POLITECNICO DI TORINO

Corso di Laurea Magistrale
in Ingegneria Gestionale

Tesi di Laurea Magistrale

Alphabetic bias: l’effetto dell'ordine alfabetico sul valore dell’impresa e sul costo del capitale

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Anno Accademico 2021-2022

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List of Abbreviations

ADV: Advertisement

CAPM: Capital Asset Pricing Model

CSR: Corporate Social Responsibility

EMH: Efficient Market Hypothesis

GICS: Global Industry Classification Standard

LEV: Leverage

MTB: Market to Book

OLS: Ordinary Least Squares

PE: Price earnings

PEG: price/earnings-to-growth

RIV: Residual Income Valuation

ROE: Return on Equity

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ABSTRACT

Purpose - Investing is, with no doubt, a challenging process that is even tougher when considering the behavior of the stock market.

Nowadays, the rapid spread of Internet has allowed the entry of new participants in the stock market increasing both the possibilities of trading and the amount of information to be managed. In this scenario, the investment decision-making process has become very tough. Investors processing information show emotions and behave in a way that is barely rational; among these behavioral aspects, scholars found evidence that investors tend to prefer companies whose tickers/names start with earlier letters of the alphabet.

The purpose of this master thesis is to deep dive on the just mentioned matter by investigating on whether and how alphabetic bias may impact both on companies' firm value and implied cost of equity capital.

Structure – After a brief introduction, the first chapter of this work starts with a theoretical overview from standard finance theories, relying on rational approaches, going through the most recent theories of behavioral finance, until reaching behavioral biases and, of course, the core concept of alphabetic bias. The second chapter contextualizes the reasons of this work by formulating two-research hypothesis, explaining the reasoning laying behind them and exploring the relation between firm value and implied cost of equity capital. The third chapter illustrates the econometric model implemented and the different variables composing it. The fourth chapter is about data collection, therefore the creation and description of the panel. The fifth chapter shows the results of the application of the econometric model, therefore tests the validity of the hypothesis Lastly, chapter sixth gives some conclusion remarks, highlights research limitations, and tries to suggest some avenues future research.

Design/methodology/approach – To carry out this work it has was decided to formulate two main research hypothesis, one related to the effect of alphabetic bias on firm value and one related to the effect of alphabetic bias on implied cost of equity capital. These ones are proved through the application of an ad hoc econometric model able to test their soundness. The empirical analysis is performed using data collected from Thomson Reuter's database from year 2000 to year 2020 and related to 497 firms listed in S&P500.

Findings - The results confirmed the evidence that companies having a name starting with a letter positioned at the beginning of the alphabet enjoy from the influence of the alphabetic bias; this latter is translated into an increase in firm value and, under certain conditions, a reduction in the implied cost of equity capital. Referring to this last point, it was found indeed that the alphabetical bias's effect is negatively correlated with firm size, therefore, its effect may be insignificant for large firms. Another relevant finding identified through the empirical analysis concerns the trend of the alphabetic bias phenomenon over time; in particular, it was noted how, following the publishing of studies related to the topic, the effect of alphabetic bias appeared to be less consistent.

Keywords: Behavioral bias, Alphabetic bias, Firm value, Implied cost of equity capital

INTRODUCTION

Recent years have witnessed an evolution in information technology which, in addition to radically changing habits and lifestyles, has led to an increase in the amount of information available and a change in how individuals deal with it. The field of finance, and in particular that of investment, has not been exempt from this change. Indeed, the advent of Internet trading has made it easier for investors, even the less experienced, to participate in the stock market.

Making investment decisions, however, is not easy: besides requiring technical skills, acting rationally is not always straightforward.

Most theories of behavioral finance arise from the idea that human beings are not rational, therefore, their ability to process information is limited. Over the years, the irrationality of investors has been demonstrated by the presence of market anomalies such as speculative bubbles, overreaction, and underreaction to new information. Recent studies in the field have revealed the existence of several behavioral biases that influence investment decisions. Nowadays, the behavioral biases mentioned in the literature are many, but one of them, belonging to the group of name-based biases, seems to be of particular interest: the alphabetic bias.

Nowadays, there is a widespread tendency to order data or, more generally, information in alphabetical order; this practice, which is very common in various fields, has led over time to not insignificant effects; in the academic field, for example, it has been observed that among the studies published and ordered alphabetically, the first ones receive about twice as many citations as the others placed lower down; in politics, on the other hand, it has emerged that the alphabetical order may have favored some candidates rather than others.

The investment field is not exempt from the practice of alphabetical sorting, as financial platforms are used to display information in alphabetical order.

Precisely in this context, before deciding which stocks to buy and sell, investors are confronted with a multitude of information. Even the casual investor searching an investment website is faced with the possibility of examining several thousand stocks. Having to decide which stocks to trade, investors face the inherent limitations of human cognitive ability, and, given the vast number of options, full search and use of information rarely occurs. The investor is unconsciously overwhelmed by the information, and it is at this point that the 'status quo effect' and the 'satisfying effect' come into play; the former translates into the investor's tendency to leave the information as it is shown - that is in alphabetical order -

while the latter translates into inspecting the information from top to bottom by selecting the securities that meet requirements previously determined by the investor himself. This leads the investor not to view all the available options and thus not to find the optimal solution.
The attitude of the alphabetically biased investor has an effect on the companies among which he/she invests; in particular, it is argued that alphabetical bias can affect the firm value and the implied cost of equity capital of companies on an alphabetically ordered list.
All that said so far lays the foundations for this master thesis work of which purpose is to deep dive into the above-mentioned evidence trying to understand whether alphabetical sorting can really influence investment decisions and, as a consequence, the firm value and the implied cost of equity capital of firms presented in an alphabetically sorted list. Therefore, this work intends to provide an improved understanding of the role of alphabetic bias as a determinant of increased firm value and decreased implied cost of equity capital by collecting the main literature of the domain, gathering the most relevant outcomes, and proving two different developed hypotheses:

- (H1) Firms with a stock ticker/name at the beginning of the alphabet have a higher valuation

- (H2) Firms with a stock ticker/name at the beginning of the alphabet have a smaller implied cost of equity.

To achieve the above-mentioned purpose, this work is organized into a 6 chapters structure. The first chapter reviews the most relevant literature related to investors' behavior; therefore, it starts by quickly exploring the standard traditional theories, which revolve around the basic assumptions of individuals' rationality and market efficiency, continuing with behavioral finance, reaching the role of behavioral biases, and concluding with the definition of the alphabetic bias. The second chapter goes deeper into the core of the the work by contextualizing the path to reach the two developed research hypothesis - which are expected to be confirmed -; therefore, the impact of alphabetic bias both on firm value and implied cost of equity capital is presented as well as the eventual relation between firm value and implied cost of equity

capital. Moving forward, the third chapter is about the explanation of how the empirical model was built; this section explores and describes the variables composing the model, these are the variable of interest, the dependent variables, and the control variables. Further, chapter fourth is dedicated to the panel construction and, consequently, to some hints of descriptive statistics. The results coming from the application of the developed model, both for firm value and implied cost of equity capital, are shown in the fifth chapter. Lastly, the sixth chapter sums up the conclusion of this master thesis highlighting the crucial aspects, discussing the limitation points and trying to give some hints on eventual future research.

1. LITERATURE REVIEW

Before going into a deeper analysis on how alphabetic bias may affect the firm value and, eventually, the implied cost of equity capital, it is first necessary to lay the theoretical foundations to understand the main topics driving this study.
On this matter, this chapter aims at reviewing the most relevant literature related to investors' behavior, first, in the first paragraph the standard traditional theories, namely the Expected Utility Theory, the Markowitz portfolio model, the capital asset pricing model, and the Efficient Market Hypothesis, will be quickly explored; then, in the second paragraph some hints on the birth and development of behavioral finance and its main theories will be given; further, the third paragraph will discuss on name-based bias focusing on the alphabetic one; lastly, the fourth paragraph will show the role of behavioral biases in finance, core concept of this work.

1.1 Investment decision: traditional approach

Over time standard finance theories have been developed to find mathematical explanations to real-life financial problems. Fundamental and common assumption laying at the base of these latter was people's rationality.
To begin with one of the most accepted theories in financial literature, it is the case to mention Bernoulli's Expected Utility Theory. According to this latter, market participants make their decisions under risk by comparing the expected utility values of the available alternatives. Rational investors act, indeed, to maximize their expected utility which is calculated as weighted sums of utility values multiplied by their respective probabilities. Bernoulli's theory categorizes the decision-makers into risk-averse, risk-neutral, and risk-loving individuals, and explains the concavity of the utility function for a risk-averse person. This last point explains that for the same amount of utility a risk-averse person would like to take less risk than a risk-loving person. Bernoulli's theory was a great explanation of the difference between investors' behavior with respect to their risk tolerance where the rationality of the agents turned out to be the key to unlocking the stock market behavior. Alongside this assumption, several corresponding theories developed, predominant amongst these were the Markowitz portfolio theory and the capital asset pricing model.

Starting with the first-mentioned one, in 1952 Markowitz introduced the portfolio selection model describing the process of optimal portfolio construction by selecting several risky securities and a risk-free asset. This theory dealt with maximizing the expected return of the portfolio for a given amount of risk or minimizing the risk for a given amount of expected return. Markowitz not only helped in the diversification of the portfolio by selecting securities with the most optimal risk-return opportunity but also formed the basis of one of the most central asset pricing models in finance, the previously mentioned capital asset pricing model (CAPM). Developed by Sharpe, Lintner, and Mossin, the CAPM theory is about the relationship that should be observed between the risk of the asset and its expected return. The expected return of an asset derived from this model provides an estimate of fair or benchmark return. The CAPM theory aims at helping investors to make an educated guess of the expected return of securities that are not yet traded in the stock market[1].
The basic assumptions of the CAPM, aiming at ensuring the homogeneity in the behavior of individuals are listed here as follows:

- It considers that there are many individuals in the market, each with a certain amount of wealth which is small as compared to the total wealth of all investors
- All investors have an identical holding period, and their expectations are myopic such that they would ignore everything that might occur at the end of the period
- Investments are limited only to publicly traded financial assets.
- Investors do not pay any taxes on returns and there are no transaction costs on trading securities
- All investors are rational, and they would try to optimize the risk-return tradeoff of their personal portfolio.
- The investors try to mimic the market portfolio, which is efficient as it incorporates all the relevant information about the universe of securities. Therefore, all the securities in the market portfolio are priced in a fairway.
- Investors are as alike as possible, and they analyze the securities in the same way.

[1] See Bodie, Z., Kane, A., Marcus, A. J., & Mohanty, P. (2002), p. 258

The unsophistication of CAPM made it the most widely used asset pricing model until it started producing anomalies inconsistent with market efficiency and traditional theorists abandoned it in favor of the Fama and the French's three-factor model[2]. On this ground, it is the case to roughly introduce Fama as the responsible for the efficient market hypothesis (EMH).

Fama defined the efficiency of the market as a condition in which security prices always fully reflect the available information and where investors are well-informed and rational individuals aiming to maximize their profits. Therefore, if the EMH is valid, thus it exists, investors cannot hope to beat the market. The EMH was an enormous empirical success in the first decade of its conception as it improved the standard finance literature by considering irrational traders and noting that these latter can temporarily distort prices until their effect is eliminated by arbitrageurs. Another aspect related to Fama's theory is that it categorized the old information into three types giving rise to three forms of market efficiencies: weak, semi-strong, and strong. In the weak form, the past prices and returns are taken as old information, and here technical or trend analysis cannot yield superior abnormal returns. In the semi-strong form, any publicly available information is considered old, and its fundamental analysis also fails to give superior returns meaning that, as soon as the information becomes public, it gets incorporated into security prices. However, investors can still earn abnormal returns by having information that is not made public i.e., insider trading. In the strong market efficiency, even insider trading cannot provide abnormal returns as this information leaks out quickly and gets incorporated into security prices.

After having roughly explored the main theories related to the traditional approach, it is possible to draw some summary points as follows:

- Investors are rational.
- Markets are efficient.
- Investors should design their portfolio according to the rules of the mean-variance portfolio
- Expected returns are a function of risk and risk alone[3].

For a very long time all the above-mentioned standard theories have been the final justification for investor and market behavior. Nevertheless, over time, scholars have observed that traditional theories, usually based on oversimplified assumptions, do not always

[2] See Statman, M. (1999), p. 21.
[3] See Statman, M. (2008), p. 1.

hold true in actual market conditions; their foundations are built on how market participants ought to behave rather than how they actually behave. Here is the moment to talk about Behavioral finance.

