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The Impact of Digitalization on Performance and Risk of Bankruptcy of Italian Listed Companies

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Abstract

This thesis has the aim to get insights about the impact of digitalization on performance and risk of bankruptcy of Italian listed companies.

The topic has been chosen with the goal of bringing a new perspective in a field of studies that is pretty uncovered in the literature, due to an undoubtedly recent birth, evolution and development of this phenomenon. Connecting digitalization to performance and risk of bankruptcy is however a straightforward decision in the moment the interest is in attempting to know what has been the concrete effect on companies, starting from a theoretical review of how they managed these radical changes in their business models in recent years and getting to the core objectives of creating value and surviving.

With this purpose have been performed multiple descriptive statistics and regressions, collecting data for a panel of 122 Italian listed companies for the part referring to performance and 71 for what concerns risk of bankruptcy. With a view to greater completeness, the data gathered were relative to the 5-year time horizon between 2015 and 2019.

The empirical analysis provided consistent results, proving a concrete positive effect between digitalization and performance and a similar outcome was obtained through the evidence deriving from an increase in digital maturity on the risk of bankruptcy. Even in this case, reviewing all the data gathered, emerged a positive relationship, showing that firms with a higher digital maturity are less subject to the risk of being bankrupt.

Introduction

Digitalization has been identified as one of the major trends affecting and shaping society and business in the near and long term future (Kääriäinen, Parviainen, Teppola, & Tihinen, 2017). Due to its unbelievable impact many authors agree on comparing it to the industrial revolution.

The pioneer of this belief has been Klaus Schwab, founder and executive chairman of the World Economic Forum, that in 2016 annual meeting of Davos (Switzerland) introduced the term and theme of the "fourth industrial revolution".

According to Schwab (2016), digital transformation is the core of this process, but unlike previous revolutions these breakthroughs have evolved at an unprecedented speed. Opportunities of billions of people to connect through their own devices, with a higher processing power, storage capacity and access possibilities were achieved through the implementation of emerging technologies.

Consequently, breadth and depth of these changes led, and are still leading, to the transformation of entire systems of production, management and governance.

Notwithstanding the huge indisputable impact that the process is having on the business models of firms, the aim of this thesis is to evaluate if digitalization has a positive effect even in terms of performance and lower likelihood of incurring in bankruptcy, referring specifically to a panel of Italian listed companies.

Indeed, one of the major challenges to obtain an outstanding success refers to the capability of exploiting this revolutionary phenomenon, re-shaping the vision of the company in a way oriented to embed digital realities in everyday business and operations, knowing that this process is constantly evolving. In this perspective, not simply reaching success, but especially the ability to continue innovating and maintaining the attractiveness and interest of clients is a crucial responsibility to preserve the positioning achieved.

In this context the work begins with a chapter on digitalization. The initial part has the aim to contextualize this word, after which a brief history of this process is provided, in order to look at the principal steps that made possible the actual level of advancement. In this context, is suggested a case study helpful to get an understanding of how much being able to master this evolution and predicting future needs of the clients, based on these fast-growing necessities, is becoming crucial to permanently succeed, with a "lesson from the losers" (Nokia), not successful to preserve the predominant role achieved.

The next paragraph is aimed at highlighting some technologies that made digitalization so useful and indispensable in the actual scenario, getting the possibility of obtaining some competitive advantages for those companies really capable of understanding their potential.

In the following part is studied how firms have to adapt to digitalization, with a deep dive on adjusting business models in a way suitable to face the new needs. In addition, has been recognized that this process can affect differently the Small and Medium-sized Enterprises (SMEs) respect to what can happen to the big giants, analyzing also the concrete difficulties that any of these two categories have to face to fit their old business models to another more digitized. For doing so, has been taken the perspective of digital champions as a guideline to show the right investments and ideologies to follow, with the purpose of doing a sound process. Then, the interest has been shifted from a global perspective to the Italian situation, given that this study has the aim of focusing on the effect of this process on national companies.

The last paragraph of the chapter has instead the purpose to turn to a more practical approach, analyzing how digital maturity of a country of a specific firm can be practically assessed.

