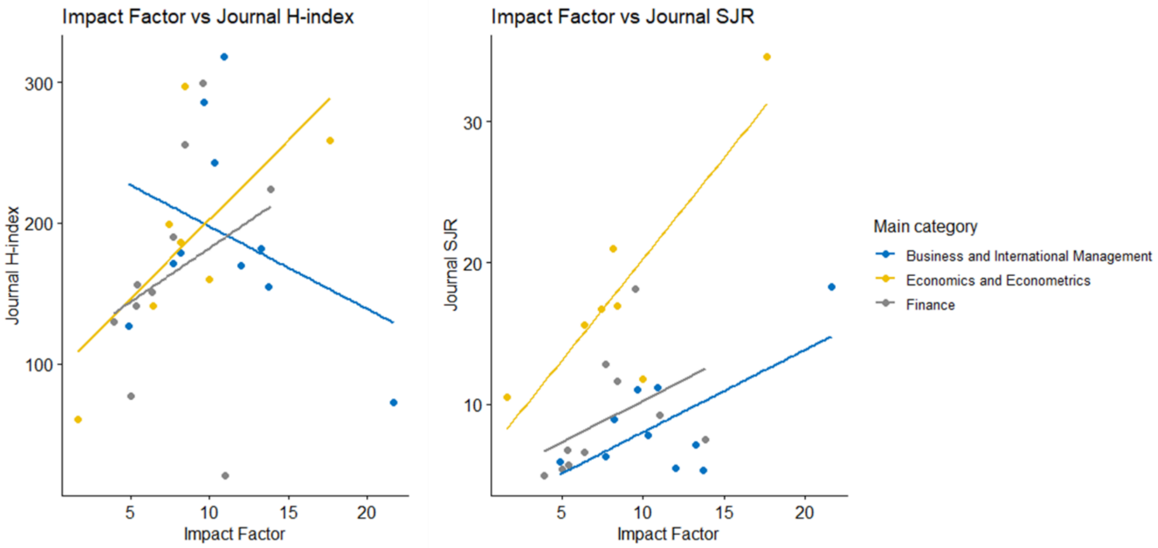


Figure 10 - Impact Factor vs Journal H-index (left) and Journal SJR (right)

After, the previous correlation results the hypothesis of some being non-linear was raised. Thus, after experimenting exhaustively with numerous combinations using non-linear regressions, it was decided the following pairs needed further analysis:

- Editor H-index and Journal H-index/SJR,
- Nº Docs and Journal H-index/SJR
- Editor H-index and Impact Factor
- US-based and Journal H-index/SJR

Median Editor H-index vs Journal H-index/SJR

Given that both of these measures are continuous values, in Figure 11 it was first used loess (locally estimated scatterplot smoothing), a non-parametric regression method that fits the points locally, by fitting a smooth curve in the data (black line in the Figures bellow), in an attempt to capture the general pattern and therefore understand the model that would suit best the data. After, several types of polynomial functions experimented with specifications with degree 3 curve were considered.

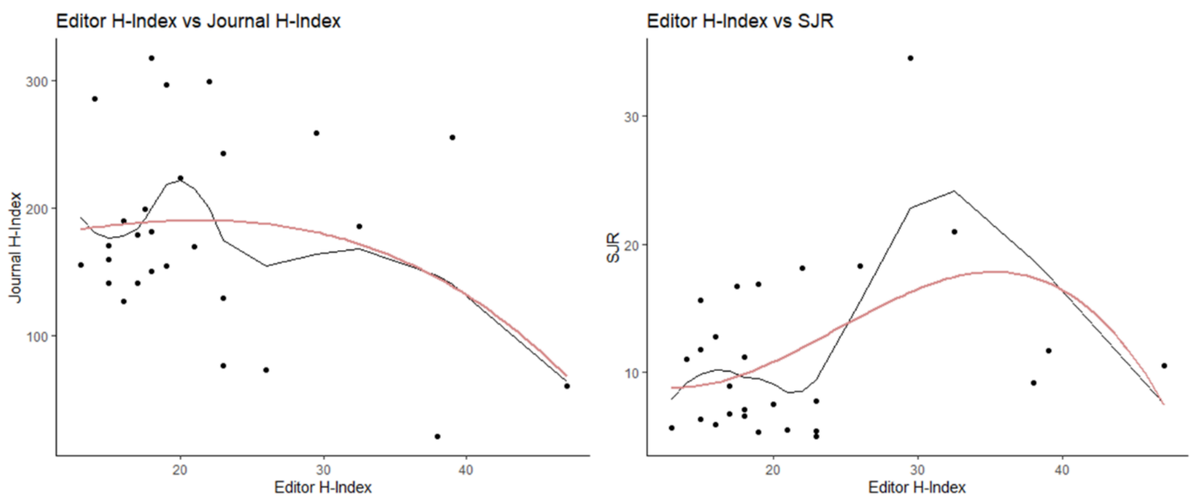


Figure 11 - Non-linear regressions between Median Editor's H-index vs Journal H-index (left) and Journal SJR (right)

When analyzing the R^2 results and other statistical values, such as the p-value, for the Editor H-index and the performance measures, Journal H-index and SJR, the results confirmed that the regression models were not a good fit (R^2 of 0.11 and 0.19, respectively), and not statistically significant, implying strongly that there is no relationship between these two variables being studied. On the other hand, when doing this analysis by category it was found that economics journals' H-index shows a variance explicability of around 87% while for the business and economics studies SJR, respectively, 61% and 46% of the variance is explained by the editor's impact.

Nº Docs vs Journal H-index/SJR

Regarding the number of published papers, between 2017 and 2019, initially, it was found a strong linear positive relation with the H-index and weak with the SJR. Therefore, the analysis was performed by categories separately again. The possibility of non-linearity was checked using a polynomial regression of degree 3 (see Appendix 11 with polynomial regression for all categories). The results were organized in a table to ease the understanding of some important statistical values.

Table 15 - Polynomial regression of total published documents vs journal performance measures between categories

	Journal H-index		Journal SJR	
	R^2	**p-value**	**R^2**	**p-value**
Business studies	0.7	.045	0.9	.001
Economics studies	0.8	.14	0.3	.77
Finance studies	0.7	.077	0.1	.82

From Table 15, is clear that only the business journals' models are statistically significant, seen by the p-value < 0.05, implying robust evidence against the null hypothesis (no relationship exists between the two variables). So, we can say that in the case of the business journals, 70% of the Journal H-index and 90% of the SJR variations can be explained by the number of documents published.