1.1Behavioral Finance

The presence of market anomalies like speculative bubbles, overreaction, and underreaction to new information, is proof that the financial decision-making process involves more than a cold, calculative rational agent. Thus, the need for understanding such anomalies and shortcomings of human judgment involved with them opened a path towards behavioral finance. This latter provides, indeed, with an alternative for each of the above-mentioned summary points related to traditional theories; it states, indeed, that investors are “normal” and not rational, that markets are not efficient, even when they are difficult to beat, that investors do not design their portfolio on mean-variance theory and that the expected returns are measured by more than just risk[4]. Focusing on the factor that influenced the most the birth of behavioral finance, investor irrationality is not something new. Stepping backward in history, it is possible to refer to one of the most famous asset bubbles and crashes of all time to discuss investors' irrationality: the well-known "Tulipmania". Everything started in the Dutch Golden Age when the introduction of a new flower ‘Tulip’ led people excited to invest money in it. Over the years, investments in tulips became a trend which caused the prices to always increase until a single bulb was sold for more than 10 times the annual income of a skilled worker. It was when people started realizing the illogicality of their investments, they quickly disposed of their tulip stocks leading the price to go down and, consequently, making the market collapse[5]. The tulip mania event is, with no doubt, the greatest example of investors' irrationality and one of the reasons why various researchers raised the dilemma that investor behavior does not always conform to traditional financial theories. On this matter, among the changes introduced by Behavioral Finance, it is surely worth mentioning theories such as the Behavioral Asset Pricing Model, a new interpretation of CAPM proposed by Shefrin and Statman. The authors of this new theory suggested the interaction of two groups of traders in the market, the informational traders and the noise traders, whereas the informational traders are rational traders who follow the CAPM and noise traders are, instead, the ones not

[4] See Statman, M., (2008), p.2.
[5] See Mackay,C (2003), pp 89-97.

following the CAPM and committing cognitive errors; for this latter, the expected return on securities is determined by their behavioral betas.

At this point, trying to give a more accurate definition of behavioral finance, it is possible to state that behavioral finance is a relatively new school of thought that relaxes the limitations of traditional finance theories and deals with the influence of psychology on the behavior of financial practitioners and its subsequent impact on stock markets[6]. Therefore, denotes the role of psychological biases and their specific behavioral outcome in decision making. Meir Statman restricted all that was said until this moment by stating *"People in standard finance are rational. People in behavioral finance are normal"*[7].

The concept of normality is related to all individuals, and it includes behaviors, ideas, attitudes, and sentiments; all these factors converge into one of the most important sides of behavioral finance, the crucial focus of this master thesis study, that is: the role of behavioral biases. Behavioral biases are a huge topic of which the classification has been largely debated over time. According to Pompeian[8] behavioral biases can be divided into cognitive and emotional. The first ones include aspects like overconfidence, representativeness, anchoring and adjustment, framing, cognitive dissonance, availability, mental accounting, etc., while the second ones are related to endowment bias, loss aversion, optimism, and status quo. Another point of view is one of Shefrin[9] who categorized biases into heuristic-driven and frame-dependent. Starting with heuristic-driven biases, these ones identify that financial practitioners use heuristics to process data and make decisions, to make an example, people believe that future performance of the stock can be best predicted by past performance. Continuing with dependent biases, here the decision process of financial practitioners is also affected by the way they frame their options.

Going more into details, it is necessary to give some further details on heuristic-driven and dependent biases separately. About the first ones, previous research shows a distinction within heuristics itself; in particular, biases like representativeness, availability, and anchoring are responsible for overreaction, or underreaction, in the stock market, while other ones like overconfidence and optimism can create an increase in trading volume and even speculative bubbles. Discussing studies on frame-dependent biases, instead, they reveal that biases like loss aversion can increase investors' risk-seeking tendencies when facing the probability of

[6] See Sewell, M., (2010), p.1.
[7] See Statman, M., (1999), p.26.
[8] See Pompian, M (2011), p44.
[9] See Shefrin, H (2000), pp 13-32.

heavy losses, in fact, the disposition effect can make investors sell shares whose prices have increased while holding stocks that have dropped in value. Always concerning frame-dependent biases, other ones are narrow framing and mental accounting; in narrow framing, investors consider only their current risk and neglect the risks of their previous investments, while in mental accounting, investors separate their wealth into different mental accounts according to the different purpose their wealth serves. In addition to the heuristic and frame-dependent biases, there are other biases having equal importance: the herding and the status quo biases. To begin with, herd, as well as optimistic behaviors, are one of the main causes of speculative bubbles and the eventual crashes in the stock market; this is because people have the tendency to follow the decision of the masses rather than trusting their own reasoning.

The second relevant bias is the status quo. In this case, investors' tendency is to keep their existing position instead of choosing the options about which they feel uncertain. Due to the importance of the link with the core of this study, the implications related to this bias will be further developed in the next sections.

The consciousness coming from behavioral biases gives a tougher insight into the underlying psychology of market participants, furthermore, it underlines the detail that investors are used to making certain mistakes because of their psychology or, more simply, their nature as humans. Considering the cost that these mistakes may have in financial markets, it is not possible to neglect them. For this reason, nowadays behavioral finance is an extremely noteworthy matter which assists financial practitioners in recognizing their own mistakes as well as those of others, but also in understanding the reasons laying behind these mistakes and in avoiding them. Despite all these benefits coming from the biases' knowledge, these are not free from limitations. First, after making people more sensible about their psychological errors during the decision-making it does not give any clarification on how to use any irrationality in monetary terms; then, after making people more aware of stock market mispricing, it does not provide any technique to beat it[10]. Lastly, the models existing in this field still do not include all the types of existing biases, making them not generalizable and, consequently, still relying on traditional theories[11].

Drawing some conclusions, what said so far, permits us to have at least a general understanding of this thesis' field of study. It has been clarified how investment decisions are not always taken by following mathematical reasoning and that individuals' characteristics

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[10] See Bodie, et al., (2009) , p. 355.

[11] See Harrington, B. (2010), The Society Pages.

strongly affect the decision-making process. The biases illustrated so far represent just some hints of the huge biases' universe; nevertheless, for the purpose of this research work, it will be enough to focus only on the most pertinent. The next paragraph will go through Name-Based Bias specifically focusing on the alphabetical order effect.

1.2 Name-Based Bias: Alphabetic Bias

This paragraph intends to explain how simply a name can affect investment decisions and why choosing one name rather than another may reveal to be crucial. Therefore, it is time to talk about the so-called name-based bias and its extension in alphabetical bias.

As just said, recent studies made it possible to understand how investment decisions are strongly influenced by name-based bias such as the memorability and/or the fluency of the names. This was demonstrated by many scholars who, with the passing of time, found even more evidence on this topic. According to Head[12] indeed, companies with memorable ticker names, i.e reminiscent of real words, generate higher daily returns. A similar opinion is the one of Bao[13] who, studying the marketing sector, understood how the ease of a product's name pronunciation helps the brand to be more recognized. In the financial field, a further contribution was given by Green and Jame[14] who noted that companies with a more fluent names had a higher turnover and a lower impact on transaction prices; this situation is mainly explained by the fact that fluency is recognized as having the role of externalizing a sense of familiarity and therefore trust that leads to increasing liquidity and trading shares at significant premiums. This larger investor base and improved liquidity cause the stocks to be traded at significant premiums.

A development of name-based biases is the alphabetic one. Similar to the previous reasoning, if the fluency or the ease of pronunciation of a name can be a crucial factor, also names starting with the first letters of the alphabet appear to be indirectly preferred or more memorable. Alphabetic bias arises when people interact with an information environment that conventionally uses alphabetical order to list information. This convention, together with the predisposition of people to be superficial, - and therefore the tendency to focus on the first (primacy effect) or last points (recency effect) of a list - can favor names placed in the first positions. Speaking of which, the effects of this bias have been observed in various fields. In political trends, for instance, it was found that candidates placed at the top of a voting list are more likely to be voted. In the same way, this bias affects academia; in fact, considering the

[12] See Head, A., Smith, G., Wilson, J. (2009), p. 551.
[13] See Bao, Y., Shao, A. T., & Rivers, D. (2008), p. 148.
[14] See Green, T. Clifton & Jame, Russell, (2013), p. 813.

best financial and economic journals, recent studies show that articles placed in the first position of an issue receive about 50% more future citations than articles placed at the end of an issue. A percentage that drops to 26% and 17% for the second and third positions, respectively.

Authors still do not know what can be the cause leading to this placement as the position of the articles in the first positions can be either due to the knowledge of the editors - who consider them of higher quality and therefore rightly more cited - or simply due to the limited academics' ability to focus on the first pages of an issue. However, a great deal of evidence points to the idea that the answer lies precisely in people's attitudes, and that these effects are exactly attributable to the widespread convention of sorting by alphabet. Always in the academic field, Einav, Yariv, and van Praag demonstrate how researchers whose surname initials belong to the first letters of the alphabet can benefit from greater visibility, and consequently, can lead them to have a greater probability of obtaining a chair in a university department and/or even prestigious awards and recognition[15]. Making another instance of alphabetic bias in the academic field, Richardson[16] finds evidence on how editors of well-established medical imaging journals rely on an alphabetically ordered list of potential referees and, as a consequence, reviewers whose last name starts with an A receive almost twice as many review invitations as their colleagues whose last name starts with another letter, especially if placed towards the end of the alphabet.

In short, all that was said so far has led to the hyperbolical conclusion:

"Over the past century, all kinds of unfairness and discrimination have been denounced or made illegal. But one insidious form continues to thrive: alphabetism. This, for those as yet unaware of such a sad affliction, refers to discrimination against those whose surnames begin with a letter in the lower half of the alphabet"[17].

1.3 Alphabetic Bias in finance

Since the convention of alphabetization is a fact of everyday life and since top-down listing browsing is a natural human habit, alphabetic bias is not limited to politics or academia, but it extends also to the financial field.

[15] See Einav, L. and Yariv, L. (2006), p. 176.
[16] See Richardson, M. L. (2008), p. 213.
[17] As easy as ZYX (2001), The Economist, in https://www.economist.com/leaders/2001/08/30/as-easy-as-zyx, (14.01.2022).

The objective of this paragraph is, indeed, to understand how the alphabetic bias emerges also in finance and, specifically, during investment decisions. Two crucial concepts in this discussion are “Satisficing” and “Status quo”.

Introducing the first concept, “Satisficing” is a decision-making strategy or cognitive heuristic postulated by Simon and implying that in analyzing information there is a tendency of investors to proceed from the beginning to the end of a list, stopping only when solutions that meet the standards that the decision-maker had set were found. According to Simon, this scenario happens when investors are subject to a huge amount of information and, having to face so many variables, which would require a great deal of effort, they tend to satisfice, preferring to stop in front of an option deemed acceptable. In a nutshell, it is like looking for a second-best option but not a first-best option. The concept of satisficing meets the one of alphabetic bias when, following the previous reasoning, investors are faced with a list of stocks and, not willing to go through all the information, they will be more likely to satisfice buying and selling stocks appearing toward the beginning of the list; confirming that the initial ordering significantly matters in the selection of stocks to sell and buy.

Moving to the second concept concerning the alphabetic bias, let’s now discuss the “Status quo”. Before the advent of the internet, it was standard to present paper form information sorted in alphabetical order. Since the advent of the internet, new features have been introduced to facilitate the search of information, and also the way companies' information is displayed has changed. On this ground, investors are nowadays given the opportunity to enter a list of predetermined criteria to filter their investment choices and get a customized selection suiting their needs. Hence, with the advent of online trading and the Internet, the decision-maker is no longer forced to accept the default order, the so-called “status quo”, but can customize the ranking of the data provided to meet personal needs, i.e. considering market capitalization and/or price-earnings. Then, where is the issue? The answer is easy; if on the one hand, the advent of the Internet gave investors the possibility to go for more customized information, on the other hand, it has exponentially increased the amount of it.

Numerous research widely discussed in the literature how the increase in the amount of information that individuals must manage has led to an increased reliance on the status quo, i.e. default options[18]. The reason for this passiveness to keep things as they are is further explained by Kahneman who argues that this preference is the result of an additional effect, the so-called endowment effect[19].

[18] See Dean, (2008), p. 14.

[19] See Kahneman, D., Knetsch, J. L., and Thaler, R. H., (1991), p. 205.

This latter describes a circumstance in which individuals place a higher value on an object that they already own; this effect, in turn, derives from loss aversion, which refers to a phenomenon where a real or potential loss is perceived by individuals as psychologically or emotionally more severe than an equivalent gain. In other words, alphabetical sorting, then alphabetic bias, still prevail as the mode of viewing information. A further contribution to the analysis of the status quo phenomenon is given by Itzkowitz. This latter, who also argued the insignificance of the alphabetic bias in a scenario without status quo, finds evidence on how firms whose name begins with a letter that is closer to the beginning of the alphabet enjoy from a statistically significant higher level of liquidity, market-to-book ratios and trading volume among retail investors. And that is exactly the increased liquidity which, according to authors like Itzkowitz, Amihud, and Mendelson, is synonymous with lower rates of return and thus higher firm values, bringing to the conclusion that alphabetic bias not only exists but also that its impact is always more effective.