The second chapter has instead the goal to get insights in terms of performance and risk of bankruptcy. The first paragraph gives an overview of how performance measurement can be contextualized, after which, is performed a recap of the most important models for performance measurement proposed in the literature. To conclude the part of the chapter relative to performance a practical approach has been followed, highlighting the most common indicators used by practitioners for studies similar to the one of this thesis.

The following paragraph is an introduction to the concept of bankruptcy and an overview of the incidence of this phenomenon from the 2008 crisis onwards. The final part consists instead in the practical study of those models mostly suitable to estimate the risk of bankruptcy of companies.

The third and last chapter provides an empirical analysis aimed at assessing the impact that digitalization has on performance and risk of bankruptcy of Italian listed companies. First of all, the research questions have been clearly stated, based on the intuitions derived from the literature and in a successive moment all the data necessary for the purpose of the thesis have been searched. In this part, the first choice pertained to the selection of the panel of companies and the choice of the most purposeful variables to use in the regression analysis.

Before passing to the regressions, some descriptive statistics have been proposed to present the evidence that should have been further tested in the following paragraphs. After this introductory part, has been chosen the most suitable model to deal with panel data (given that the study has been conducted over a five-year horizon between 2015 and 2019).

Once accounted for all the details, the effective regressions have been run and all the results achieved have been discussed to obtain an answer to the previously stated research questions.

Finally, the limits of the analysis undertaken and some suggestions to expand the research of the thesis have been disclosed.

CHAPTER 1 - DIGITALIZATION

1.1 What is Digitalization?

Digitalization is the process of employing digital technologies and information to transform business operations (Kulkarni, Liu, Muro & Whiton, 2017). This phenomenon has incredibly influenced the landscape for companies operating in every kind of sector, from those working directly in IT technologies and software development to even transport or food manufacturing. But digitizing is not as easy as it seems and it doesn't simply consist in converting paper documents into electronic files to keep in a computer.

Digitalization is a complex path, extremely important and at the same time difficult for firms already operating in the market since many years. In the last decades in fact global industries not only have faced technological changes that have led to opportunities such as greater flexibility, reactivity and product individualization, but also have presented different challenges such as rapid technological change, increased complexity and changing customer preferences and legal requirements (El-Darwiche et al., 2012).

According to El-Darwiche et al., (2012) these major features led many companies to strongly adapt some aspects of their business models or even to radically change them. To perform these changes and exploit efficiently digitalization opportunities is important to face these challenges with a conscious and prepared environment, principally in terms of human resources. In recent years are so extremely important, for managerial roles, professionals with advanced digital skills in order to drive the transformation process looking at the financial business and innovating it properly.

Instead from the perspective of Gray & Rumpe (2015) digitalization is simply a word used to represent the integration of various technologies into all aspects of everyday life. According to this view to get advantage from this process is of course necessary to rely on quantitative analysis, but most of the time data alone are not suitable to draw effective information. For this peculiarity they should be integrated in different models, aggregating relevant characteristics and abstracting from many of the numerous irrelevant data. Being able to get rid off what could be misleading, allows to obtain benefits in terms of efficiency and to exploit digitalization properly in everyday life and in specific fields. For instance, in the business domain these advices can be helpful to understand where and what to buy and sell, how and when to make an advertisement campaign, how to produce and transport goods and how to attract and retain customers.

1.2 Brief History of Digitalization

According to Press (2015), even if digitalization is an extremely new process, the first milestone can be dated back to 1679. In that year the philosopher and mathematician Gottfried Wilhelm Leibniz developed the modern binary number system (published in 1703 in his book *Explication de l'Arithmétique Binaire*). With the formulation of that structure, he wanted to accomplish his dream of creating a universal language, capable of representing every concept simply using numbers. This desire can be classified as an ancestor, not even so rudimentary, of the actual concept of digitalization and the binary system is still nowadays the basis for computer technology.

''*But instead of the progression of tens, I have for many years used the simplest progression of all, which proceeds by twos, having found that it is useful for the perfection of the science of numbers.''* (Gerhardt, 1849).

On the other side the beginning of digitalization as intended nowadays can be dated back to the 1950s, where it was perceived the need to reorganize knowledge in a more efficient way, but until the end of twentieth century the potential effect of it was not even perceived by ordinary people, while was principally seen by governments as a military aid.