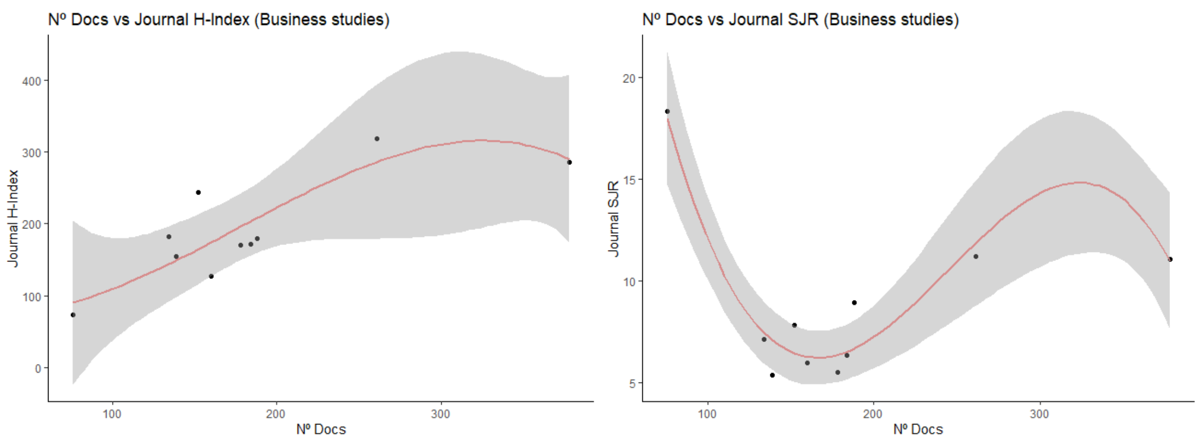


Figure 12 - Fitted regression between Nº of documents and journal performance measures for the Business category

Regarding the economics and finance journals, either the models are a poor fit for the data or there is no relationship between dependent and independent variables. Thus, for the economics journals, a better fit was found - a logarithmic regression - when relating the number of documents with the Journal H-index[22]. The SJR once more shows no relationship between the variables.

[22] $R^2 = 0.6$; ρ (Nº docs vs Journal H-index) = .042

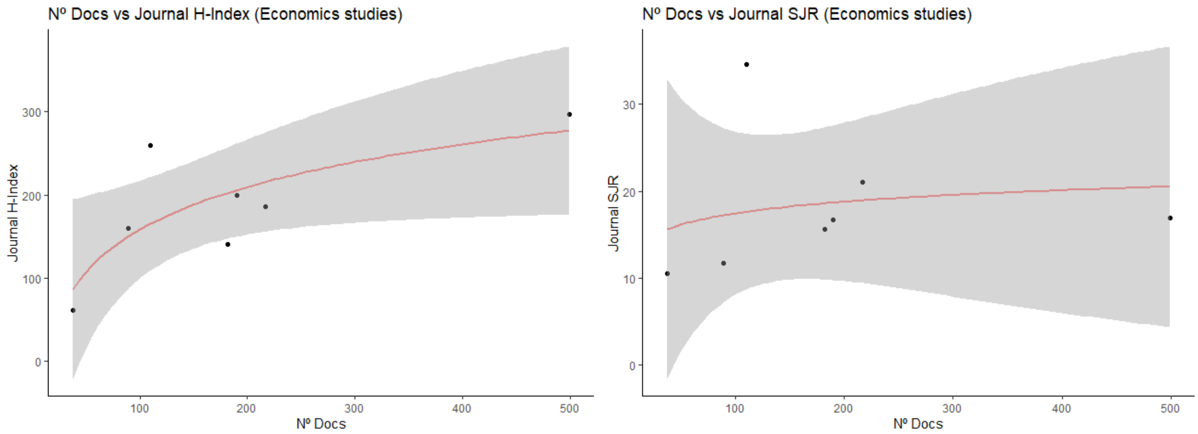


Figure 13 - Fitted regression between Nº of documents and journal performance measures for the Economics category

Finally for the finance journals, even though the significance is not so strong, the polynomial regression previously done shows 70% of the dependent variable variance explained. Thus, another model that gave better results[23] and seemed to be a better fit for the data was a simple OLS Regression. With this model, 58% of the Journal H-index variations can be explained by the number of documents published.

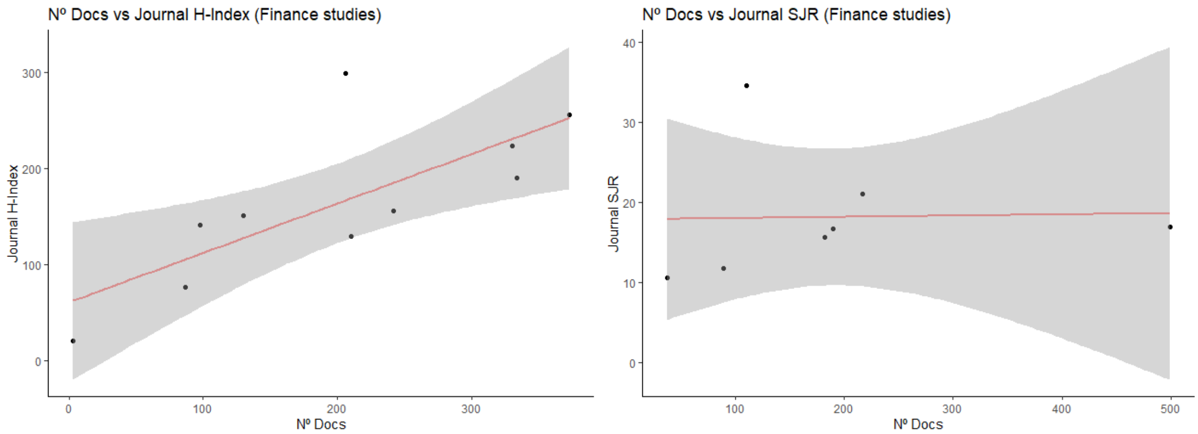


Figure 14 - Fitted regression between Nº of documents and journal performance measures for the Finance category

[23] $R^2 = 0.57$; ρ (Nº docs vs Journal H-index) = .01

Therefore, we can consider that the main takeaway from this topic is that the Journal H-index seems to be influenced partly by the number of documents published. And, that the Business category presents the strongest correlation implying that its' performance might be more vulnerable to this variable than the other studies journals.

Median Editor H-index vs Impact Factor

Considering that, in the Pearson correlations above these two variables presented an almost zero coefficient, the non-linearity between the median editor H-index and the Impact Factor was checked using polynomial regression, degree 4 [$f(x) = c_0 + c_1x - c_2x^2 + c_3x^3 + c_4x^4$].

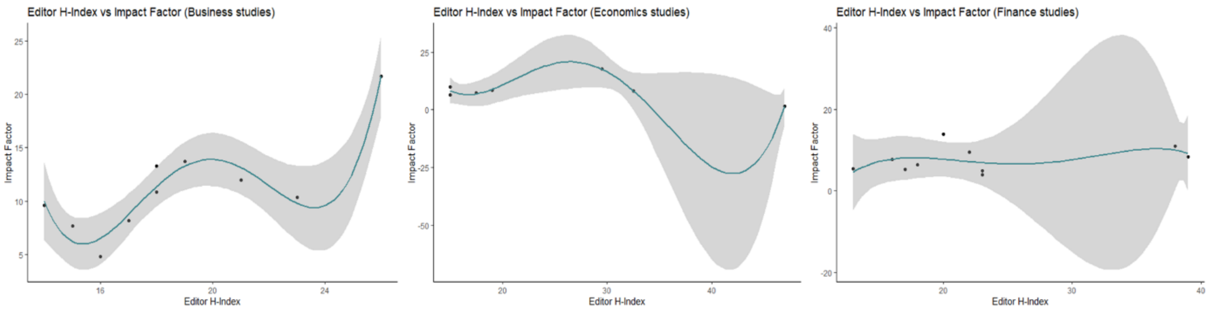


Figure 15 - Fitted regression between Median Editor's H-index and Impact Factor for each category

Not surprisingly the business journals show[24] a strong non-linear relationship between the variables with 94% of the IF variations explained by the editor's H-index. In addition, even though in the economics journals there is also a strong relationship between the variables, 95% of the data fit the model, and the p-value a bit above the threshold indicates that the model is still slightly significant. On the other hand, finance journals seem not to have any relation between these variables.