2. HYPOTHESIS DEVELOPMENT

While the previous chapter represents a theoretical introduction to the main topics related to the field of research of this master thesis, this second part aims to go more into detail by collecting evidence on the existence of the alphabetical bias and its relative effect both on firm value and cost of equity. Speaking of which, two hypotheses concerning the impact of alphabetic bias on firm value and cost of equity are formulated, enriched, and contextualized through the use of the existing literature.

2.1 The impact of Alphabetic Bias on firm value and implied cost of equity

As previously mentioned, Itzkowitz[20] demonstrates how firms with an early alphabet name see a statistically significant higher level of liquidity and trading volume, therefore an increase of the firm value, among retail investors. Jacobs and Hillert find the same positive correlation between trading activity and liquidity with alphabetical ranking also analyzing whether a name change has an effect on trading volume and liquidity. Although the final results are found not to be statistically significant, even given the small amount of data available, they still find the same effects of alphabetical bias [21].

Aiming at replicating the previously cited studies, the following hypothesis has been formulated:

> (H1) Firms with a stock ticker/name at the beginning of the alphabet have a higher valuation

After having proved the consistency of this hypothesis, this study intends also to verify whether its effect persists even after the influence of the alphabetical ordering has been made public to investors through the publication of the previously cited studies.
Starting from scratch for explaining the reason why the following hypothesis has been formulated - and why it is expected to be confirmed - it is first necessary to explore the

[20] See Itzkowitz, et al., (2015), p. 689.
[21] See Jacobs et al., (2015), p. 696.

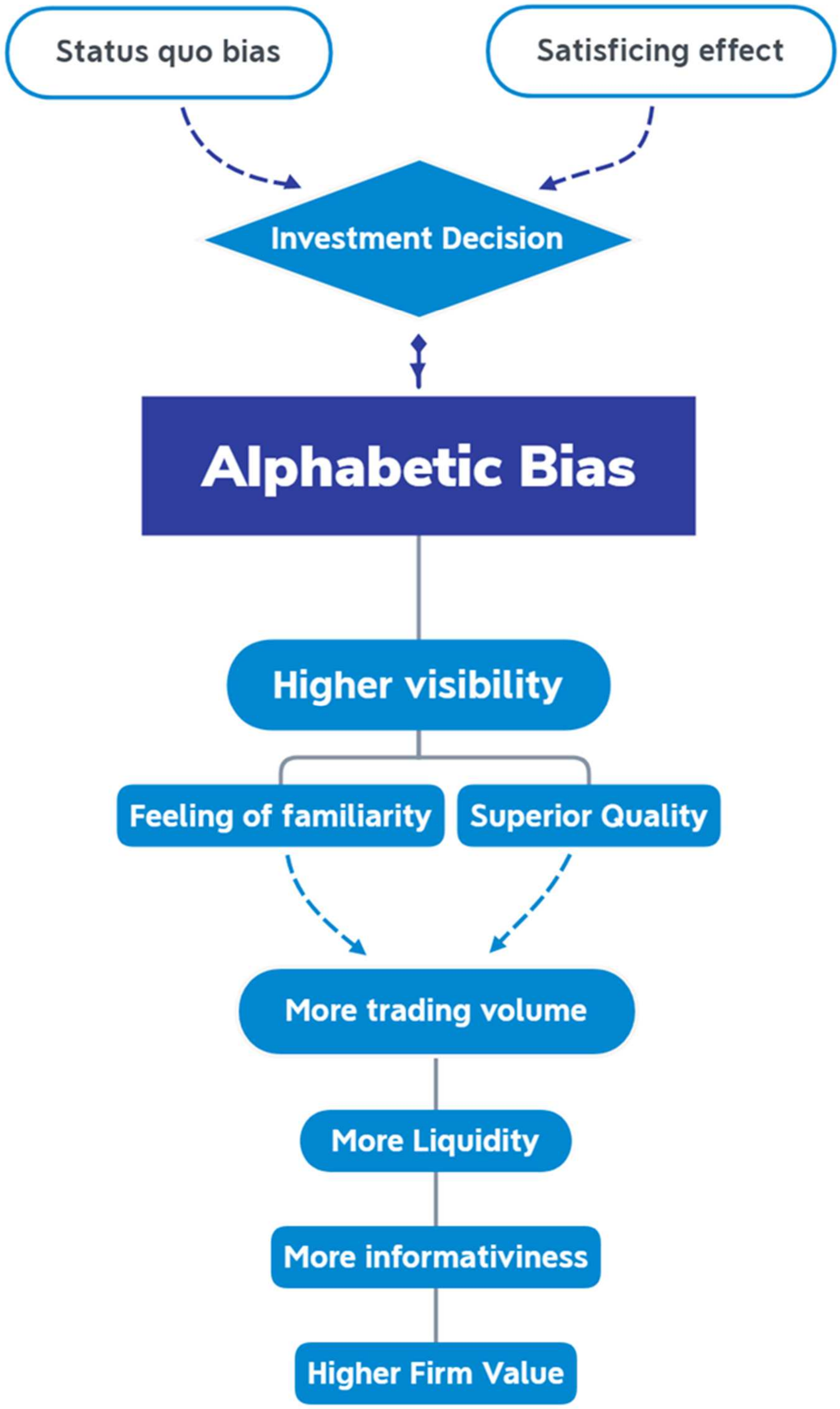

Figure I: Influence of behavioral biases on firm value mechanism that generates the relationship between the alphabetic bias and the firm value. Speaking of which, Figure I is a graphical representation of the whole process affecting firm value. As it is possible to see, everything starts when the choice of investment is made. The alphabetical order of shares increases their visibility leading to a greater volume of exchanges and a greater liquidity which, in turn, translates into greater price informativeness. It is this last effect that generates an increase in value for the company.

From the graphical representation, it is now time to go deeper into all these concepts by making reference to the existing literature. Defining trading volume, it refers to the total number of shares or contracts traded between buyers and sellers of security during trading hours on a given day. It is considered a measure of market activity and liquidity over a given period of time. Having high trading volumes is definitely considered a positive indicator, in fact, higher volume for security is synonymous with greater liquidity in the stock market[22]. Talking about liquidity, instead, it is an essential factor, it is said that the market is liquid if shares can be sold quickly and if at the same time these transactions do not significantly affect the price of the stock. The characteristic of more liquid stocks is that they attract more interest from investors and have a lower bid-ask spread. This means that the price a buyer offers per share, that is the bid price, and the price a seller is willing to accept, that is the ask price, will be fairly close to each other[23]. Then, how can alphabetical ordering affect these two important indicators?

There are several mechanisms through which a higher alphabetical ranking may lead to greater trading volume and liquidity, one of these is with no doubt the one of increased visibility. Being placed near the top of an alphabetically ordered stock list is, indeed, a way to increase visibility and be better known. The increased visibility is often synonymous with familiarity, which, according to Heath and Tversky, may translate into an increase in perceived knowledge and competence of evaluating a stock's prospects[24]. The familiarity can induce both higher trading activity[25], and liquidity[26]. Furthermore, from the literature it is possible to learn how numerous other scholars believe that companies that are more visible tend to be both more recognized by investors - hence chosen for trading - but also associated with a higher level of quality, which makes them more attractive to investors' eyes[27]. Making an example, Fedenia, Hirschey, Ang, Chua, and Jiang found that some investors might unconsciously associate the first stock on an alphabetically ordered list with superior quality.

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[22] Se A. Twin (2022), Investopedia, in https://www.investopedia.com/terms/v/volumeoftrade.asp , (01.03.2022).
[23] See A. Hayes (2021), Investopedia, in https://www.investopedia.com/terms/l/liquidity.asp, (01.03.2022).
[24] See Heath, C. and Tversky, A. (1991), p. 5.
[25] See Huberman, G. (2001), p. 659.
[26] See Grullon, G., Kanatas, G., and Weston, J. P. (2004), p. 439.
[27] See Grinblatt, M. and Keloharju, M. (2001), p. 1053.

In conclusion, more visible firms have a higher chance of being selected for trading and also tend to be more liquid[28].

A direct consequence related to liquidity is that it increases price informativeness. Financial markets play an important role by aggregating different sources of information together; asset prices act as a public signal to any outside observer, potentially influencing individual decisions, encouraging informed trading. In fact, increased informativeness, in turn, can allow the manager but also all other market participants to learn from prices by implementing quality investment decisions positively influencing the value of the firm[29]. Numerous studies identify that the availability of an informed environment has positive effects on the financial market. Foucault and Gehrig show that firms that are able to make the most profitable investment decisions are those listed on the stock exchange, as they are the ones that obtain more information from the stock market[30]. Roll, Schwartz and Subrahmanyam describe, instead, how the positive effect of trading activity on firm valuation occurs precisely because of price informativeness[31]. Fang, Noe, and Tice explain that increasing the information content of market prices and performance-sensitive managerial compensation contracts increases firm liquidity[32]. This implies that the manager whose compensation is tied to the stock price has greater incentives to improve the value of the firm. Therefore, by improving stock price informativeness, aggregate trading by individual investors should have a positive effect on firm value. Wang and Zhang also arrive at the same conclusions that trading by investors increases the value of the firm through improving the informativeness of the stock price and reducing the bid-ask spread[33].

A second effect that this thesis wants to investigate concerns the effect of alphabet bias on investors' expected return, that is the implied cost of capital. The reason why it is interesting to investigate this other effect lies in the evidence coming from previous literature. According to Easley and O'Hara, indeed, firms enjoy of a lower cost of capital when investors receive more and better-quality public information[34]. Similarly, the studies of Naiker, Vic, et al. confirms that firms with a higher volume of options trading exhibit a lower implied cost of capital[35], explaining how trading volume can be considered a variable to measure both the participation rate of informed investors and the richness of the information environment.

[28] See Ang, Chua, and Jiang, (2010), p. 40.
[29] See Wang, Qin Emma and Zhang, Jun, (2014), p. 27.
[30] See Foucault, T., Gehrig, T., (2008), p. 146.
[31] See Roll, R., Schwartz, E., Subrahmanyam, A., (2009), p. 345.
[32] See Fang, V., Noe, T., Tice, S., (2009), p. 150.
[33] See Wang, Qin Emma and Zhang, Jun, (2014), p. 27.
[34] See Easley, D., and M. O'Hara., (2004), p. 1553.
[35] See Vic Naiker, Farshid Navissi and Cameron Truong., (2013), p. 261.

The combination of these studies suggests that alphabetical ordering, here again, can directly affect the cost of equity, leading to the formulation of the following hypothesis:

> (H2) Firms with a stock ticker/name at the beginning of the alphabet have a smaller implied cost of equity.

2.2 The relation between firm value and implied cost of equity

After defining the two research hypotheses, the main question is about whether these are really independent of each other or if there is a correlation between the two.

A first answer to this question can be deduced from the studies of Fama and French. These ones suggest that the cost of equity is negatively correlated to the market-to-book ratio, in other words, they found that the higher the valuation of the company, the lower the cost of equity[36]. Going into the specific case of this study, the negative correlation between firm value and cost of equity can also be derived from the valuation models of Ohlson and Juettner-Nauroth[37] and Easton[38], which will be used to calculate the cost of equity.

All valuation models start with the idea that the value of an investment is based on the cash flows it is expected to deliver. The motivation to create a valuation model based only on earnings forecasts arose given the investor community's focus on earnings.

The model is derived from the dividend capitalization model:

$$V_o^E = \sum_{t=1}^{\infty}\left(\frac{dps_t}{(1+r_E)^t}\right)$$

where V_o^E is the intrinsic value of an equity share, dps_t is the expected dividend per share paid to a shareholder of the firm in period t and r_E is the expected rate of return on the equity investment. The resulting model is referred to as the Abnormal Growth in Earnings Valuation Model and anchors the valuation of equity on capitalized future earnings and then makes adjustments to this value via future expected abnormal growth in earnings agr.

$$V_0^E = \frac{eps_1}{r_E} + \sum_{t=2}^{\infty}\left(\frac{agr_t}{r_E \times (1+r_E)^{t-1}}\right)$$

[36] See Fama and French (1992), p. 428.
[37] See Ohlson, J.A., Juettner-Nauroth, (2005), p. 354.
[38] See Easton, Peter. (2004), p. 83.