The first business use of a computer for a firm is instead dated 1954. In that year General Electric's Appliance Division in Louisville (Kentucky) installed the

UNIVAC I computer, with duties of payroll processing and manufacturing control for dishwashers, refrigerators and dryers (Press, 2015).

However, the step able to extend the impact of digitalization has been Internet and the birth of the World Wide Web in 1991.

"*The World Wide Web project merges networked information retrieval and hypertext to make an easy but powerful global information system. It aims to allow information sharing within internationally dispersed groups of users, and the creation and dissemination of information by support groups.''* (Berners-Lee, 1992).

If in the first years after its birth, Internet was principally perceived and used as a network for the scientific community, starting from 1993 there is a huge spread in access even by private users with their personal computer.

From the 1990s onwards the impact of this major innovation on the proliferation of digital technologies can be undoubtedly identified: the number of personal computers in use worldwide rose from 100 million in 1990 to 1.4 billion in 2010, mobile phone users from 10 million in 1990 to more than 5 billion and the number of internet users grew at an even higher rate, passing from 3 million to 2 billion in the same period (El-Darwiche et al., 2012).

Furthermore, in the last years some other goals connected to the phenomenon of digitalization have been reached as the introduction of payment systems based on cryptocurrencies as Bitcoin or Ethereum or the choice of preferring digital channels such as social networks instead of magazines and newspapers for advertising.

In general, many people and even many companies understood the impact of the digital revolution for everyday life and business, gradually starting to digitize their operations. While some firms chose this path, many other preferred not to change their prolific businesses, avoiding to invest huge amount of money in new technologies and software, believing this wave of renewal not sufficiently strong to reshape the scenario.

Notwithstanding this process, according to a study of McKinsey Global Institute, the level of digitalization reached even by the most developed economies in the world is still not extremely satisfactory, but being a very new phenomenon, there are flourishing opportunities for evolution. From this perspective a research shows that US economy is just exploiting 18% of its digital potential, estimating however that digitalization could add up to $2.2 trillion to annual GDP by 2025 (Khanna et al., 2015).

1.2.1 Nokia Case: When Understanding Digitalization can be Crucial for Survival

To understand practically the importance of continuous innovation and digitalization is noteworthy the case of Nokia.

Nokia is a Finnish multinational company established in 1865 and operating in businesses as communication, information technology and consumer electronics, becoming quickly one of the biggest giants in these sectors. The company obtained its highest peak starting from October 1998, when it became the most important mobile phone's brand in the world. In accordance with this, even operating profits had an upsurge passing from $1 billion in 1995 to barely $4 million in 1999.

In the following years Nokia was initially able to consolidate its success, investing concretely in R&D and finding the right business architecture and product segmentation. With this strategy the company remained the preferred choice for the majority of users and has been able to meet each segment's desires and needs (Alibage & Weber, 2018).

In 2003 Nokia proposed its first smartphone, the Nokia 6600, based on Symbian OS software and in the next years proposed many other models (even 35 in 2006), continuing to pursue the ideology of creating many different models for different users according to their needs. In the light of this path the company arrived to obtain a predominant position in the market without any effective competitor and a market share in smartphone market of 53% during 2007 (while the first competitor, BlackBerry, was at 11%) (Alibage & Weber, 2018).

In that period the hegemony of Nokia seemed to be unstoppable, but the perspective changed soon. In the same year that this peak has been reached in fact Apple launched its first iPhone and in 2008 has been the turn of the first version of Google's Android. From that moment on Apple and Samsung began their rise, rapidly conquering the market.

Figure 1: Nokia's Market Share between 2007 and 2013 (Alibage & Weber, 2018).

The above figure shows the fall of Nokia's market share from 2007 to 2013. The company has not been able to keep up with new competitors and between 2011 to 2013 they lost more than 5 billion of euros.

Ascertained the collapse of the sales and profits of the company is necessary to understand the causes that led this giant to be blown away despite the dominant position gained the previous years.

According to Joshi & Panigrahi (2020) Nokia did many mistakes, especially in the fields of innovation and digitalization, some of which are listed below:

- Between 1995 and 2013 the firm released 406 different models, with a peak of 47 in 2008. Even if, theoretically, this occurred to give a wider range of choices to customers, allowing to choose what was the best model for certain specific needs, the strategy led to an overcrowding of types, with important drawbacks. Indeed, the decision to produce too many models every year, led to a lack of product focus and improvement of them, obtaining the outcome of not being effectively competitive neither with Apple nor with Samsung.