[24] Business journals: $R^2 = 0.94$; $\rho = .003$; Economics journals: $R^2 = 0.95$; $\rho = .09$; Finance journals: $R^2 = 0.22$; $\rho = .84$;

4.3. STOCHASTIC FRONTIER ANALYSIS

Following the previous exploratory data analysis of all variables in our data, the next step was to create the SFA model. The stochastic production frontier model, aiming to measure and analyze a journal's efficiency given the characteristics of its editors, was developed according to the suggested framework of Aigner et al. (1977) and Meeusen & van Den Broeck (1977). Additionally, the functional form used to estimate the production function was the Cobb-Douglas log-linear specification.

The 'sfaR' package in R developed for cross-sectional frontier models is considered. This package assumes a linear functional form thus, to estimate the Cobb-Douglas production function, all the variables both inputs and outputs were used in a logarithmic form.

This study presents a large range of input (resources used during the production process) and output (outcome of the production process) variables. So, deciding on the best possible variables was supported by the descriptive analysis performed in the previous chapters, which allowed us to understand better our variables and how they related to each other, becoming easier to understand which variables should or should not be used for our new model.

Initially, it was considered that the journal performance measures (y) might be influenced by several variables in our dataset: (1) the integration of a certain number of editors on an editorial team; (2) the editors' performance rankings; (3) number of females that integrate the team; (4) number of US-based editors on the team; (5) number of academic editors on the team; (6) the average number of citations per document produced on the last 3 years; or (7) the number of repeated authors. However, in practice, when combined only a few revealed to be significant to the model, such as *Editorial Board count*, *Nº Females*, and *Citations per Doc*. Table 16 presents the estimated results of the production frontier such as the coefficients and their significance levels in the model.

Table 16 - SFA estimation results

Components of SFA	Coefficient	Std. Error	Significance level [25]
Intercept	3.323	0.432	***
Ln *Editorial Board count* (x_1)	0.437	0.119	***
Ln *Females* (x_2)	-0.302	0.105	**
Ln *Citations/Doc* (x_3)	0.561	0.179	**
u (one-side error term)	-1.537	0.502	**
v (two-side error term)	-4.332	1.425	**
sigma	0.478	-	-
gamma	0.942	-	-
lambda	4.043	-	-
skewness test on OLS residuals	-0.646	-	-
Log-likelihood for OLS	-5.159	-	-
LR statistic	2.187	-	-
Chi-square value (by kodde-palm)	5.41	-	-

Thus, as reviewed above, our chosen frontier model is given by the expression:

$$(5)\ \ln y = \beta_0 + \beta_i \ln f(x_i) + \varepsilon_i$$

Where y represents the output variable of the model *Journal H-index,* β the coefficients returned from the model, x the chosen input variables - *Editorial Board count, Females, Citations/Doc,* and ε the error component. In addition, the error component can be further specified as: $\varepsilon_i = v_i - u_i = -4.332 - (-1.537) = -2.795$.

Thus, the stochastic frontier efficiency model is represented by the following equation:

$$\ln y = \beta_0 + \beta_1 \ln f(Editorial\ Board\ count) + \beta_2 \ln f(Females) + \beta_3 \ln f(Citations/Doc) + \varepsilon_i$$

$$\Leftrightarrow\ y = 3.323 + 0.437\, x_1 - 0.302\, x_2 + 0.561\, x_3 - 2.795$$

According to Table 16, the results from the stochastic frontier function for the journal H-index show that all coefficients have positive values except *Females.* So, two out of the three variables specified in the model positively influence the performance of the journals and are highly significant. This means that an increase in the editorial board size *(x_1)* and in the citations per document *(x_3)* of one percent could increase 0.437 and 0.561 percent the H-index of a journal, respectively. Implying that both these variables are important contributors to the improvement of technical efficiency in research production performance. On the contrary, a one percent increase in the number of females will result in a decrease of 0.3 percent of the journal H-index. Additionally, the likelihood ratio (LR) test was performed to check the presence of a technical inefficiency which was 2.18 and inferior to the chi-square value of 5.41,

[25] Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

meaning that the null hypothesis of no technical efficiency was accepted. The gamma value of the MLE is 0.94, implying that 94% of the variability of journal performance is due to technical efficiency, and the remaining 6% can be attributed to random noise. Regarding the overall (in)efficiency, the frontier model shows that the expected unconditional efficiency is 72% while the inefficiency is 37%. On the other hand, the conditional (in)efficiencies calculated using the sfaR package were obtained following the proposals of Jondrow et al. (1982) and Battese & Coelli (1988), respectively.

Table 17 - SFA firm-specific estimates (%)

Journal	**Inefficiency**	**Efficiency**	**Journal Category**
Academy of Management Annals	121.59%	29.83%	Business
Academy of Management Journal	8.30%	92.22%	Business
Accounting Review	26.67%	77.04%	Finance
American Economic Review	6.17%	94.14%	Economics
Econometrica	20.56%	81.83%	Economics
Entrepreneurship Theory and Practice	75.96%	47.08%	Business
Foundations and Trends in Finance	NA	NA	Finance
Journal of Accounting Research	16.98%	84.76%	Finance
Journal of Accounting and Economics	26.29%	77.32%	Finance
Journal of Business Venturing	66.41%	51.79%	Business
Journal of Consumer Research	27.34%	76.53%	Business
Journal of Economic Literature	12.61%	88.45%	Economics
Journal of Finance	8.51%	92.03%	Finance
Journal of Financial Economics	24.05%	79.06%	Finance
Journal of Financial Intermediation	79.15%	45.60%	Finance
Journal of Management	52.79%	59.35%	Finance
Journal of Marketing	19.18%	82.95%	Business
Journal of Marketing Research	32.31%	72.83%	Business
Journal of Monetary Economics	33.87%	71.71%	Finance
Journal of Political Economy	42.79%	65.59%	Economics
Journal of the Academy of Marketing Science	61.50%	54.40%	Business
Marketing Science	47.99%	62.27%	Business
NBER Macroeconomics Annual	41.66%	66.34%	Economics
Quarterly Journal of Economics	27.47%	76.43%	Economics
Review of Economic Studies	44.03%	64.79%	Economics
Review of Financial Studies	9.18%	91.44%	Finance
Strategic Management Journal	20.12%	82.19%	Business

Regarding journal-level efficiency, according to our model, the most efficient journals are the *American Economic Review*, and the *Academy of Management Journal*. As expected, these are also the ones with the lowest inefficiency estimations. Contrariwise, the *Academy of Management Annals* is by far the least efficient among our population, followed by the *Journal of Financial Intermediation* with only around 45% of efficiency.

Furthermore, the efficiencies for each category were calculated to understand the performance within areas of study, and if it existed major gaps between categories of study as well as for each journal to identify their individual productivity. This analysis comes in sequence with the approach that Coelli et al. (2005) proposed about the calculation of a firm's average of the predicted efficiencies resulting in the industry efficiency.

Table 18 - SFA industry-specific estimates (%)

Journal category	**Average Efficiency**
Business	65.2 %
Economics	76.8 %
Finance	75.4 %

According to Table 18, the most efficient study area is Economics, closely followed by Finance. Surprisingly, Business studies journals present a lower average efficiency.

The distribution of the efficiency estimates[26], tells us that most journals in all research areas have been operating at an efficient level (around 70% - 80%). The distribution per category shows that business journals are the discipline with the smallest probability density area, and therefore, there is a lower chance of business studies' efficiencies having a higher range of efficiency than economics and finance studies. Further, we can suppose that economics and finance studies increase the overall efficiency of the whole research industry while business is a step behind in terms of production efficiency.