Easton suggests the following modification, consider the special case with zero growth rate $g_{agr} = 0$. This implies that $agr_2 = agr_3 = \cdots$

In other words, if we assume that next year's forecast of earnings is sufficient for valuation, and the next period's expected abnormal growth in earnings provides an unbiased estimate of all subsequent periods' abnormal growth in earnings, the above formula becomes:

$$P_0 = \frac{eps_2 + r_E dps_1 - eps_1}{r_E^2}$$

Additionally, being interested in reverse engineering to determine the expected rate of return implied by this market price, Easton replaces the intrinsic value V with market price P0.

On the basis of what was said so far, it is evident that, from the analysis of the above-mentioned formulas, the firm value and the implied cost of equity capital are expected to be inversely proportional - if one increases the other decreases - that is, if alphabetical bias increases firm value, it may also be a determinant of a lower cost of capital.

3. EMPIRICAL MODEL DESIGN

This chapter marks the beginning of a more practical approach paving the way to reach the empirical evidence that can confirm the two previously formulated hypotheses. To do this, the steps illustrated in the following section are: first, the description of the econometric model, then, the introduction and explanation of the variable of interest, the dependent and the control variables. The aim of this section is to present all the variables that will be used in the implementation of the predictive models but without going into the merits of their significance in the explanation of the analyzed phenomenon. Not all these variables are included in each of the single models implemented to test the hypotheses; therefore, all the initially thought variables will be listed, then, the models will be introduced, and the subset of variables used for each of these latter will be indicated.

3.1Model description

There are several ways to study the relationship between two variables. Using regression, one seeks to construct a model through which to predict the values of a dependent variable from the values of one or more independent or explanatory variables. Therefore, the purpose is to estimate the causal effect on Y (dependent variable) of a change in X (independent variable). In this analysis, multiple linear regression, which is an extension of simple linear regression, was used, using the Ordinary Least Squares (OLS) method.
Econometric analysis was performed using the following model:

$$Y_{it} = \beta_0 + \beta_1 X_{it} + \beta_2 C_{it} + u_{it}$$

$t = 1, \dots, T$ indicates the number of years in the period under examination.
$i = 1, \dots, n$ indicates the number of companies that are part of the panel.
Y_{it} is the dependent variable.
X_{it} is the variable of interest
C_{it} is a regressor representing the set of control variables.
u_{it} is the residual error of the regression that collects all the omitted factors, i.e. the other factors other than X that influence Y.

Before going deeper into details with the explanation of the dependent and control variables, a brief introduction on the interest variable is due. This latter, named "TOP 20" and identified as a proxy of the Alphabetic Bias, is a dummy variable equal to 1 if the company is in the first 20% of a list of alphabetically sorted companies, vice-versa, it is equal to 0.

3.2 Dependent Variables

This section introduces and explores the two dependent variables which are used in the econometric models - according to whether referring to hypothesis 1 or 2 - these are: firm value and implied cost of equity capital.

3.2.1 Firm value

Firm value represents investors' perception of a company's success. This is reflected in the company's stock price and many other indicators. Rising stock prices can be seen as a sign of investor confidence in the company. They are willing to pay more because they expect a higher profit return in the future. Therefore, the positive evaluation that the market gives of companies can provide a good signal to attract the interest of investors in making investment decisions.

For the purpose of this work, considering the numerous determinants to take into consideration to compute the firm value, it has been decided to consider the market to book value (MTB) as a proxy of firm value. This was also done in Itkowitz's studies [39]. MTB ratio provides a valuable reality check for investors seeking profitable investment and is often looked at in conjunction with return on equity (ROE), a reliable growth indicator. The higher MTB ratio causes the company value to be higher. Calculating the MTB value, a first formula consists in defining it as the ratio of the market price per share over the current book value of equity per share; thus:

$$MTB = \frac{Price\ per\ share}{Book\ Value\ of\ Equity\ per\ share}$$

[39] See Itzkowitz, J., Itzkowitz, J. and Rothbort. S., (2015), pp 675

Using this formula, it has been noted, however, that some critical issues may arise; one of these could be how the book value of equity is calculated. In particular, if there are multiple classes of shares outstanding, the price of the various classes of shares may be different and it is not easy to understand how the book equity should be allocated among the shares. A second issue is that preferred stock should not be included in the calculation of the book value of equity because the price per share refers only to common equity.

To reduce the magnitude of the problems listed above, it was decided to test the hypothesis that alphabetical order also affects firm value by estimating regressions in which the dependent variable is the ratio of the total market value of equity to the book value of equity, rather than values per share. Therefore, the formula to take into consideration is:

$$MTB = \frac{Market\ Value\ of\ Equity}{Book\ Value\ of\ Equity}$$

The market value of the equity in a firm reflects the market's expectation of the firm's earning power and cashflows. The book value of equity is the difference between the book value of assets and the book value of liabilities, a number that is largely determined by accounting conventions. In the United States, the book value of assets is the original price paid for the assets reduced by any allowable depreciation on the assets.

3.2.2 Implied cost of equity capital

The cost of equity capital refers to two separate concepts and depends on the involved party points of view; for investors, the cost of equity is the rate of return required on an investment in equity, while, for companies, the cost of equity determines the required rate of return on a particular project or investment[40]. It seems clear that the term "cost of capital" is commonly used to describe the implied expected rates of return, but this description does not always hold unless the market prices are efficient, and the earnings forecasts are the market's earnings expectations. For this reason, according to Easton, a more precise term to describe the cost of

[40] See W. Kenton (2021), Investopedia, in https://www.investopedia.com/terms/c/costofequity.asp#:~:text=The%20cost%20of%20equity%20refers,a%20particular%20project%20or%20investment (02.03.2022)

capital would be *"the internal rate of return implied by market prices, accounting book values and analysts' forecasts of earnings"* [41].

The empirical literature that calculates the cost of capital based on market prices and accounting data reverse engineers the accounting-based valuation models to obtain estimates of the implied expected rate of return, which, in turn, is used as a proxy for the cost of capital. The significant benefit of the reverse-engineering approach is that estimates of the expected rate of return are based on forecasts rather than extrapolation from historical data. On this matter, well-known accounting-based valuation models were diffused in 1995 by Ohlson when he introduced the model of residual income valuation (RIV), this latter relating a firm's market value to its book value and future residual incomes under the assumption of a clean surplus relation[42] (CSR). Clarifying this last concept, a clean surplus relationship is an assumption related to residual income models and according to which it is assumed that a firm's ending book increases in the same value as its retained earnings [43]. To implement the residual income valuation model introduced by Ohlson forecasts of book value are required; despite these latter are simple to obtain by using earnings and dividends forecasts, the obvious focus by the investment community on earnings led to a valuation model based only on earnings forecasts, the so-called Abnormal Growth in Earnings Valuation Model.

In the light of all this, this study implemented two models to measure the implied cost of capital based only on earning forecast: one developed by Easton[44] and another one by Ohlson and Juettner-Nauroth[45]. These two models calculate the internal rate of return in such a way that the present value of the expected future residual income, obtained from analyst consensus earnings forecasts, equals the current stock price, but they differ in some aspects. While Ohlson and Juettner-Nauroth replace book value with capitalized next-period earnings and require only subsequent abnormal earnings growth to determine a firm's value, Easton introduces a special case consisting of a valuation based on the price-earnings (PE) ratio and on the PEG ratio (the PE ratio divided by short-term earnings growth). Here as follow the two formulas showing in turn Easton and Ohlson and Juettner-Nauroth models.

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41 See Easton, P. (2009), p. 246.

42 See Ho, K.-C. *et al.* (2017), p. 561.

43 See Accounting Tools, (2021), in https://www.accountingtools.com/articles/2017/5/14/clean-surplus-concept#:~:text=The%20clean%20surplus%20concept%20states,liabilities%20are%20included%20in%20earnings, (02.03.2022)

44 See Easton, Peter. (2004), p. 83.

45 See Ohlson, J.A., Juettner-Nauroth (2005), p. 354.

$$r_{EA} = \frac{DPS_{i,t}}{2 \times P_{i,t}} + \sqrt{\left(\frac{DPS_{i,t}}{2 \times P_{i,t}}\right)^2 + \frac{EPS_{i,t+2} - EPS_{i,t+1}}{P_{i,t}}}$$

$$r_{JN} = A + \sqrt{A^2 + \frac{EPS_{i,t+1}}{P_{i,t}} \times \left(\frac{EPS_{i,t+2} - EPS_{i,t+1}}{2 \times EPS_{i,t+1}} + \frac{1}{2} \times LTG_{i,t} - i_t\right)}$$

$DPS_{i,t}$ is expected dividend per share at time t ;

$EPS_{i,t+x}$ is earnings per share forecast for year $t + x$;

$P_{i,t}$ is current stock price at time t;

i_t is expected perpetual earnings growth at time t;

LTG is long-term earnings growth mean forecast at time t;

$A = \frac{1}{2}\left(i_t + \frac{DPS_{i,t}}{P_{i,t}}\right)$

After identifying the variable of interest and the two single dependent ones, it is time to move the attention to the control variables.

3.3 Control Variables

The control variables are not necessarily of direct interest, but variables to be included in the model to correct the analysis and reduce the residual error (u). Excluding control variables can lead to omitted-variable bias; the error u occurs, indeed, because of variables, which affect Y but are not included in the regression function. Omitted variables are very common and their omission can also lead to a bias in the OLS estimator.
For such a bias to occur, the omitted variable Z must meet two conditions:

- Z is a determinant of Y (i.e., Z is part of u);

- Z is correlated with the regressor X (i.e., corr (Z, X) ≠ 0).

Both conditions must occur for omission of Z to lead to omitted variable bias[46].

[46] See Stock J, Watson MW (2003), p.175.

This brief introduction lays the foundations to start discussing the control variables included in the model applied to prove the hypothesis developed in the previous chapter. Speaking of which, based on the existing literature, with a special focus on Itzkowitz's study[47], the control variables proposed as determinants of firm value and implied cost of equity capital are mentioned as follow. On the evidence that as firms get older their profitability seems to decline[48], the first control variables included in the regression are the natural logarithm of total revenues as a measure for size (SIZE), the natural logarithm of age (AGE), as a measure of risk, and the firm's profitability index, namely Return on Asset (ROA). Further, another significant variable is related to whether the firm operates in the field of technology (TECH) - that is in software, hardware, electronics manufacturing, artificial intelligence, semiconductors, e-commerce, internet and related services -; this latter is explained by the significance of the industry in the US both at a domestic and international level. Also, taking into consideration the factors that may influence investors decision, it was worth to include the investment in advertising (ADV), this one may, indeed, increase the firm value through improved recognition and visibility. To control for agency problems, a further control variable of the regression is the Leverage (LEV) as a lower cash flows could limit the manager's ability to implement value destroying investment decisions. Moreover, on the idea that past returns could influence trading activity and the perception of the firm value, the Total Return (TOT_RET) control variable is added to measure the impact of the past stock performance. Introducing two last control variables not included in the models explored in the previous literature, it was worth to add Corporate Social Responsibility (CSR) and systematic risk (BETA). About the first one, its growth represents the most significant and contentious corporate trends of the last decade; previous research shows the positive correlation between CSR and corporate financial performance, Jo and Harjoto found a strongly positive impact on firm value for firms engaging in CSR[49], similarly, CSR has also the potential to reduce the cost of equity, but only in combination with effective investor protection that safeguards the shareholders[50]. Regarding the second one, the beta of a company measures how the company's equity market value changes with changes in the overall market, since investors demand higher compensation in return for higher risk taking, a negative relation between beta and firm value is expected.

[47] See Itzkowitz et al, (2015), p.1.
[48] See Loderer, Claudio F. and Waelchli, Urs, (2010), p.1.
[49] See Jo, H., Harjoto, (2011), p. 351.
[50] See Breuer, W. and Müller, T. and Rosenbach, D. and Salzmann, A. J., (2018), p. 25.

Here below a synthesis of the used control variables:

- SIZE (Total Revenues, M$)

It is calculated as the natural logarithm of Total Revenues. It represents revenue from all a company's operating activities after deducting any sales adjustments and their equivalents.

- AGE

It is calculated considering the date of organization founded year.

- ROA (Return on Asset)

This value is calculated as the income After Taxes for the fiscal period divided by the Average Total Asset and is expressed as percentage. Average Total Asset is the average of Total Asset at the beginning and the end of the year.

- TECH

It is a dummy variable of value 1 if the company is classified within Information Technology Industry according to the Global Industry Classification Standard (GICS), 0 otherwise. GICS classified companies with increasing granularity by Sector, industry Group, Industry and Sub-Industry.

- ADV (Advertising Expense in M$)

It represents the cost of advertising media and promotional expenses. Advertising Expense may include outsourced advertising expenses for marketing.

- LEV (Leverage)

This is the ratio of Total Debt as of the end of the fiscal period to Total Equity for the same period and is expressed as percentage. Total Debt outstanding, which includes Notes Payable/Short-Term Debt, Current Portion of Long-Term Debt. Total Equity consist of the equity value of preferred shareholders, general and limited partners, and common shareholders, but does not include minority shareholder's interest.