- Another central issue has been the lack of innovation. Nokia, having been at the top of the sector for many years felt to be in an extremely advantageous position compared to other companies of the same industry. As previously stated, in 2007 Nokia strongly controlled the market for smartphones with a 53% stake, with the nearer competitor lagging at around 10%. This predominance made the company feeling pretty quiet about its positioning, that never thought at a radical change in the needs of customers.
- The operating system Symbian OS (the one used by Nokia), albeit sufficiently successful when firstly introduced in 2002, has not been able to create an ecosystem with enough application for its users. Moreover, this system has not been adequately innovated and adapted in the following years, finding itself to be extremely outdated when iOS and Android jumped in the market (Alibage & Weber, 2018).
- While Nokia was losing the challenge for the high segment of smartphones principally in favor of Apple and Samsung, a threat came from the lower segment as well. This portion of the market was indeed conquered by Chinese companies as for example Xiaomi, that was able to provide customers a good performance at a much lower price. Losing market share on both ends Nokia found itself in a situation where it no longer had the strength to compete with new giants, but neither had the ability to cut costs enough to fight for the cheaper segment.

These mistakes suggest a path to understand the rationale behind such a big failure.

In the Nokia case in fact the problem is not due to an effective lack of investment, because in fact between 2000 and 2008 investments in R&D more than doubled, but a misunderstanding in what customers needed (Alibage & Weber, 2018).

This issue was crucial in perceiving the problem. Nokia invested a great amount of its money merely on the hardware, creating new models, without concentrating on the effective strengthening of the performance of these phones. This was instead the desire of customers, that due to the ongoing digitalization process started to need also a more stable and well-established software in their phones (Joshi & Panigrahi, 2020).

With the advent in the market of Apple and Samsung these needs were covered, with smartphones starting to work like a computer in a clear and rapid way.

In the light of this, the principal fault of Nokia was not being able to understand the process of digitalization. Having simply a beautiful phone or of a renowned brand was no more all: smartphones had to ensure fast internet access, the possibility to quickly download the best apps and an adequate ecosystem that Nokia's Symbian OS was never able to build.

Representative of this lack of foresight is the following sentence of Stephen Elop, CEO of Nokia at that time, before the selling to Microsoft in 2013:

'We didn't do anything wrong, but somehow, we lost'.

1.3 Technologies Fostering Digitalization

Nokia case is a concrete example of how things can turn rapidly bad in such a fast-growing scenario of digitalization, however, keeping the pace of this process, is not an easy job, especially because of the need to understand the right direction to get advantages from it. For the abovementioned reason, in this paragraph are exposed two technologies that are the foundations of a sound digitalization path and from which is necessary to be able to draw for having a great result.

1.3.1 Machine Learning

Machine Learning can be defined as a mix of computational methods using experience to improve performance or to make accurate predictions. In such a context experience refers to previous information available to the learner, which use to take form of electronic data collected and made available for the analysis (Mohri, Rostamizadeh & Talwalkar, 2018).

Technically it is a branch of artificial intelligence that can be intended as an evolution due to the intersection between Computer Science and Statistics. In fact, while Computer Science focuses principally on how to manually program computers, Machine Learning concentrates its efforts on how to get computers to program themselves from experience, letting to humans just the initial structure. Statistics instead is primarily interested on conclusions that can be inferred from data, whereas Machine Learning goes beyond wondering whether computational architectures and algorithms can be used to most concretely grab, store and mix these data in order to be helpful for the system to understand and improve (Mitchell, 2006).

Machine Learning due to its features is so having a strong impact in the digitalization of companies and according to Elliot, Noga & Wellers (2017) it is improving firms' work and value creation processes, with the following eight direct benefits:

- **Personalizing customer service:** Allows to improve customer service, lowering costs through the combination of historical customer service data, natural language processing and algorithms continuously learning from interactions.
- **Improving customer loyalty and retention:** It permits to detect customers that are at high risk of leaving and combined with profitability data it gives the chance to personalize to these clients a sound and favorable offer.
- **Hiring the right people:** Given the high number of applications received for a new job position, Machine Learning can help to provide a shortlist of candidates who have the credentials most likely to achieve success in that specific company.
- **Automating finance:** It significantly increases the number of invoices that can be matched automatically, letting finance staff time to focus on strategic tasks.