By combining and averaging the estimated efficiencies of the individual journals per location, an efficiency estimation can be made to identify inequalities that may possibly occur between journals located in Europe or the US. Thus, Table 19 shows a slightly higher technical efficiency in Western European journals but nothing major that might lead to further assumptions that the geographical location would heavily impact the journal's performance. When drilling down to a country's level, journals located in the Netherlands do show higher efficiency.

[26] See Appendix 12.

Table 19 - SFA estimates per continent and country (%)

Journal continent	Average Efficiency	Journal country	Average Efficiency
Western Europe	73.6 %	Netherlands	70 %
		United Kingdom	77.3 %
North America	71 %	United States	71 %

In an attempt to explore further the efficiencies of each journal and category, each journal's efficiency was compared against other variables which allowed us to understand the type of relationship that existed between the data points if any per category. In the following plots, three variables were taken into consideration for this scrutiny - the size of the editorial board, the number of female editors, and the median H-index of the editorial board. Figure 16 and Figure 17 show a pattern where editorial size and the number of female authors have a positive relationship but only for business journals while economics and finance studies seem to not be affected by such factors. For the latter subjects, as the efficiency increases, the overall number of editors and females tends to remain constant.

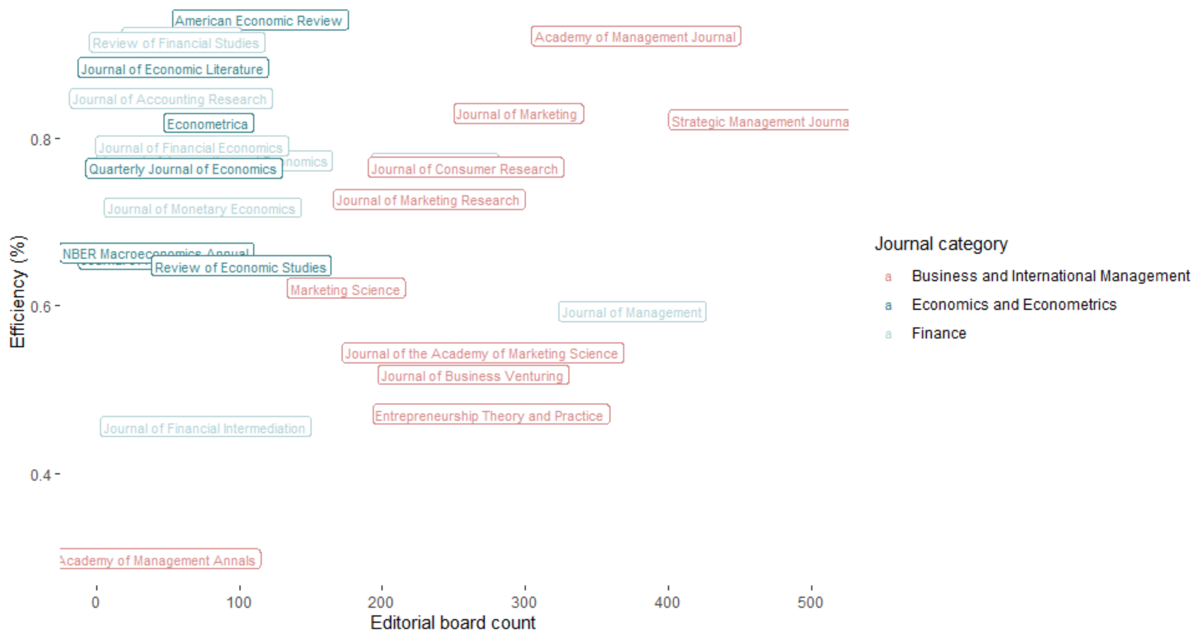


Figure 16 – Journals' efficiency (%) vs Editorial board count segmented by category

Figure 17 - Journals' efficiency (%) vs Nº of female editors segmented by category

Contradicting the previous results, Figure 18 shows a random display of the data points regarding the overall performance of the editorial teams. These results indicate that editors' performance does not directly influence the efficiency of the journal they are associated with. Not even when this analysis is broken down into categories.

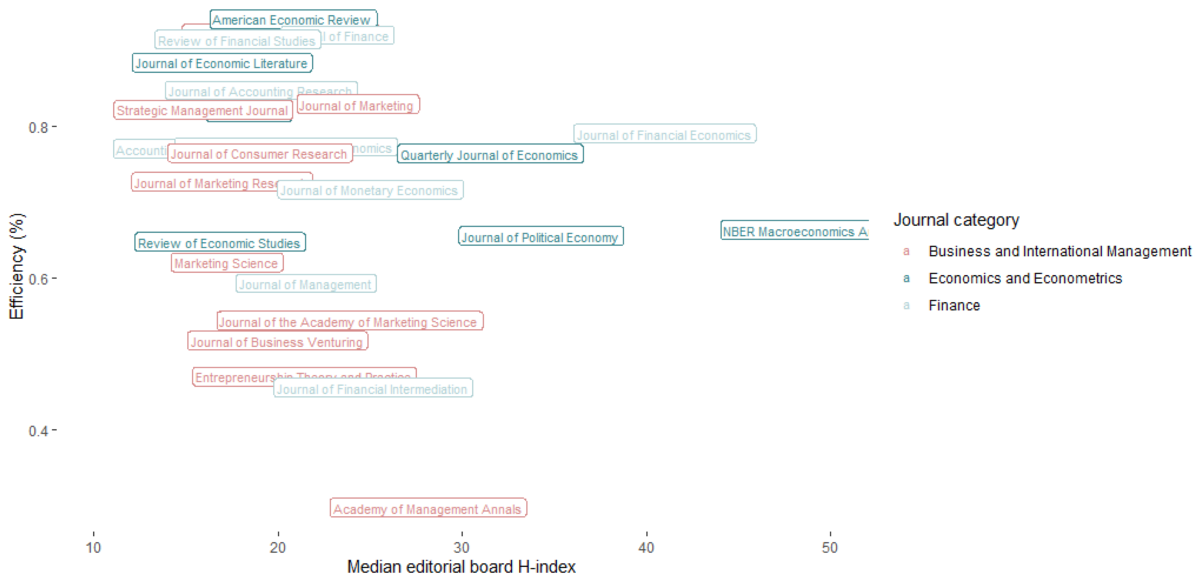


Figure 18 - Journals' efficiency (%) vs Median editor's H-index segmented by category

As has already been shown, the result of this analysis implies that there is a significant relationship between editorial size, female editors, and efficiency in business journals. However, its' estimates show that, even though this research field tends to be above the average size in terms of editors, its' efficiency levels are the lowest among the considered subjects. One reason for this could be that business studies are more susceptible to such characteristics than the other subjects, and therefore, this will have an impact on their productivity level.

5. DISCUSSION

By studying the editor's characteristics, we were able to discover some important points about editorial governance and its composition, as well as their effects on knowledge dissemination across different studies. However, are research work considering the right editorships? According to empirical studies, further exploring editorial boards members' personal information, such as names, location, gender, affiliated institutions, and individual performance measures allows for the measurement of the academic reputations, of both editors and journals, and the impact of institutions (Wu et al., 2018). In this work, we take a closer look into such attributes from editors as well as from journals. This matters because such attributes could influence the performance or composition of editorial boards and consequently the knowledge that is shared with the public.