- TOT_RET (Total Return)

The total return incorporates the price change and any relevant dividends for the specified period. Compounded daily return for the specified period is used to calculate Total Return and it is effectively the dividend reinvested Total Return methodology. The most recently

completed trading day is set as the default period. The Dividend type used is the most widely reported Dividend for a market and it is either Gross or Net.

- CSR (Corporate Social Responsibility)

It is considered the average of environmental pillar score and social pillar score. The environmental pillar measures a company's impact on living and non-living natural systems, including the air, land, and water, as well as complete ecosystems. It reflects how well a company uses best management practices to avoid environmental risks and capitalize on environmental opportunities to generate long term shareholder value.
The social pillar measures a company's capacity to generate trust and loyalty with its workforce, customers, and society, through its use of best management practices. It reflects the company's reputation and the health of its license to operate, which are key factors in determining its ability to generate long term shareholder value.

- BETA

CAPM Beta is a measure of systematic risk and represents how much the stock moves for a given move in the market. It is the covariance of the security's price movement in relation to the S&P500 market's price movement.

4. DATA COLLECTION

Once explained the empirical model implemented to test the two different hypotheses developed in the second chapter of this work, it is now time to move the attention to the construction and description of the panel used to implement the model itself.

To do this, this chapter is divided into three sections. The first one – titled Panel creation - describes how, where and in which way data were collected, but also the tools used for the analysis; the second one, titled Descriptive Analysis, is instead about the description of these collected data; lastly, the third paragraph, titled Correlation Matrix, is, as the name suggests, about the creation of a correlation matrix among the different variables of the analysis.

4.1 Panel creation

To confirm - or not - the validity of the formulated hypotheses, data referring to different companies over different periods of time are required. This paragraph discusses the collection of these data flowing into a panel dataset.

To begin with the data source selection, the database used to conduct the study was created from data made available by the Eikon platform provided since 2010 by Thomson Reuters Corporation. Eikon brings together a set of tools to monitor and process complex financial data in real time. Thomson Reuters Database was considered the only source where to collect information regarding companies. Data coming from this latter were further filtered through the set-up of different inclusion and exclusion criteria.

In this regard, it was decided to restrict the information related to companies only to the U.S. stocks market and, specifically, by referring to the Standard and Poor's 500 stock market index in the time range going from the year 2000 to 2020. The S&P 500 is a stock market index tracking the performance of 500 large companies listed on stock exchanges in the United States and it is one of the most followed equity indices including corporations such as Apple, Microsoft, Alphabet, Amazon.com, Meta Platforms, Tesla, Nvidia, Berkshire Hathaway and JPMorgan Chase[51]. Furthermore, only companies that presented completeness of data, like the ones referring to Total Equity and Company Market Capitalization, were selected; this last step reduced the initial sample of 506 companies to 497.

Moving to tools, Stata software was the only tool used for data management, statistical analysis, simulations, and regressions. In this latter, the obtained statistical results were

[51] See Gabe. A (2021), Top 10 S&P 500 Stocks by Index Weight, Investopedia, https://www.investopedia.com/top-10-s-and-p-500-stocks-by-index-weight-4843111, (10.03.2022).

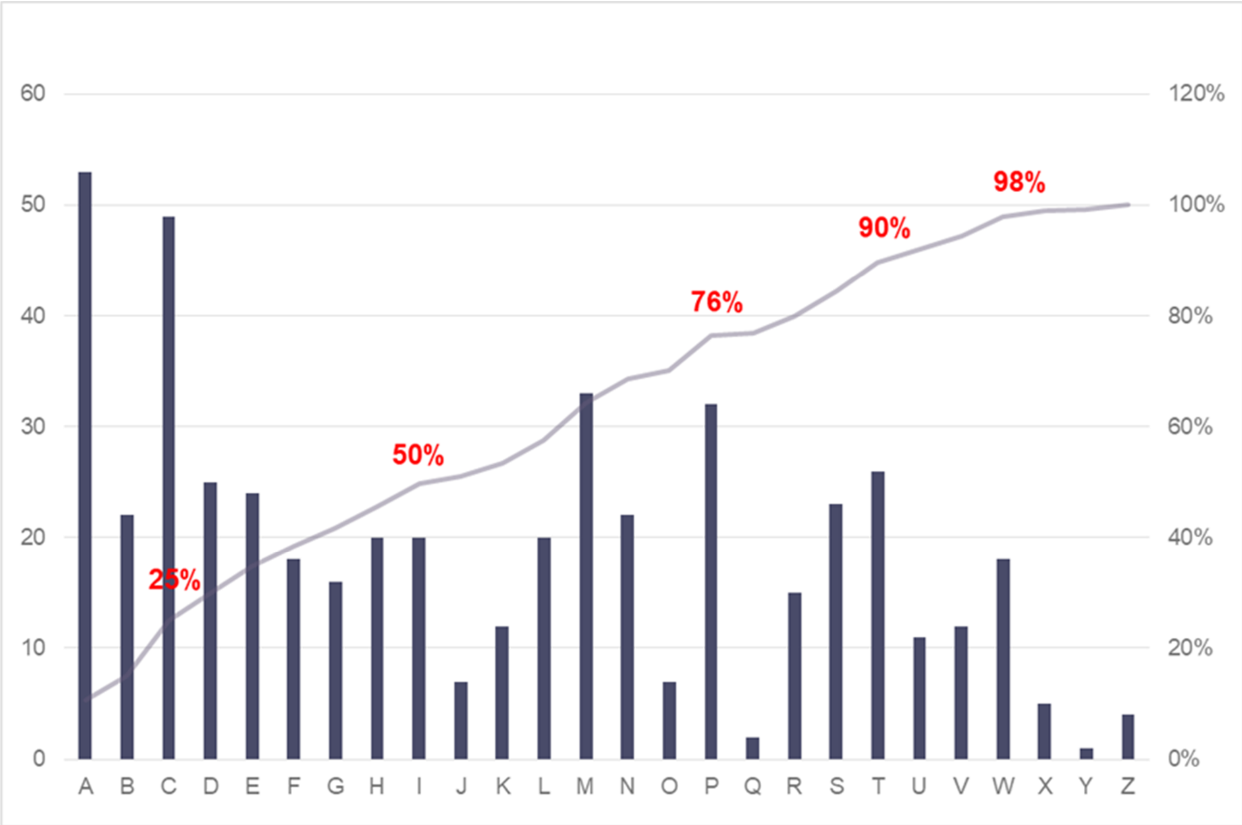

Figure II: Distribution of panel names

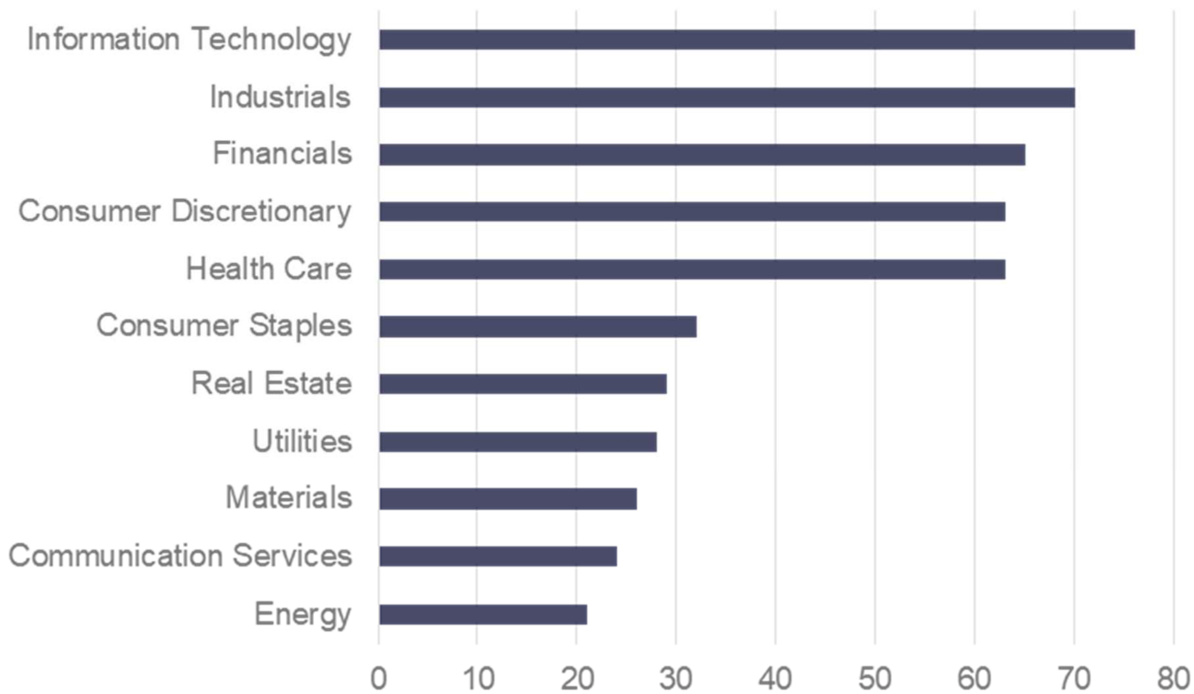

Figure III: Distribution of companies by sector analyzed considering “acceptable” significance levels of 10%, meaning that variables with a p-value lower than 0.1 were considered statistically significant. Moreover, since cases of homoscedastic standard errors are rare, the standard errors robust to heteroscedasticity were used in the estimates made and the robust command was used for this.

4.2 Descriptive Analysis

After the brief parenthesis on the database selection, inclusion and exclusion criteria, and tools used for data management; it is the moment to start describing the obtained panel data. Speaking of which, from Stata it was possible to see how the panel dataset, having some missing observations, is not balanced; this is not a particularly relevant factor as Stata allows to work also with unbalanced panels.

Figure II shows the distribution of firm names by first letter of the alphabet. As it is possible to observe, the 50% of firm’s names in the sample starts with the first nine letters of the alphabet, that is from A to I, reaching its peak with letter A (over 50 companies) and its lowest point with letter G (less than 20 companies); more specifically, the 25% of company names belonging to the panel dataset starts with the first three letters of the alphabet, that is from A to C. This observation suggest that companies may believe in the increased visibility due to rank effects and consider being at the top of the alphabetical list as an objective. The remaining 50% of companies’ names is distributed among the last seventeen letters going from J to Z, where letters M and P contains the highest number of names, even more than letter B. Lastly, letters Z, Q and Y seem to be the less popular for firm names (less than 5 companies each).

Another graphical descriptive representation of the panel dataset regards the sector in which companies operate; in this regard, Figure III shows the distribution of the companies belonging to the panel according to their sector of reference. In particular, the definition of the 11 sectors shown was obtained using Refinitiv Eikon which provided this breakdown according to the Global Industry Classification Standard (GICS). Of the 497 companies of the panel, the five most represented sectors are respectively: Information Technology (76 companies), Industrial (70 companies); Financial (65 companies); Consumer Discretionary (63 companies) and Helth Care (63 companies). The remaining 30% of the panel is represented by companies operating in the following sectors, in turn: Consumer Staples (32 companies), Real Estate (29 companies), Utilities (28 companies), Materials (26 companies); Communication Services (25 companies) and Energy (21 companies).