- **Measuring brand exposure:** Allows corporate sponsors to see the return on investment of their sponsorship investment with a careful analysis of quantity, duration and placement of corporate logos.
- **Detecting fraud:** Estimations say that organizations lose around 5% of their revenues due to fraud. Through models on historical transactions, social network information and other data, Machine Learning algorithms are capable to evidence anomalies or exceptions, helping to detect fraudulent transactions in real time.
- **Predictive maintenance:** It can detect anomalies, for instance acknowledging that the temperature of a machine has risen and it will need a quick check up in order to prevent it from breaking, with advantages in term of money and production timing.
- **Smoother supply chains:** Machine Learning permits to discover, searching through public data and news, if there are any problems in the factories that supplies the fundamental goods to your company in order to quickly find a remedy to not harm your business.

1.3.2 Big Data Analytics

To understand correctly what is meant by the term above is necessary to focus firstly on what are big data.

Big data is a term used for huge data sets having large, varying and complex structure with the difficulties of storing, analyzing and visualizing for further processes or results (Sagiroglu & Sinanc, 2013).

From the definition of big data emerges that obviously size matters, but there are other important attributes that are relevant for this field. According to Russom (2011), willing to crack the myth that this science is just referred to data volume, to account for big data are necessary the '*three Vs'*:

- **Data Volume:** Obviously the first attribute, but to account for dimensions there are multiple definitions. Most of the users define them in terms of terabytes, but they can be either quantified by counting records, transactions, files or even time.

- **Data Variety:** This is a feature connected to the fact that data are coming from an always greater variety of sources compared to the past. They can come for instance from web sources, supply chain applications or semi structured data from business-to-business process.
- **Data Velocity:** The speed of data can be thought as the frequency of data generation or as the frequency of data delivery. Actually it is extremely widespread for the collection of real time clickstream data from Web sites, allowing to make targeted purchase recommendation to Web visitors.

Given the incredible increase of data potentially available, the ability of a simple software to elaborate an outstanding quantity of information is gradually decreasing.

In the light of this, big data analytics come in support, with the application of analytical techniques to big datasets with the purpose to reveal and leverage business changes (Elgendy & Elragal, 2014). In such a competitive environment these insights, executed as accurately as possible, can turn out to be an extraordinary competitive advantage, fostering in recent years the attention beyond this science.

Of course, big data analytics faces a high degree of challenges to try to overcome as: data quality and validation, data cleaning, high dimensionality and data reduction, data representations, data sampling, scalability of algorithms, real time analysis and decision making, crowdsourcing, tracing and analyzing data provenance, parallel and distributed computing, exploratory data analysis and interpretation (Khoshgoftaar et al., 2015).

Such a quantity of problems, some of which neither superable in many cases, require to synthesize the overall picture constructing models that grant the possibility of a final decision.

According to Eckerson (2007) there are three steps to pass from the data gathered and reorganized to the moment in which the model makes functional the results obtained. First of all, is necessary to find the right combination of variables that have to be embedded in the model in order to analyze as deep as possible the phenomenon. Once constructed, is necessary to score it, after which the model is applied to the various records in the company's database. An important part of this step is how frequently to score the models, given that the scoring process can consume a lot of time and processing power, but of course more often a company is capable to renew the scoring, more accurate are the outcome obtained. According to a survey conducted over 161 respondents by Eckerson (2007), the best practice is to score the model monthly (45%), but a high number of organizations (19%) is able to score them dynamically. Usually, these models are scored with a value between 0 and 1, however most of the time the hardest issue is interpreting the result obtained and use it in a helpful way for the business, where successfully interpretating the model means to find the right cutoff score. Achieve this goal allows the company to pass to the implementation of the model, embedding it into an operational application capable to drive business movements autonomously. A classic example (consistently used for online sales and marketing) is to create a statement around the score of the type: "if a customer purchased on the Web a certain object which exhibits a product affinity of 0.75 or more, then show pictures of the following items with the caption 'you could be interested in buying also these other items'".