From the 27 journals, 3575 editorial board memberships, 2783 individuals, 497 affiliated institutions, 37 countries, and 13 publishing houses present in our database, initial findings indicate that developed countries are overrepresented in the editorial population, especially regions such as North America and Western Europe (e.g., US, UK, and Canada). Also, where are located the publishing houses present in our dataset? In specific, our results show that the US alone has an unmatched high influencing power when it comes to academic research. Such outcomes corroborate findings of several other works that studied journal's editorial boards of various fields regarding the geographical distribution of editors, where unsurprisingly the US holds the most of the editorial power and, consequently, has a larger influence on most editorial teams (Goyanes & Demeter, 2020; He et al., 2021; Mendonça et al., 2018; Xie et al., 2020). On the contrary, female and non-academic editors are underrepresented among the editorial population even though this pattern of a minority in academic research has been diminishing over the years in terms of gender diversity (Fox et al., 2019; Harzing & Metz, 2011; Manlove & Belou, 2018; Mauleón et al., 2013). This research is significant since it is very likely that one's surrounding environment, culture, and background of someone affect their thinking, and thus, if an editorial team does not represent enough geographical, gender, or knowledge diversity within, it could lead to limited perspectives or even show bias towards those within their "circle". Therefore, if academic editors are also driven by this proximity, then we may assume that academic power is concentrated within an elite, resulting in a lack of fairness and objectivity in academic works review. So, the power of these editors in academic journals where they decide what is published or not is important and should be carefully placed (Heckman & Moktan, 2020).

Another key finding is related to editor's performance measures whereas male and US-based editors show a higher H-index while belonging to a specific discipline do not affect the individual performance. Accordingly, it is reasonable to assume that scholars are subject to a gender bias when it comes to their own impact. Likewise, academics that hold more than one position in scholarly journals present a higher overall H-index, the median H-index of the repeated editors is higher than the overall median. As Petersen et al. (2017) discussed, and assuming that editorial board members are chosen by knowledge and experience, individuals that show the best performances are more likely to intake multiple academic positions as well as have a wider choice option of which journals to serve. Consequently, this decision will also be influenced by the impact of the journals which in turn will contribute to their own individual scientific reputation. Thus, having several repeated authors in various journals could mean that there is a sharing of inside knowledge among organizations and so lead to biased works and less competition among them.

On a journal level, regarding the composition of editorial boards, higher editorial board counts relate to a higher journal H-index while it shows no impact on the SJR. This outcome can be further narrowed down according to the three fields in analysis, while business and economics studies have a significant positive influence, finance journals seem to not correlate. Also, smaller editorial boards show a higher diversity in terms of geography and gender in favor of female and non-US editors as well as a smaller number of overall publications and citations. Similar results from other researchers were found in journals with smaller editorial boards where females represented a higher proportion of editors than in larger teams (Xie et al., 2020) as well as the geographical position of editors (Petersen et al., 2017), therefore influencing positively journal's impact and amount of published research. Furthermore, the more editors a journal has the lower its' scholars individual performance rankings.

Overall, it seems that business journals' performance is influenced by the several attributes present in the data, such as the editors' H-index, the size of the editorial board, and the amount of research published. In the case of finance journals, it appears that they are more affected by the editorial board count and the number of papers while in economics only the H-index of editors seems to impact journals' performance. Economics journals H-index and SJR are highly related to the IF.

Table 20 - Summary of the attributes that seem to influence the performance of each discipline

Business	Economics	Finance
Editors' H-index Editorial board size Number of published documents	Editors' H-index	Editorial board size Number of published documents

The proportion of female editors only seems to positively affect the SJR of the business studies journals' while for finance topics it follows a slightly negative pattern, i.e., the higher the female presence in editorial teams the lower a journal SJR. Regarding the location, the higher the proportion of US-based editors the more negatively affected will the Journal H-index be in business journals whereas the SJR tends to increase along with the percentage of editors from the US. Finance studies journals show a positive impact on the H-index while in economics the editors' location does not seem to be related to a journal's impact. Other studies on these journal subjects show that management and economics journals' quality is not affected by editorial board diversity and even though it has been demonstrated in past research this has not been corroborated by our study for all the research areas (Petersen et al., 2017; Wu et al., 2020).

The stochastic frontier analysis suggests that having a larger editorial board and more citations per document increases journals' H-index while a higher number of female editors decreases it. The overall mean efficiency results imply that the research sector as a whole stay fairly efficient and, on average, produces 72% given the same inputs as if it was fully efficient. It is also worth mentioning that the effect of such characteristics on the efficiency estimation is expected to be slightly biased as the model was created from cross-sectional data and thus is dependent on the period of time that the data was collected.

As shown previously, the SFA analysis results suggest that there is a positive relationship between the size of the editorial board and efficiency as well as between the number of female editors and efficiency estimates for business-related journals while economics and finance do not seem to have a pattern. In contrast, as already expected from the prior analysis, editors' performance does not seem to influence journals' efficiencies, not even when separated by search area. It could be speculated that due to editorial boards composition variations within short periods it makes it hard to keep "track" of its members or certain researchers since when using publications or citing published works we do not take into consideration the whole journals team. Perhaps, it could happen that a specific scholar that is particularly recognized and thus its performance would have had an impact but not likely the whole team's performance.

At the same time, Economics and Finance journals appear as the discipline to have the highest average level of relative efficiency overall. Although, this conclusion cannot be fully attributed merely to the journal governance or internal structure since other external factors might play a part in justifying these values. When looking at the efficiencies for each journal individually the journals with the highest and lowest technical efficiencies are from the US, which could support the efficiency result gotten for the country itself given that it's the country with the highest amount of workforce and resources.

The UK seems to emerge as having the most efficient journals which could be explained by two main reasons (1) is not limited by language barriers since English is the research production main language thus native English speakers might have an advantage in writing and publishing papers and (2) according to the *Times Higher Education World University Rankings list* the UK is home to many highly prestigious universities, and as the vast majority of research is conducted by academic institutions, the reputation of universities is enhanced even further falling into a vicious cycle.

All in all, larger editorial boards with more women in their' composition tend to be more efficient than smaller editorial boards but only for the business category.

6. CONCLUSION

Evidence in this work suggests that in all categories together, the performance of research journals' is influenced by the size of the editorial board and diversity in terms of geographical location and gender but not by the individual performance of each scholar. So, are journals choosing quantity over quality? There is, if the journal management decides to have more scholars but with a lower impact over a smaller editorial board but with high influential editors, what could be the reason? According to our research, on the one hand, larger editorial boards have a higher workforce which will be reflected in more research produced and in turn lead to more citations and recognition, on the other hand, smaller editorial boards are taking on more recognized editors which on its own increases the reputation of the institutions. Equally important to mention, is the overwhelming presence of US-based, male, and academic editors among the editorial boards herein as well as a dominance of US institutions represented by editorial board members. Thus, national biases could also play a considerable role in the structure of editorial boards. This is a pattern observed across all the research fields and constantly acknowledged in already published works and yet even though there has been a slight change throughout the years, it has not been significant enough. A further contribution from this study is the comparison between the three research fields in question where was seen that business and economics journals are more susceptible to editorial board sizes and the H-index of the editors as a team while finance does not seem to be significantly affected. The business and finance journal's h-index is the most impacted by the number of published documents.

The conclusions attained from the use of the stochastic frontier model give evidence about the efficiency of research journals and some study fields while at the same time accounting for the existence of inefficiency. Of course, these results are only valid for a certain period of time since the data used is a snapshot of a limited interval of time. Overall, the research industry present in our sample remains efficient showing that for the given inputs being used there is still a margin for improvement. Nevertheless, the location of where the research is coming from shows some differences but nothing significant. Moreover, the analysis also hints that economics and finance journals tend to be more efficient than business journals likely because throughout the analysis the latter has shown to be consistently the most strongly affected by the composition of the editorial board**.** Hence, the descriptive analysis along with the stochastic frontier model results could be a major step up for journal governance to increase their productivity and efficiency while becoming a more inclusive industry to currently underrepresented classes and build a more balanced and strategic spread of knowledge. Could also be that some of the journals or academics present in our data already hold a strong market position in the industry or a certain location.