Variable	Mean	Std. Dev	Min	p25	Median	p75	Max
R_EA	0.099075	0.038778	0.004273	0.076103	0.090572	0.110627	0.241463
R_JN	0.097888	0.029712	0.014601	0.08014	0.093552	0.109252	0.203142
RAVG	0.099074	0.032896	0.020912	0.078917	0.092586	0.109711	0.222303
MTB	4.08357	7.468399	-23.0151	1.39409	2.662779	4.826774	48.01666
TOP20	0.191676	0.393637	0	0	0	0	1
ADV	455.9651	776.5994	0.9	30	126.15	57	3341
AGE	38.05634	30.19907	1	19	28	48	137
TOT_RET	15.06087	33.2929	-60.4102	-1.17003	10.72603	30.92358	146.9033
ROA	9.273906	8.496218	-18.9922	3.94685	8.114305	13.86684	35.27274
SIZE	8.583323	1.633488	-3.29684	7.668844	8.69084	9.587896	12.02432
LEV	103.0488	166.3716	0	16.48915	55.02371	116.7516	1128.273
TECH	0.150905	0.357974	0	0	0	0	1
CSR	46.14196	24.1587	4.369317	25.05307	45.74845	67.26497	89.32889
BETA	0.779857	1.190451	-1.63363	0.064833	0.565094	1.109671	6.736936

Table I presents descriptive statistics for our full sample of N = 10,437 observations from 497 firms over the period 2000- 2020

Table I: Descriptive Statistics

	R_EA	R_JN	RAVG	MTB	TOP20	ADV	AGE	TOT_RET	ROA	SIZE	LEV	TECH	CSR	BETA
R_EA	1													
R_JN	0.9084	1												
RAVG	0.9818	0.9713	1											
MTB	-0.1926	-0.1976	-0.1994	1										
TOP20	0.0084	0.0195	0.0135	0.0314	1									
ADV	-0.0644	-0.0507	-0.0597	0.0093	-0.0439	1								
AGE	-0.1517	-0.1625	-0.1601	0.0526	-0.0078	0.1203	1							
TOT_RET	-0.1225	-0.166	-0.1452	0.1599	0.0126	-0.0585	-0.0461	1						
ROA	-0.2557	-0.2309	-0.2504	0.3034	0.0627	-0.0277	0.0756	0.0519	1					
SIZE	0.1196	0.147	0.1348	-0.0808	-0.0842	0.577	0.0315	-0.1063	-0.0929	1				
LEV	-0.0538	-0.0571	-0.0565	0.2675	0.0344	-0.0358	-0.0129	0.0373	0.0429	-0.1032	1			
TECH	0.0489	0.051	0.051	0.0689	0.0339	-0.0611	-0.2686	0.0707	0.1002	0.0485	-0.0491	1		
CSR	-0.0014	-0.0207	-0.0102	0.0536	-0.0208	0.325	0.1039	-0.0337	0.0143	0.5199	-0.0484	0.1006	1	
BETA	0.1166	0.1144	0.1183	-0.052	0.0528	-0.0035	-0.1684	0.1562	-0.0876	0.0344	0.0072	0.416	0.2255	1

Table II: Correlation Matrix

Moving to descriptive statistics, the command “Summarize" in Stata gave the possibility to obtain, for each of the considered variables, the mean, the median, the standard deviation, the minimum, and the maximum. Table I illustrates the descriptive statistics of the main variables of this analysis. An important aspect related to this table concerns the Min and the Max; in particular, during the analysis it was possible to identify some extreme values that may have influenced the results – also called outliers - whose effect has been further reduced using the command “Winsor2”.

The mean (median) of implied cost of capital estimated using the EA model, JN model are 9.9% (9%), 9.7% (9.3%), respectively. The mean (median) of the implied cost of capital measured using the average of the two models is 9.9% (9.2%). The companies used in the analysis have an implied cost of equity of about 10%, which means that the required rate of return for capital market participants is of about 10%. Firms classified within Information Technology Industry account for 15% of the total sample. The market to book (MTB), the measure used as proxy of firm value previously mentioned, has a mean (median) of 4.1% (4.8%). Lastly, the panel companies range in age from 1 to 137 years, with an average age of 38 years.

4.3 Correlation Matrix

To evaluate the relationship between variables a correlation matrix has been created. This is shown in Table II.

The correlation values can range from -1 to +1, where an absolute value of 1 indicates a perfect linear relationship, while a correlation close to 0 indicates no linear relationship between the variables; furthermore, if the two variables increase and decrease together, the correlation value is positive, vice versa, if one variable increase and the other decreases, the correlation value is negative.

Looking at the mains variables, the correlation between TOP20 and MTB is positive (0.0314), which may suggest that alphabetical order is associated with a higher market to book ratio, this could be a positive sign that being at the top of an alphabetically ordered list may increase firm value.

The correlation between MTB and control variables is as follows: TECH (0.0489), ADV (0.0093), AGE (0.0526), TOT_RET (0.1599), ROA (0.3034), LEV (0.2675), and CSR (0.0536) shows a positive relationship with MTB. Further, SIZE (-0.0808), and BETA (-0.052) show a negative relationship with MTB. Furthermore, the correlations between TOP20 and the three measures of implied cost of equity (R_EA, R_JN, and RAVG) are positive

suggesting that alphabetical order is associated with a higher cost of equity. In particular, the correlation coefficients are 0.0084 for the Easton measure, 0.0195 for the Ohlson and Juettner-Nauroth measure, and 0.0135 for the measure expressing the average between the two previous measures. This may already suggest that being positioned at the top of a list does not lead to a decrease in the implied cost of equity. In addition, while on the one hand the correlation between RAVG, the average implied cost of capital, and control variables - MTB (-0.1994), ADV (-0.0597), AGE (-0.1601), TOT_RET (-0.1452), ROA (-0.2504), LEV (-0.0565), and CSR (-0.0102) - shows a negative relationship with RAVG, on the other hand SIZE (0.1348), TECH (0.051) and BETA (0.1183) show a positive relationship with RAVG.
In closing, by observing the correlation between the dependent variables representing firm value and the implied cost of equity, it can be seen that, the correlations between MTB and the three measures of implied cost of equity (R_EA, R_JN, and RAVG) are negative meaning that higher valuation implies a lower cost of capital. In particular, the correlation coefficients are for the Easton measure -0.1926, -for the Ohlson and Juettner-Nauroth measure 0.1976, and for the measure expressing the mean between the two previous measures -0.1994. This may suggest that alphabetic bias could indirectly contribute to lowering the cost of capital being a variable that contribute to increase the firm valuation.

5. EMPIRICAL RESULTS

As the title of this chapter suggests, this section is dedicated to findings. Therefore, in this section an empirical analysis is carried out to identify if, and in which measure, a statistically significative relationship holds between:

- the alphabetical order and the firm value, and
- the alphabetical order and the implied cost of equity capital.

On this matter, the first macro section reports the results for the test of hypothesis that examines the association between alphabetic bias and firm valuation, while the second one reports the results for the test of hypothesis that examines the association between alphabetic bias and implied cost of equity capital.

5.1 Alphabetic bias and firm value

The multiple linear regression using the Ordinary Least Squares (OLS) method was used for this analysis. The econometric analysis was performed by using the previously explained model, here set up as follows:

$$
\begin{aligned}
Firm\,Value_{i,t} = {} & \beta_0 + \beta_1 TOP20_{i,t} + \beta_2 ADV_{i,t} + \beta_3 AGE_{i,t} + \beta_4 TOT\_RET_{i,t} + \beta_5 ROA_{i,t} \\
& + \beta_6 SIZE_{i,t} + \beta_7 LEV_{i,t} + \beta_8 TECH_{i,t} + \beta_9 CSR_{i,t} + \beta_{10} BETA_{i,t} + u_{i,t}
\end{aligned}
$$

When analyzing the results of the regressions it is important to have to pay attention to several aspects, in particular the sign and the modulus of the coefficients obtained but also the number of observations must be adequate. In addition to the sign and modulus of the coefficients, it is important to check their significance; every time a regression is run, the software includes a statistical test for each estimated coefficient that allows to see if it is different from zero in a robust way. Operationally, the easiest way to assess the significance of a coefficient is to analyze the p-value shown in parentheses; the smaller this value, the higher the probability that the coefficient is different from zero. In fact, being significantly different from zero means that the variable being considered strongly influences the dependent variable.

Table III reports OLS regressions for three different time periods. The dependent variable is the market value of equity divided by the book value of equity. ADV is the amount of money spent on advertising. AGE is the number of years since the firm foundation. TOT_RET is the average of the monthly returns for each stock. ROA is measured as operating income before depreciation divided by total assets. SIZE is the natural log of total revenue. LEV is a ratio of debt to total equity. TECH indicates whether the firm is in technology. CSR is the average of environmental engagement and social engagement, and BETA is a measure of systematic risk obtained by regressing individual stock returns on the corresponding returns from the S&P500 index. P-values are shown in parentheses. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	2000-2020	2000-2014	2015-2020
TOP20	0.45664**	0.55511***	0.194004
	(0.018)	(0.005)	(0.652)
ADV	0.000757***	0.000542***	0.001184***
	(0.000)	(0.000)	(0.000)
AGE	0.162004**	0.320965***	0.168244
	(0.027)	(0.000)	(0.324)
TOT_RET	0.040412***	0.028596***	0.07747***
	(0.000)	(0.000)	(0.000)
ROA	0.160089***	0.15098***	0.177617***
	(0.000)	(0.000)	(0.000)
SIZE	-0.54259***	-0.4423***	-0.72141***
	(0.000)	(0.000)	(0.000)
LEV	0.008181***	0.007108***	0.009557***
	(0.000)	(0.000)	(0.000)
TECH	1.625193***	1.129844***	2.074803***
	(0.000)	(0.000)	(0.001)
CSR	0.023074***	0.007197**	0.008714
	(0.000)	(0.021)	(0.316)
BETA	-0.14066	-0.0722	-0.24415
	(0.121)	(0.429)	(0.432)
Intercept	4.202735***	3.225404***	6.721325***
	(0.000)	(0.000)	(0.000)
Number of Obs	9075	6239	2836
R^2	0.11	0.11	0.12

Table III: The effect of alphabetical order on stock value over time

Table III divides the results of the sample into three distinct time periods. Initially, it was analyzed the period between 2000-2020, subsequently an attempt was made to divide the same period into two parts, to show how the effect of alphabetical order on firm value has changed over time and, especially, if the market has reacted to the distortion caused by the publication of Itzkowitz' s studies. In each regression, the dependent variable is the firm's market-to-book value. Starting with the first the column, that is the one ranging from year 2000 to 2020, it is possible to see that the coefficient is positive (0.45664) with a statistical significance at 5%, indicating that alphabetical order is found to be significantly positively related to market to book equity ratio (t-statistic 2.37). Also, this result confirms the evidence found by Itzkowitz. However, looking at the two other columns, it is possible to see how from year 2000 to 2014 early alphabet stocks have a market-to-book ratio which is larger than later alphabet firms with a significance level of 1%, while, it is different for the period going from year 2015 to 2020 in which the value of early alphabet stocks is not statistically different from later alphabet stocks; this latter can, indeed, confirm the hypothesis that traders would have changed their behavior in the last few years. This aspect seems to be something new in relation to the topic, hence there is no evidence about it in the previous literature.

To better isolate the effect of TOP20 on the firm value, in each of the regressions it was included a series of control variables. Generally, it was found that these control variables enter the models with the expected signs and are statistically significant. In particular, the results show negative and significant coefficient for firm size (SIZE) positive and significant coefficients for advertisement expense (ADV), positive and significant coefficients for firm leverage (LEV), positive, significant coefficients for total return (TOT_RET) and positive and significant coefficients for firms into the information technology sector (TECH), all these values are in line with the previous study by Itzkowitz[52]. In addition, this analysis differs from the Itzkowitz one for two more variables that have been added: BETA and CSR. BETA has a negative coefficient but does not appear to be statistically significant, while Corporate Social Responsibility (CSR) turns out to be an influencing one with a positive and significant coefficient in the first two columns, but not statistically significant in the third one.

At the end of this analysis, it is certainly possible to state that these results are in line with previous studies and despite the addition of further variables such as BETA and CSR the effect of alphabetical order bias persists. Furthermore, R^2 - the percentage of the variance in the dependent variable that the independent variables explain collectively - is also in line with the previous study.

[52] Itzkowitz, Jennifer and Itzkowitz, Jesse and Rothbort, Scott, (2015), pp 674

Table IV reports OLS regressions for three different time periods. The dependent variable is the market value of equity divided by the book value of equity. ADV is the amount of money spent on advertising. AGE is the number of years since the firm foundation. TOT_RET is the average of the monthly returns for each stock. ROA is measured as operating income before depreciation divided by total assets. SIZE is the natural log of total revenue. LEV is a ratio of debt to total equity. TECH indicates whether the firm is in technology. CSR is the average of environmental engagement and social engagement, and BETA is a measure of systematic risk obtained by regressing individual stock returns on the corresponding returns from the S&P500 index. TOP(END) 20 is an indicator for whether the stock ticker is in the first (last) 20%. P-values are shown in parentheses. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
TOP20	0.45044**	0.43226**	0.424774**	0.450441**
	(0.017)	(0.025)	(0.029)	(0.023)
END20			-0.03894	-0.02563
			(0.847)	(0.901)
ADV	0.000772**	0.000803***	0.000825***	0.000757***
	(0.000)	(0.000)	(0.000)	(0.000)
AGE	0.189816***	0.216992***	0.233073***	0.162381**
	(0.008)	(0.003)	(0.001)	(0.027)
TOT_RET	0.039652***	0.040864***	0.040034***	0.040411***
	(0.000)	(0.000)	(0.000)	(0.000)
ROA	0.161231***	0.15933***	0.159571***	0.160114***
	(0.000)	(0.000)	(0.000)	(0.000)
SIZE	-0.53457***	-0.32129***	-0.33505***	-0.54261***
	(0.000)	(0.000)	(0.000)	(0.000)
LEV	0.008018***	0.008246***	0.008056***	0.00818***
	(0.000)	(0.000)	(0.000)	(0.000)
TECH	1.62161***	1.638642***	1.712455***	1.626359***
	(0.000)	(0.000)	(0.000)	(0.000)
CSR	0.021412***			0.023064***
	(0.000)			(0.00)
BETA		-0.07378		-0.14106
		(0.409)		(0.12)
Intercept	4.015499***	2.899042***	2.912638***	4.208233***
	(0.000)	(0.000)	(0.000)	(0.000)
Number of Obs	9492	9075	9492	9075
R^2	0.11	0.10	0.10	0.11

Table IV: Ruling out alternative explanations

5.1.1 Alternative explanation: END20 and Firm Size

The just illustrated results show that firms at the top of an alphabetically sorted list have a higher value confirming the existence of the alphabetic bias.