Moreover, to understand the major impact of big data analytics on the companies, in 2011 has been realized a survey that intended to find out the biggest benefits related to the implementation of such a type of process. The outcome of the survey showed that the five most relevant benefits are: better targeted social influencer marketing, more numerous and accurate business insights, segmentation of customer base, recognition of sales and market opportunities and automated decisions for real time processes (Russom, 2011).

1.4 Impact of Digitalization in Companies' Businesses

Digitalization (or digital transformation) is changed from being business support to being the business itself. Moreover, this process must not simply be seen as the necessity of incorporating new technologies or upgrading the already installed systems, but is important to let it have a concrete impact even in the adopted business models (Ahmed, Alraja & Hussein, 2021).

Being able to keep the pace of this process and adapt it to the needs of the firm is nowadays a key point for success. A concrete example of a segment of business that went through a radical shift is that of customer relationship: to manage them is indeed always more essential the presence of the firms on the most common social media as Facebook, Instagram, Twitter or LinkedIn (Ahmed et al., 2021).

While the adoption of social media is practically a prerogative to survive, embrace other challenges linked to digitize their business models can be an effective competitive advantage for companies in following years.

Before looking at the impact that such a transformation can have is necessary to understand when a business model can be defined 'digital'. According to Bican & Brem (2020) a business model can be defined as 'digital' if changes in digital technologies trigger fundamental changes in the way business is carried out and revenues are generated.

Notwithstanding the easy and clear definition this process needs years and a workforce (especially the top management) able not only to bear, but, above all, to lead the change.

The figure below represents the roadmap to the digital transformation of business models with the various phases necessary to guide the revolution.

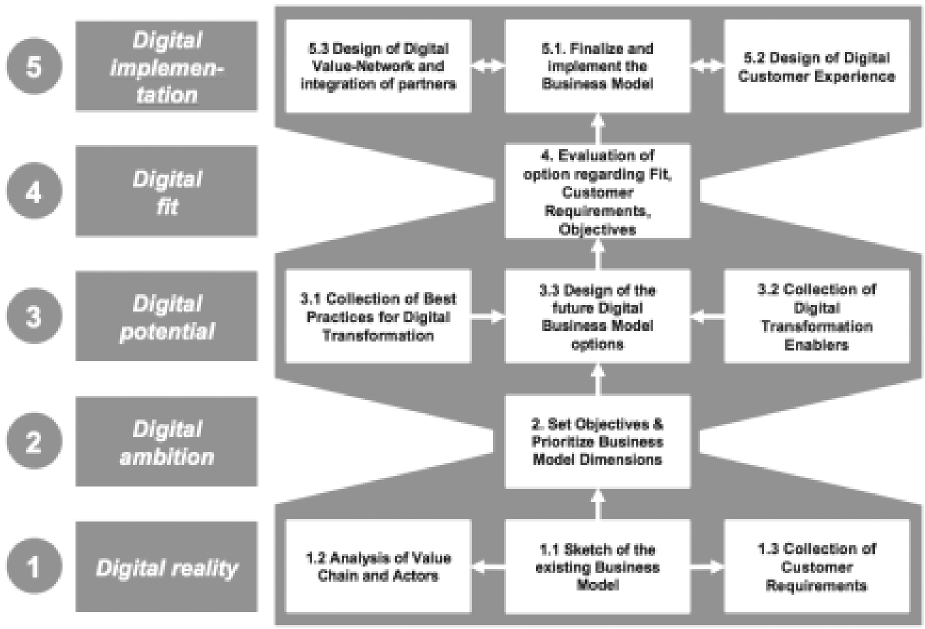

Figure 2: Roadmap for Digital Transformation of Business Models (Boardman et al., 2017).

According to Boardman et al., (2017) this ambitious change is articulated in five steps:

- **Digital reality**: First of all the existing business model is studied and are performed a value-added analysis related to stakeholders and a survey to understand customer requirements. Once got all these data, is obtained an overall picture of the 'digital reality' of the company for different areas.
- **Digital ambition**: Understood the as-is situation in the first phase, is then time to define concrete objectives in terms of digital transformation required, relating to time, finances, space and quality. Ultimately 'digital ambition' provides the necessary goals which should be considered for the business model and its elements, prioritizing them based on their relevance.
- **Digital potential**: In this step are established best practices and enablers[1] for the digital transformation, that are necessary to understand the 'digital potential' and as

[1] "Enablers are a support and facility necessary to allow the implementation of applications or services to be used for the digital transformation" (Boardman et al., 2017)

a starting point for the preparation of the forthcoming digital business model. In order to do so, many options and combination are derived.