It is also important to address some believed limitations of this research namely the cross-sectional data, which means that this study is based on a snapshot of the data regarding editorial board composition at a certain point in time. Thus, future development of this work could be using panel data as it would be interesting to understand how these patterns have been evolving over time as well as the efficiency since it highly variates. Another limitation is the use of the H-index to compare editors across different fields since there are big discrepancies between categories and specialties, in this sense not only the H-index should be taken into consideration since it might introduce some bias. And lastly, the way the editorial board data was collected is a lengthy task as journal websites do not always include the complete name of editors but only the first name's initial. The improvement of the full name would allow more easily the correct identification of scholars throughout several study areas and make the data retrieval more efficient. Which is also a recommendation from this work. Such limitations should be taken as an opportunity to further develop and improve editorship analysis for future research. Some ideas could be to (1) increase the number of journals in the data sample by expanding the top ranking of journals retrieved or the study fields to integrate more categories and observe the differences between them, (2) include another type of input variables such as production costs, affiliated institutions ranking, or time that an author has been a member of the team, (3) standardize the roles between journals so a comparison within hierarchies could be included on the analysis, (4) create a model to predict the popularity of a paper, or even (5) use the efficiency estimations to predict the impact that an author joining the editorial team will have in the journals' productivity.

To conclude, such findings from research around academic journals, their structure, and research outcomes might have an impact on future management decisions, journal policies, organizational structure, and even on possible future research content. Potential effects of our findings could be that this work's conclusions help guide a decision-maker's next move or further suggest measures for the editorial team composition. Thus, an implication could be, for example, to opt for size, diversity, or geographical location of the scholars of the editorial board over an editor's ranking while deciding on which characteristics an editor should have or not have to be appointed and increase the journal's efficiency. Or, in order to enhance the journal's overall performance, small changes in journal governance such as changing strategies to spread the knowledge being published or on the way research might be revised by the reviewer team according to the field of study that a journal is inserted. Hence the importance of studying the inner works of the publishing industry and editorial teams.

APPENDIXES

Appendix 1 - Number of editors per journal

Journal	Editorial Board count
Academy of Management Annals	13
Academy of Management Journal	348
Accounting Review	219
American Economic Review	90
Econometrica	66
Entrepreneurship Theory and Practice	243
Foundations and Trends in Finance	3
Journal of Accounting Research	24
Journal of Accounting and Economics	50
Journal of Business Venturing	237
Journal of Consumer Research	231
Journal of Economic Literature	27
Journal of Finance	43
Journal of Financial Economics	40
Journal of Financial Intermediation	47
Journal of Management	354
Journal of Marketing	277
Journal of Marketing Research	205
Journal of Monetary Economics	47
Journal of Political Economy	24
Journal of the Academy of Marketing Science	231
Marketing Science	157
NBER Macroeconomics Annual	15
Quarterly Journal of Economics	34
Review of Economic Studies	76
Review of Financial Studies	32
Strategic Management Journal	440

Appendix 2 – Categories to which each journal belongs

Journal	Category 1	Category 2	Category 3	Category 4
Academy of Management Annals	Business	Organizational Behavior and HR Management	-	-
Academy of Management Journal	Business	Strategy and Management	Management of Technology and Innovation	-
Accounting Review	Finance	Economics	Accounting	-
American Economic Review	Economics	-	-	-
Econometrica	Economics	-	-	-
Entrepreneurship Theory and Practice	Business	Economics	-	-
Foundations and Trends in Finance	Finance	Economics	-	-
Journal of Accounting Research	Finance	Economics	Accounting	-
Journal of Accounting and Economics	Finance	Economics	Accounting	-
Journal of Business Venturing	Business	Management of Technology and Innovation	-	-
Journal of Consumer Research	Business	Economics	Marketing	Anthropology
Journal of Economic Literature	Economics	-	-	-
Journal of Finance	Finance	Economics	Accounting	-
Journal of Financial Economics	Finance	Economics	Accounting	Strategy and Management
Journal of Financial Intermediation	Finance	Economics	-	-
Journal of Management	Finance	Strategy and Management	-	-
Journal of Marketing	Business	Economics	Marketing	-
Journal of Marketing Research	Business	Economics	Marketing	-
Journal of Monetary Economics	Finance	Economics	-	-
Journal of Political Economy	Economics	-	-	-
Journal of the Academy of Marketing Science	Business	Economics	Marketing	-
Marketing Science	Business	Economics	Marketing	-
NBER Macroeconomics Annual	Economics	-	-	-
Quarterly Journal of Economics	Economics	-	-	-
Review of Economic Studies	Economics	-	-	-
Review of Financial Studies	Finance	Economics	Accounting	-
Strategic Management Journal	Business	Strategy and Management	-	-

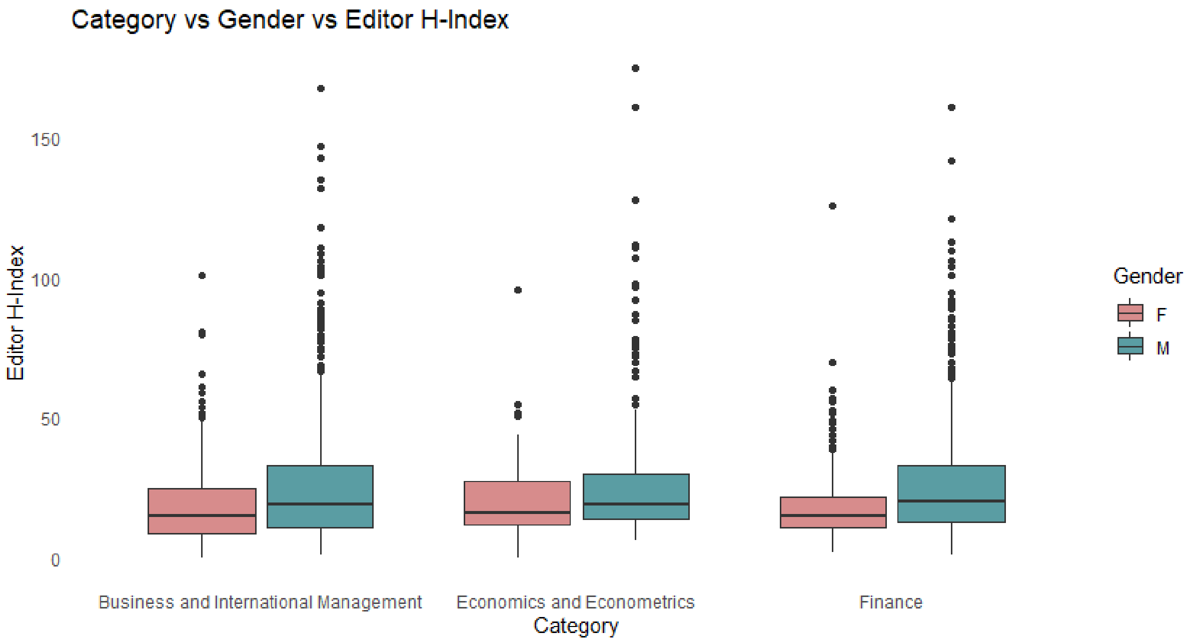
(1) Business: Business and International Management