In particular, it could be confirmed that this bias is supported by the satisficing effect, which implies that it is not the name itself that is important but the selection process that investors use to make decisions; by analyzing a list from top to bottom, it is natural that the first companies may be advantaged.

Although this reasoning is considered sound, to prove wrong any concerns that the results may be driven by the omission of other variables, it was decided to further demonstrate the validity of the satisficing effect by hypothesizing that investors' choice is no longer driven by this latter but by the memorability of a name. According to the name memorability, when looking at a list, people tend to remember better the items placed at the top and bottom of it - called primacy and recency effects. If the name memorability hypothesis was confirmed there would not be a strong advantage in having a name placed at the beginning of the alphabet because also other companies placed at the end of it would get the same advantages; in other words, being placed at the beginning of the alphabet not only will be irrelevant and negligible, but also would have no significant meaning for the firm value. To prove this, another multiple linear regression using the Ordinary Least Squares (OLS) method was used for this analysis. The econometric analysis was performed using the same model as before with the addition of a new variables: END20. This latter is a dummy variable of value 1 if a stock is in the last 20% of the list when they are listed alphabetically, 0 otherwise.

$$
\begin{aligned}
Firm\,Value_{i,t} = {} & \beta_0 + \beta_1 TOP20_{i,t} + \beta_2 END20_{i,t} + \beta_3 ADV_{i,t} + \beta_4 AGE_{i,t} + \beta_5 TOT\_RET_{i,t} \\
& + \beta_6 ROA_{i,t} + \beta_7 SIZE_{i,t} + \beta_8 LEV_{i,t} + \beta_9 TECH_{i,t} + \beta_{10} CSR_{i,t} + \beta_{11} BETA_{i,t} \\
& + u_{i,t}
\end{aligned}
$$

Table IV illustrates the results of the regression above.

Referring to this one, looking at the table from the left side, the first column shows the result of the regression carried out by using the same variables used in Itzkowitz’s study; this latter shows a negative correlation - although not statistically significant - between the variable END20 and firm value (-0.03894). Moving to the second column, the variable CSR has been added to the regression, in this case the estimated coefficient of END20 is still negative, and it is equal to -0.00273.

Table V reports OLS regressions considering the firm size. The dependent variable is the market value of equity divided by the book value of equity. ADV is the amount of money spent on advertising. AGE is the number of years since the firm foundation. TotReturn is the average of the monthly returns for each stock. ROA is measured as operating income before depreciation divided by total assets. lnTotRev is the natural log of total revenue. Leverage is a ratio of debt to total equity. Tech indicates whether the firm is in technology. CSR is the average of environmental engagement and social engagement, and BETA is a measure of systematic risk obtained by regressing individual stock returns on the corresponding returns from the S&P500 index. P-values are shown in parentheses. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)		(2)	
	SIZE		SIZE	
	Small	Large	Small	Large
TOP20	0.704555***	0.2292324	0.556612***	0.3427213
	(0,004)	(0.42)	(0,027)	(0.242)
END20			-0.5864342***	0.4909001
			(0,021)	(0.119)
ADV	0.00016	0.0005969***	0.0005775	0.000607***
	(0.782)	(0.000)	(0.705)	(0.000)
AGE	0.094943	0.2097606**	0.09875	0.2011258**
	(0.359)	(0.036)	(0.340)	(0.043)
TOT_RETURN	0.021273***	0.0640657***	0.021273***	0.0640018***
	(0.000)	(0.000)	(0.000)	(0.000)
ROA	0.10723***	0.2066257***	0.1077138***	0.2060418***
	(0.000)	(0.000)	(0.000)	(0.000)
SIZE	-0.89543***	-0.550797***	-0.8972044***	-0.5514303***
	(0.000)	(0.000)	(0.000)	(0.000)
LEV	0.007741***	0.0086366***	0.0077299***	0.0086368***
	(0.000)	(0.000)	(0.000)	(0.000)
TECH	1.92976***	1.022759**	1.998701***	1.030068**
	(0.000)	(0.015)	(0.000)	(0.015)
CSR	0.0119***	0.016098***	0.0116962***	0.016305***
	(0.003)	(0.001)	(0.004)	(0.001)
BETA	-0.33828***	0.0165164	-0.350049***	0.024873
	(0.001)	(0.926)	(0.001)	(0.926)
Intercept	7.863661***	4.069878***	8.012727***	3.977044***
	(0.000)	(0.000)	(0.000)	(0.000)
Number of obs	4327	4748	4327	4748
R^2	0.11	0.13	0.11	0.13

Table V: The effect of alphabetical order on firm value by size

Lastly, the fourth column is about the regression taking into consideration all the variables where the estimated coefficient of END20 is equal to - 0.02563. From these results it can be seen that in no case was a statistically significant correlation found, this reinforces the theory that the first letters of the alphabet make the difference. Further, the results confirm the fact that Alphabetic bias is related to the way the information is searched and not to the name memorability. Moreover, taking into account the other control variables different than END20 in the relationship between the control variables and the market to book, there is no difference from the previous regression shown in Table III.

After memorability, another investigated aspect is whether investment decisions, made by following alphabetical rank, affect large and small firms in an equal way. The choice of exploring this aspect was considered of particular relevance because of Jacobs'study identifying that rank effects are stronger among less visible - that is, smaller - firms[53].

For this type of analysis, it was decided to include all the previously mentioned control variables, in particular, initially a regression was carried out without controlling for the variable END20 and then it was also chosen here to assess whether being positioned at the end of a list could be relevant depending on the size of the companies.

The results listed in Table V show that the positive effect of alphabetic bias on firm value is statistically significant for small firms but not for large firms. Looking for possible explanations, it could be that being large companies better known, their position in a list does not really limits investment by investors; to make an example, despite not being among the top positions in a list, Meta is one of the largest companies in the world by market capitalization.

Analyzing the regression where the control variable END20 was added, another interesting aspect to highlight is how, for small companies, this variable has a negative coefficient and is statistically significant with a p value minor than 1%. This brings out how small companies at the end of a list are strongly disadvantaged while it strengthens the hypothesis that companies placed at the beginning of an alphabetically sorted list have a positive return and a higher firm value. Looking only at large companies instead the coefficient is positive but not statistically significant.

All that was said so far is more than sufficient to remark again the validity of the first hypothesis of this research study and to conclude this paragraph by stating that firms with a stock ticker/name at the beginning of the alphabet have a higher valuation.

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[53] Heiko Jacobs, Alexander Hillert, (2016), p 711.

Table VI reports OLS regressions for three different implied cost of capital measure. The dependent variables are Easton (2004), Juettner-Nauroth (2005) and the average of the two (RAVG). ADV is the amount of money spent on advertising. AGE is the number of years since the firm foundation. TOT_RET is the average of the monthly returns for each stock. ROA is measured as operating income before depreciation divided by total assets. SIZE is the natural log of total revenue. LEV is a ratio of debt to total equity. Tech indicates whether the firm is in technology. P-values are shown in parentheses. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively

	R_EA	R_JN	RAVG
TOP20	0.02071	0.0823	0.053477
	(0.987)	(0.371)	(0.604)
ADV	-0.0041***	-0.0003***	-0.0003***
	(0.000)	(0.000)	(0.009)
AGE	-0.2945***	-0.2187***	-0.2591***
	(0.000)	(0.000)	(0.000)
TOT_RET	-0.01579***	-0.0163***	-0.0167***
	(0.000)	(0.000)	(0.000)
ROA	-0.1031***	-0.063***	-0.0839***
	(0.000)	(0.000)	(0.000)
SIZE	0.47903***	0.4903***	0.5220***
	(0.000)	(0.000)	(0.000)
LEV	-0.00479	-0.002116	-0.003215
	(0.401)	(0.362)	(0.136)
TECH	-0.3129*	-0.0518	-0.2113
	(0.057)	(0.686)	(0.137)
CSR	-0.01560***	-0.01770***	-0.0167***
	(0.001)	(0.000)	(0.000)
BETA	0.61535***	0.5088***	0.5594***
	(0.000)	(0.000)	(0.000)
Intercept	8.3319***	7.5237***	7.7017***
	(0.000)	(0.000)	(0.000)
Number of Obs.	5134	5270	5063
R^2	0.10	0.10	0.11

Table VI: The effect of alphabetical order on implied cost of equity

5.2Alphabetic bias and implied cost of equity capital

After having confirmed the first hypothesis is now time to move forward empirically testing the validity of the second one.

As for the first hypothesis, the multiple linear regression using the Ordinary Least Squares (OLS) method was used for this analysis. The econometric analysis was performed by using the previously explained model, here set up as follows:

$$\begin{aligned} Implied\ cost\ of\ equity_{i,t} &= \beta_0 + \beta_1 TOP20_{i,t} + \beta_2 ADV_{i,t} + \beta_3 AGE_{i,t} + \beta_4 TOT\_RET_{i,t} + \beta_5 ROA_{i,t} \\ &+ \beta_6 SIZE_{i,t} + \beta_7 LEV_{i,t} + \beta_8 TECH_{i,t} + \beta_9 CSR_{i,t} + \beta_{10} BETA_{i,t} + u_{i,t} \end{aligned}$$

The results presented in Table VI show the relation between the variables of the formula above with the three different measures of implied cost of equity, in turn, the one of Easton, the one of Olshon and Juettner-Nauroth and the average value coming from the two ones.

From the Table VI it is possible to notice that most of the control variables have a significant negative relationship with the implied cost of equity capital, meaning that the higher the value of the variable, the lower the implied cost of equity capital. In particular, the results show a negative and significant coefficient for firm age (AGE), a negative and significant coefficient for advertisement expense (ADV), a negative and significant coefficient for Corporate Social Responsibility (CSR), a negative significant coefficient for total return (TOT_RET) and a negative significant coefficient for the profitability index (ROA).

Concerning the control variables that showed a significant positive relationship with the implied cost of equity it is worth to mention BETA and SIZE. As previously said, BETA represents the volatility indicator and, as it is obvious to think, - also in this case - it indicates that the higher the risk the higher the implied cost of equity capital.

TOP 20 is the variable of interest, in this case it turned out to have a positive - even though not statistically significant - relationship with the implied cost of equity capital, leading to think that the second hypothesis might not be confirmed; this last aspect paves the path to the further analysis.

5.2.1 *Possible explanation: Firm Value and Firm Size*

As just said, the just obtained not significant but positive relationship between the dummy variable TOP 20 and the implied cost of equity capital might disprove the positive effect of alphabetic bias on implied cost of equity capital hypothesized in chapter 2. Wanting to deep dive on this aspect, it has been decided to further investigate it by following two different reasonings.

The first reasoning to prove right that the alphabetic bias leads the implied cost of equity capital to decrease has been thinking about the previously investigated relationship between firm value and implied cost of equity capital; in particular, holding their relationship true and having already confirmed the positive effect of alphabetic bias on firm value, it was thought that the alphabetic bias may have implicitly influenced also the implied cost of equity capital. On this matter, a new regression analysis has been carried out this time substituting the TOP20 dummy variable with the market to book value as a proxy of the firm value.

For this analysis it is necessary to point out that a different estimator was used, in fact, unlike the previous regressions, in this case a panel regression was performed using the fixed effects estimator, also known as the "within estimator".

Fixed effects regression is a method to control for omitted variables in panel data when the omitted variables vary among entities, in this case the entities are firms, but not over time. Regression models with fixed effects have n different intercepts, one for each firm considered. These intercepts can be represented by a set of binary variables that represent each individual firm; these variables capture the influences of all omitted variables that differ from one entity to another but are constant over time. In addition, to perform a thorough study it was decided to also control for temporal fixed effects, temporal effects control for variables that are constant across firms but evolve over time.

The fixed effects regression model then becomes[54]:

$$Y_{it} = \beta_0 + \beta_1 X_{it} + \beta_2 C_{it} + \alpha_i + \delta_t + u_{it}$$

$t = 1, \dots, T$ indicates the number of years in the period under examination.

$i = 1, \dots, n$ indicates the number of companies that are part of the panel.

[54] Stock J, Watson MW (2003), p 278.