- **Digital fit:** Once the various options and combination are identified, they need to be evaluated to determine the one that fits the most with the existing business model. This is necessary to be aware that the one selected will be capable to fulfill both customer needs and the achievement of business objectives.
- **Digital implementation:** This last phase includes the completion and activation of the selected digital business model. During the implementation are crucial phases those of the design of a digital customer experience and the digital value creation network to assess the feature referred to the integration with partners.

If this can be seen as an appropriate framework to understand how a business model can be able to comply with the digitalization wave that is shaping companies in recent years, to have a wider perspective on how this change can be successful is helpful to look at the role of the so-called ‘enablers’.

Enablers are the capabilities that drive a transformation and from a digital standpoint they represent collectively the engine that allows the company to reach its vision (Bain & Company, 2018).

To maintain the focus on the digital transformation of the business model they can practically be useful to allow application and services to be used and according to Bouée & Schaible (2015) four major categories can be identified:

- **Digital data:** Extrapolating, processing and analyzing digital data allows to facilitate and improve predictions and decisions.
- **Automation:** Consists in combining traditional technologies with artificial intelligence, giving rise to systems increasingly able to work autonomously and organize themselves. This permits to reduce error rates, increase speed and decrease operating costs.

- **Connectivity:** Interconnecting the entire value chain through high-speed broadband telecommunications allows to synchronize supply chains, leading to a reduction in production times and innovation cycles.
- **Digital customer access:** Mobile internet enables new intermediaries to have direct access to customers, to which are offered high levels of transparency and new innovative services.

1.4.1 What Impacts on the Digitalization of SMEs

If large corporations are more experienced and have a bigger capital base to deal with advanced digitalization, small sized companies are often more flexible and faster when is the moment to implement new technologies and to change processes (Härting, Jozinovic & Reichstein, 2017).

Although flexibility and speed can be competitive advantages in some cases, the 2017 OECD report described a negative trend between the G20 countries stating: ”*the uptake of digital technologies remains particularly low among small firms even for technologies that seem particularly relevant for SMEs, such as cloud computing”*. This evidence shows therefore a concrete and accentuated difference between Small and Medium-sized Enterprises (SMEs) and large corporations, namely the presence of a much higher heterogeneity of digitalization’s level between the former.

In the light of this pattern two interesting studies have been conducted during last year to investigate the factors that impact the digitalization of SMEs. The choice to quote precisely these two papers is not accidental, going to take as reference target in the first case companies taken from an emerging country, while in the second firms of a developed country.

From the first study proposed by Ahmed et al., (2021) conducted on a panel of Omani companies, there is concrete evidence (tested at a 95% confidence interval) that three factors strongly influence digitalization of SMEs, which are:

- **Technological:** It consists of technology infrastructures, employee experience in the field of technology and know how to implement it. Moreover, the study showed that if the level of used Information Technology (IT) in these enterprises is sufficient, it will ease the transformation of these companies into digital businesses.
- **Organizational:** It starts from the evidence that large firms are generally more capable of undertaking innovation rather than small companies, but that the former due to higher bureaucracy are much more slowed down in timing. According to this, if a smaller enterprise is able to implement digitalization practices, its ability to quickly transform its process and activities into digital business is faster.
- **Environmental:** It refers to the context in which SMEs are growing, including various stakeholders who are capable to influence and support these firms in their digital transition or either, to block it. The level of internet permeation among people is a concrete indication for companies to digitize the business.

The second study conducted by Alford et al., (2020) is prepared sending an online survey to 4146 randomly selected SMEs in Austria and has been answered fully and correctly by 193 of them. To consider a company between the SMEs the criteria adopted has been the number of employees, that should have ranged between 1 and 249.