(2) Economics: Economics and Econometrics

Appendix 3 – Number of editors and gender diversity per country

Country	Editorial Board count	% of total editors	Females	Males	% of Females
Australia	62	1.74%	15	47	24.19%
Austria	6	0.17%	1	5	16.67%
Belgium	18	0.50%	10	8	55.56%
Brazil	6	0.17%	0	6	0.00%
Canada	169	4.73%	63	106	37.28%
Chile	2	0.06%	0	2	0.00%
China	76	2.13%	24	52	31.58%
Colombia	1	0.03%	1	0	100.00%
Czech Republic	2	0.06%	0	2	0.00%
Denmark	13	0.36%	4	9	30.77%
Finland	14	0.39%	3	11	21.43%
France	70	1.96%	17	53	24.29%
Germany	82	2.29%	18	64	21.95%
Hungary	3	0.08%	0	3	0.00%
India	7	0.20%	0	7	0.00%
Ireland	5	0.14%	1	4	20.00%
Israel	15	0.42%	2	13	13.33%
Italy	35	0.98%	8	27	22.86%
Japan	4	0.11%	0	4	0.00%
Mexico	1	0.03%	0	1	0.00%
Netherlands	75	2.10%	18	57	24.00%
New Zealand	5	0.14%	3	2	60.00%
Norway	9	0.25%	3	6	33.33%
Portugal	4	0.11%	0	4	0.00%
Russia	2	0.06%	2	0	100.00%
Saudi Arabia	1	0.03%	1	0	100.00%
Singapore	70	1.96%	16	54	22.86%
South Africa	1	0.03%	0	1	0.00%
South Korea	9	0.25%	1	8	11.11%
Spain	39	1.09%	10	29	25.64%
Sweden	18	0.50%	9	9	50.00%
Switzerland	46	1.29%	7	39	15.22%
Taiwan	6	0.17%	5	1	83.33%
Turkey	3	0.08%	2	1	66.67%
United Arab Emirates	1	0.03%	0	1	0.00%
United Kingdom	216	6.05%	73	143	33.80%
United States	2477	69.33%	769	1708	31.05%

Appendix 4 – Boxplot of Editor H-index for each category, divided by gender



Appendix 5 – Gender diversity per category

Category	Males	Females
Business and International Management	1601 (67%)	781 (33 %)
Economics and Econometrics	253 (76%)	79 (24%)
Finance	633 (74%)	226 (26%)

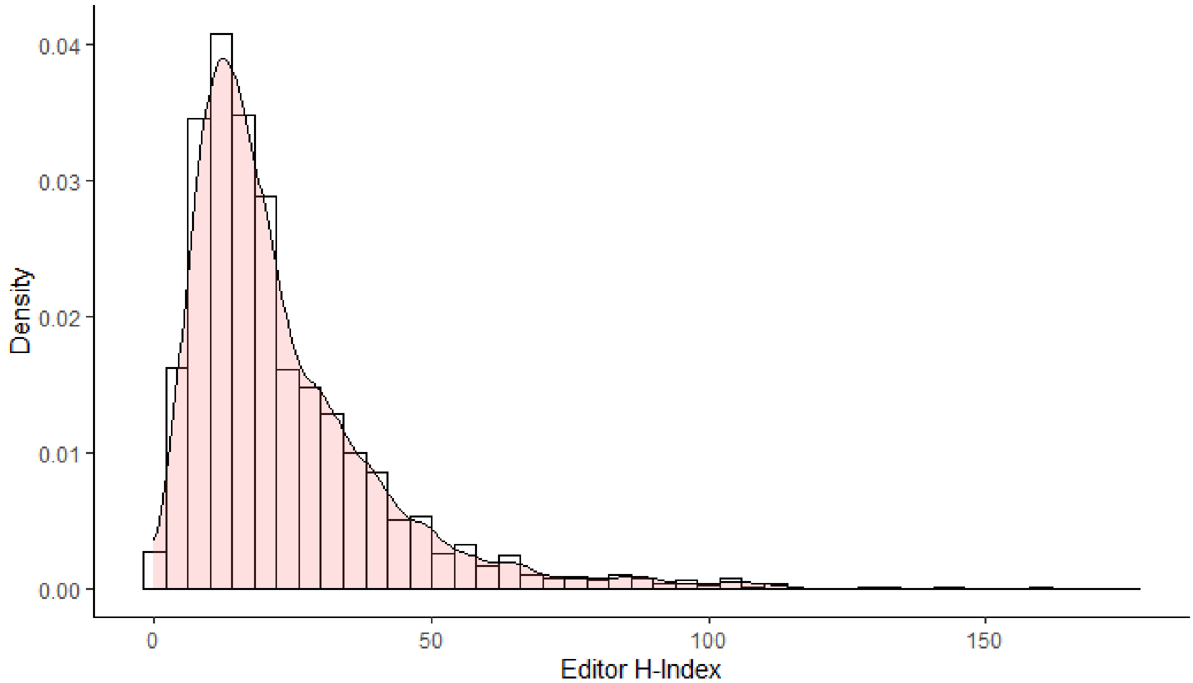
Appendix 6 - Number of editors per affiliated academic institution

Institution (Academic)	Editorial Board count	Country
University of California	95	United States
University of Pennsylvania	74	United States
University of Texas	68	United States
University of Chicago	62	United States
Indiana University	58	United States
Harvard University	55	United States
University of Michigan	50	United States
University of Maryland	49	United States
University of London	48	United Kingdom
University of Southern California	47	United States
University of North Carolina	46	United States
New York University	46	United States
Columbia University	46	United States
Duke University	43	United States
London Business School	42	United Kingdom

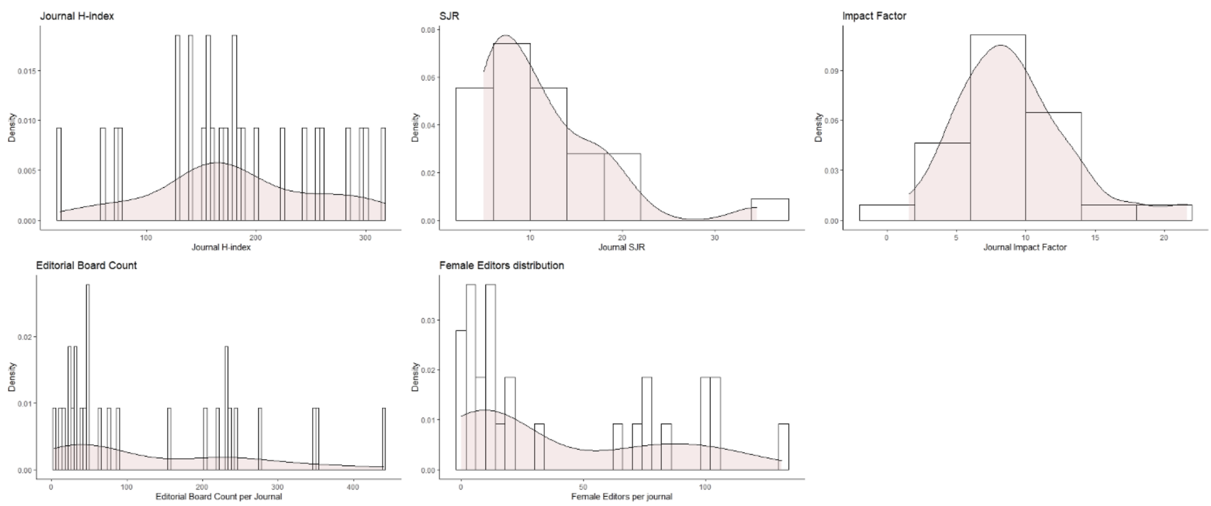
Appendix 7 - Number of editors per affiliated non-academic institution