Table VII reports panel regressions for three different implied cost of capital measure. The dependent variables are Easton (2004), Juettner-Nauroth (2005) and a mean of both (RAVG). MTB is the market value of equity divided by the book value of equity. ADV is the amount of money spent on advertising. AGE is the number of years since the firm foundation. TOT_RET is the average of the monthly returns for each stock. ROA is measured as operating income before depreciation divided by total assets. SIZE is the natural log of total revenue. LEV is a ratio of debt to total equity. Tech indicates whether the firm is in technology. P-values are shown in parentheses. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively

	R_EA	R_JN	RAVG
MTB	-0.031348***	-0.2536***	-0.02915***
	(0.000)	(0.000)	(0.000)
ADV	-0.0004***	-0.0003***	-0.00039***
	(0.000)	(0.000)	(0.000)
AGE	-0.301336***	-0.0156***	-0.04484***
	(0.000)	(0.000)	(0.000)
TOT_RET	-0.014934***	-0.01564***	-0.01591***
	(0.000)	(0.000)	(0.000)
ROA	-0.08951***	-0.0538***	-0.07167***
	(0.000)	(0.000)	(0.000)
SIZE	0.46479***	0.4732***	0.5054***
	(0.000)	(0.000)	(0.000)
LEV	0.0001724	0.000052	0.0000968
	(0.589)	(0.815)	(0.721)
CSR	-0.01465***	-0.01701***	-0.015142***
	(0.002)	(0.000)	(0.000)
BETA	0.63385***	0.49805***	0.562374***
	(0.000)	(0.000)	(0.000)
Intercept	8.3455***	7.4764***	7.6325***
	(0.000)	(0.000)	(0.000)
Number of Ob.	5134	5270	5063
R^2	0.10	0.11	0.12

Table VII: The effect of firm value on implied cost of equity

Y_{it} is the dependent variable.
X_{it} is the variable of interest
C_{it} is a regressor representing the set of control variables.
α_i is an unobserved variable that varies from one company to another but does not change over time?
δ_t is an unobserved variable that varies over time but not from one company to another.
u_{it} is the residual error of the regression that collects all the omitted factors, i.e., the other factors other than X that influence Y.
To implement this type of regression on STATA the command "xtreg" was used with the addition of the command "fe", which stands for "fixed effects". Before doing this, through the command "tsset" STATA was given the two dimensions of the panel: firms and time; in this way the software understands the two dimensions through which it must read the panel.
Considering this effect, the so-called timing variant variables are eliminated; they are effects that can distort the coefficients and in practice represent those characteristics of the company that do not vary over time or vary very slowly. A concrete example could be the effect of the management of a company, usually the CEO of a company does not change from year to year, and this is an aspect to take into consideration, as it is a factor that influences the strategy, the value and many other aspects of a company. Time fixed effects, on the other hand, were added to STATA via the "i.YEAR" command. It is also important to point out why this type of model was not applied to previous regressions. The reason is simple and is related to the variable of interest -TOP20- used in the previous regressions. In fact, by construction this variable does not change over time and has only 1 and 0 as values. For the same reasons, it was necessary to exclude also the dummy variable TECH from this specific analysis.
The new regression used has the following form:

$$\begin{aligned} Implied\ cost\ of\ equity_{i,t} &= \beta_0 + \beta_1 MTB_{i,t} + \beta_2 ADV_{i,t} + \beta_3 AGE_{i,t} + \beta_4 TOT\_RET_{i,t} + \beta_5 ROA_{i,t} \\ &+ \beta_6 SIZE_{i,t} + \beta_7 LEV_{i,t} + \beta_8 CSR_{i,t} + \beta_9 BETA_{i,t} + \alpha_i + \delta_t + u_{i,t} \end{aligned}$$

The application of this formula led to the results presented in Table VII. This table confirmed a significant negative relationship between the implied cost of equity capital and the market to book value, thus, the higher the MTB, the lower the implied cost of capital.

Table VIII reports OLS regressions for three different implied cost of capital measure considering the firm size. The dependent variables are Easton (2004), Juettner-Nauroth (2005) and the average of the two (RAVG). ADV is the amount of money spent on advertising. AGE is the number of years since the firm foundation. TOT_RET is the average of the monthly returns for each stock. ROA is measured as operating income before depreciation divided by total assets. SIZE is the natural log of total revenue. LEV is a ratio of debt to total equity. Tech indicates whether the firm is in technology. P-values are shown in parentheses. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively

	(R_EA)		(R_JN)		(RAVG)	
	SIZE		SIZE		SIZE	
	Small	Large	Small	Large	Small	Large
TOP20	-0.284032*	0.153181	-0.20872*	0.194992	-0.25757*	0.212938
	(0.095)	(0.354)	(0.100)	(0.107)	(0.054)	(0.131)
ADV	-0.0000789	-0.00045***	0.00062	-0.00031***	0.000075	-0.00041***
	(0.853)	(0.000)	(0.130)	(0.000)	(0.843)	(0.000)
AGE	-0.217605*	-0.32312***	-0.04453	-0.27933***	-0.14865*	-0.29907***
	(0.017)	(0.000)	(0.576)	(0.000)	(0.064)	(0.000)
TOT_RET	-0.006287***	-0.02112***	-0.01103***	-0.01902***	-0.00852***	-0.02124***
	(0.017)	(0.000)	(0.000)	(0.000)	(0.005)	(0.000)
ROA	-0.101546***	-0.10505***	-0.06144***	-0.0683***	-0.07996***	-0.08903***
	(0.084)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SIZE	0.3366903***	0.444497***	0.378662***	0.370674***	0.430798***	0.435515***
	(0.016)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LEV	-0.000197	-0.00067*	-0.00021	-0.00027	-0.0000039	-0.00061*
	(0.608)	(0.113)	(0.615)	(0.321)	(0.908)	(0.09)
TECH	0.1177887	-0.58487***	0.503953**	-0.37999**	0.241714	-0.5073***
	(0.615)	(0.01)	(0.01)	(0.023)	(0.232)	(0.01)
CSR	-0.022179***	-0.01079***	-0.0285***	-0.01182***	-0.02514***	-0.01106***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
BETA	0.1685592*	0.858828***	0.258262**	0.63177***	0.191936*	0.758151***
	(0.161)	(0.000)	(0.007)	(0.000)	(0.058)	(0.000)
Intercept	9.342986***	8.493614***	7.994566***	8.661587***	8.189911***	8.423273***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of Obs.	1886	3248	1757	3513	1849	3214
R^2	0.07	0.11	0.09	0.11	0.09	0.12

Table VIII: The effect of alphabetical order on implied cost of equity by size

These results reflect on the role that alphabetic bias plays and how, despite alphabetical order was found to be not significantly related to implied cost of equity capital, it is possible to deduce an indirect role.
Looking instead at the control variables there are no differences from the previous regression.
Shifting to the second developed reasoning to confirm the positive effect of the alphabetic bias on the implied cost of equity capital, it was decided to investigate the visibility effect earlier applied also along the explanation of the first hypothesis. Therefore, using the size of the firm as a proxy of visibility - where to be considered small or large a firm has to be below or above the median firm size - and based on the assumption that smaller companies are less visible than large ones, a further regression was carried out separating small from large firms.
The results contained in Table VIII demonstrate a significant negative relationship between the alphabetic bias and the cost of equity capital but only for firms belonging to the set of small firms leaving large firms unaltered by the alphabetic bias effect. An explanation of this could be that while small firms may be more subject to having to be among the first ones of an alphabetically sorted list in order to be chosen for investments large firms are not really influenced by the alphabetical ordering as they already enjoy of a solid popularity.
Looking at the control variables, there are no differences between small and large companies, the only difference concerns the variable ADV which, in relation to the variables R_JN and RAVG, has a positive but not statistically significant correlation with the cost of equity for small companies while it has a negative and statistically significant correlation with large companies.
To conclude, based on all that said so far, it is possible to affirm that the alphabetic bias can be a determinant for a lower implied cost of equity capital but only under the condition of being a small - then, a less visible, company. Therefore, only small firms with a stock ticker/name at the beginning of the alphabet have a smaller implied cost of equity.

6. CONCLUSION

6.1 Conclusion remarks

The idea for this thesis arose from the evidence that the widespread habit of sorting information alphabetically has a significantly positive impact on how people perceive and evaluate them. The benefits of this phenomenon have been found in several areas, for example in politics it has been seen to favor some candidates over others while in academia it has been seen that the authors mentioned first have had several advantages in terms of recognition and better career opportunities.

This thesis focuses on exploring the impact of alphabetical sorting in finance, in particular the mechanisms that influence investment decisions and, consequently, the effects of alphabetical sorting on firm value and the implied cost of equity capital. The main methods widely discussed in the literature that investors are used to make decisions are exposed, starting from the standard and more rational approaches, which use historical and accounting data, up to the most recent theories that also consider the irrationality of investors and their behavioral biases.

In particular, the attention is focused on the so-called Alphabetic Bias, a phenomenon that induces investors to invest in companies whose ticker/name begins with the first letters of the alphabet. It has been shown that this behavior is induced by two other behavioral factors that arise when investors are confronted with the multitude of information available. The first of these factors is the “status quo bias”, which induces investors to use the default options, in this case the alphabetical order of tickers; the second factor is the “satisficing effect”, in this case investors begin to search from the top to the bottom of an alphabetically ordered list, choosing options that satisfy specific requirements they have previously identified.

This suggests that when investors search through the information on securities, they just settle rather than investigating every single security on the list, therefore, their search stops once they have found an alternative that is deemed "acceptable" or when the search process begins to take too long. In this way, the stocks positioned at the top of a list will have greater trading activity and, consequently, greater liquidity and price informativeness translated into effects on the firm value and implied cost of equity capital of individual companies.

To test the consistency of this effect, this study focused on testing two main hypotheses. The first hypothesis focused on the effect of alphabet bias as a determinant of firm value growth. Through the application of a tailor-made econometric model, it was possible not only to

confirm the hypothesis, but also to test its robustness. In fact, the role of alphabetical sorting was examined also taking into account a different psychological process, that of memorability, according to which the most memorable - and therefore implicitly preferred - names in a list are those at the beginning and at the end of it; therefore, it was tried to demonstrate that companies at the end of a list might also be more likely to be considered. However, the results did not support this theory, showing that it is important to be at the top of the list. Lastly, with regard to the effect on firm value, a time trend was also documented. It was noted that the effect of alphabetical bias on firm value seems to be irrelevant after 2015, a date that coincides with the publication of the first studies in the field and from which investors may have begun to speculate on it.

The second hypothesis concerned the effect of alphabetical bias as a determinant in reducing the implied cost of equity capital. In particular, after performing the same empirical analysis as for firm value, the positive but statistically non-significant correlation with the TOP20 variable of interest led to investigate other aspects such as the relationship between firm value and the implied cost of equity capital and the firm size, expressed as a proxy for visibility. The results showed that the lower the visibility, and therefore the size of the company, the greater the benefit of being positioned at the top of a list. On the contrary, for large companies it was seen that their position did not make much difference as they were probably already highly regarded by investors.

This last factor was the key to asserting that alphabetic bias, particularly when it comes to small and less visible companies, is a phenomenon that leads companies to have higher firm value and lower implied cost of equity capital.

6.2 Limitation and direction for future research

Before concluding this master thesis, different limitations must be discussed.

First of all, it should be noted that the Thomson Reuters database was the main source of data, and it would therefore be advisable to use different sources for future analysis. Furthermore, the study was conducted by analyzing only the US stock market, that is S&P500; therefore, it would be interesting to extend the research to other stock markets, such as the European, Indian, Canadian and/or Australian ones, to determine how the alphabetical bias is spread globally and what could be the reasons behind these differences.

A further limitation concerns the variables used to calculate firm value and the implied cost of equity capital. It can be considered to conduct an analysis using models other than those proposed by Easton and Olshon and Juettner-Nauroth and using, for example, Tobin's q as a

proxy of firm value. Also, the dummy variable identifying the alphabetical bias TOP20 could be revised using alternative measures of alphabetical ranking, such as continuous variables that take into account the change in position over the years. Lastly, a further aspect that could be considered in order to strengthen the relevance of alphabetical ranking would be to analyze whether companies that have changed name over time may have gained an advantage or disadvantage depending on their new position in the list.

Concluding this work, the hope is that this master thesis could be a valid work that shall inspire and motivate readers to conduct additional research that will further advance the understanding of such an intriguing and continuously changing research topic.

ACKNOWLEDGMENTS

I would like to express my deepest gratitude to Univ.-Prof. Dr. Wolfgang Breuer and Dr. rer. pol. Andreas Knetsch for accompanying me towards the end of my academic career by supervising this work and guiding me through the different phases that comprise it.

I would like to thank Professor Laura Rondi for her availability and for giving me the opportunity to undertake this experience abroad.

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