Institution (Non-Academic)	Editorial Board count	Country
NBER	17	United States
Federal Reserve Bank of Minneapolis	9	United States
Federal Reserve Bank of New York	4	United States
Federal Reserve Bank of Richmond	4	United States
Centre de Recerca en Economia Internacional	3	Spain
European Central Bank	3	Germany
Federal Reserve Bank of Atlanta	3	United States
Alibaba	1	United States
Amazon	1	United States
Bank for International Settlements	1	Switzerland
Bank of England	1	United Kingdom
Center for Monetary and Financial Studies	1	Spain
Center for Research in Economics and Statistics	1	France
CEPR	1	United States
European Corporate Governance Institute	1	United States

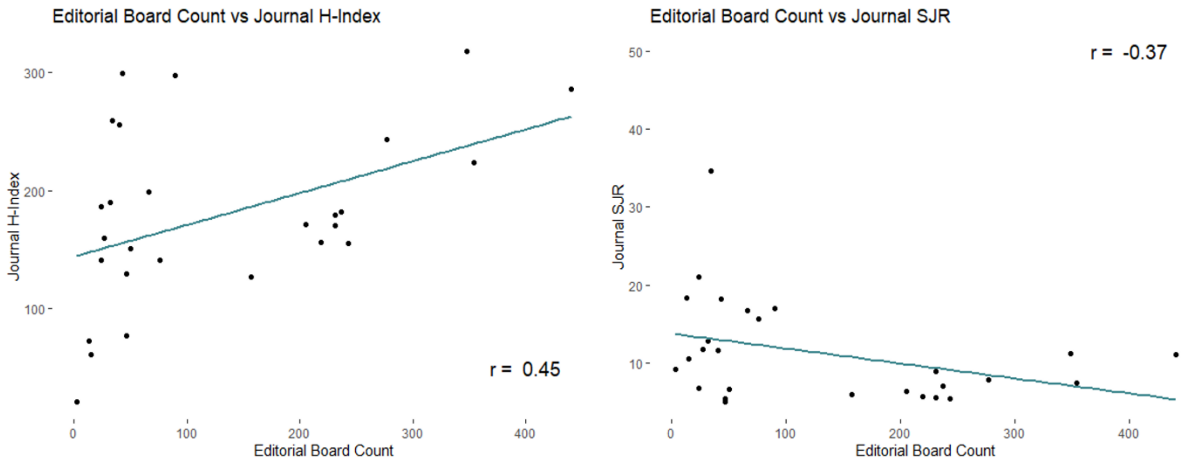
Appendix 8 – Probability distribution of the Editor H-index



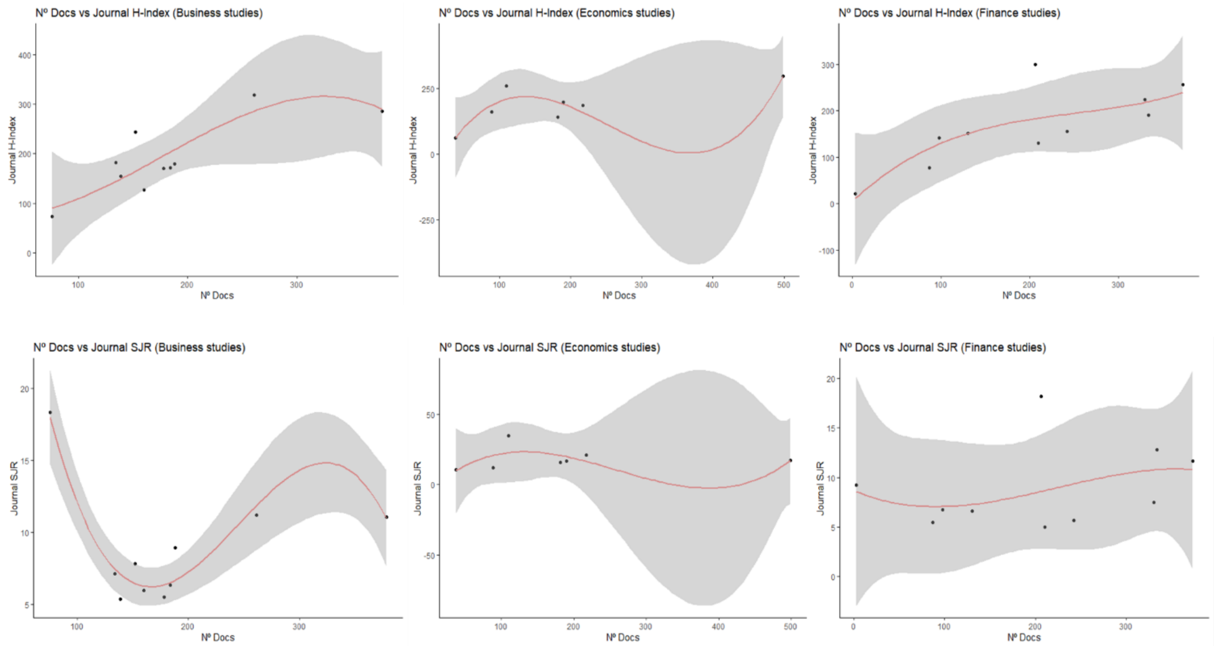
Appendix 9 - Probability distribution of journals' metrics variable



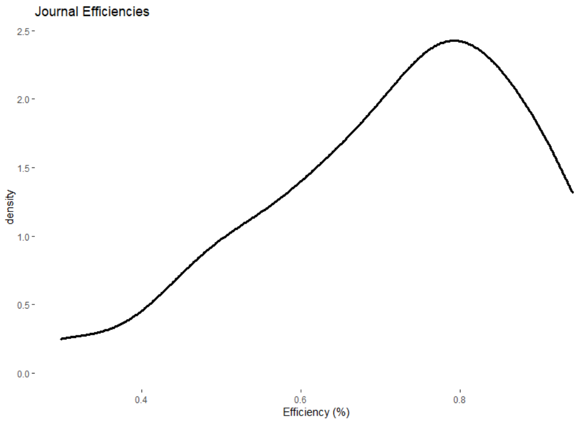
Appendix 10 – Regression between Editorial Board count and Journal performance metrics

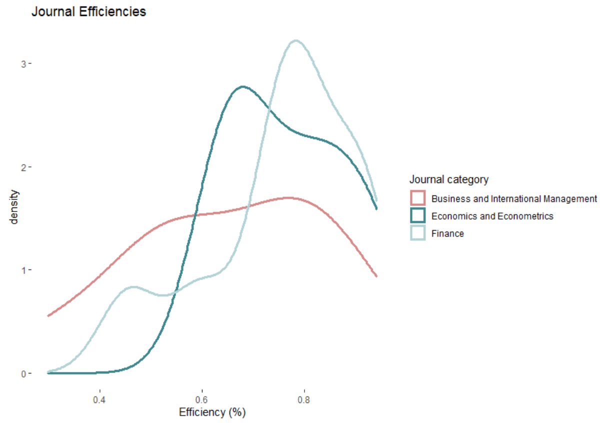


Appendix 11 – Polynomial regression between Nº Documents and Journal performance separated by category



Appendix 12 - Distribution of the efficiency estimates overall and per category





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