This paper was finalized to understand if, as according to previous studies on big enterprises, even for SMEs Information Technology (IT), employee skills and digital strategy positively relate to digitalization. Through a regression analysis with control variables the number of employees, family ownership and company age the model has provided the evidence of a positive relationship of all the three independent variables over the dependent variable (digitalization). If from the study emerges this clear path for all of them is however true that employee skills and digital strategy show a greater positive impact compared to IT. This can be easily deduced from the fact that resources as mobile technologies, social media or cloud computing[2] are obviously important for digitalization, but without concrete skills of the workers or a vision of the owners on how to deal with them, they can't have a high effect.

The findings of these two studies on digitalization of SMEs show relevant differences from a digitalization process undertaken in an emerging or in a developed country. Indeed, if for the latter the principal issues are understanding the skills of the employees, the vision of the owners and the technologies implemented for SMEs, in the former is crucial even the environmental factor. Internet access or basic digital capabilities that are taken for granted in a developed economy are instead an issue with whom SMEs have to deal in emerging countries.

1.4.2 How Digital Champions Behave

To go more in detail on the impact of digitalization on companies' businesses, can be interesting to analyze the situation from the perspective of digital champions and get an understanding of what type of investments led these firms to be considered this way. A study published by Boston Consulting Group (BCG) in 2019 and conducted by Franke, Grebe, Leyh & Rüßmann tried to answer this question.

First part of this research consisted in asking to decision makers of 1817 companies distributed across 27 countries in Asia, Europe and the US to answer a survey composed of 35 multiple choices questions in a scale ranked from 1 (lowest valuation) to 4 (highest valuation) and aimed at estimating the digital maturity of these firms. These raw scores were then converted into values between 0 to 100 for assessing the Digital Acceleration Index (DAI) of each of them and according to the score obtained the companies have been clustered in the category of "digital champions" if the outcome ranged between 67 and 100 and that of "laggards" if instead it was lower than 43 (with an average score for the first category of 77 and for the second of 28).

[2] "Technology that allows to use, via remote server, software and hardware resources (such as mass memories for data storage)". Definition given by: Oxford Languages

According to this subdivision already emerges an important discrepancy between sectors, highlighting that more of the 25% of financial institutions and telecommunications companies are classified as digital champions, while more than 40% in energy and public sector are classified as digital laggards. Clustering by region instead Asia proves to be the one with higher overall digital maturity, followed by US and with Europe at the last place.

A strong difference proposed by this research between digital champions and laggards is embedded in what the authors call “digital boosters”. These three levers that allow companies to scale up their DAI, increasing the probability of becoming digital champions, are:

- Spending at least 5% of overall operating expenses on digital projects. This is the most relevant booster (granting an average increase of 16 DAI points) and is reached by 72% of digital champions and 50% of laggards.
- Staffing more than 10% of employees in digital roles and on digital projects. This characteristic grants on average an increase of 11 DAI points and is reached by 52% of digital champions and just 18% of laggards.
- Refining and scaling up pilots into operative solutions in order to deliver full potential. This quality allows on average an increase of 9 DAI points and is reached by 35% of digital champions and 14% of laggards.

Although the above boosters describe some features of the investments undertaken by the majority of digital champions, a further specification can be highlighted even in terms of future perspectives. According to the BCG research instead these companies plan to invest even more in digital talent in following years and specifically 77% of them are planning to increase their digital workforce over 20% and 51% are planning to upskill over 20% their staff in digital. Moreover, according to the survey, these firms dedicate 22% of their digital investment to tech/IT, pretty higher than laggards do and 49 % of digital champions dedicate more than 10% of their digital workforce to Artificial Intelligence[3] (AI), while just 13% of laggards do the same.

To conclude the research Franke et al., (2019) prepared three tips useful to become digital champions, namely:

- **Create a digital talent agenda:** Companies need to develop a strategy to attract talents, reflecting the demand for new roles and skills and practice a continuous upskilling path for roles where digital talent is most needed.
- **Strive for a world-class tech function:** Invest abundantly to build a leading tech/IT function, that will not just permit to leverage new technologies like the Internet of Things[4] (IoT) and blockchain[5] to support new business models, but also to lift efficiency.
- **Create a data centric organization:** Consider data at the center of the organization to drive a sound digital transformation, facilitate new tools and obtain new competitive positions.

If in this last step the authors were interested in evidencing some desirable conditions to become a digital champion, in a related research they analyzed three features that distinguish champions from others, looking at how they bring their digital strategy to life in an operational level.

According to Franke et al., (2018), they can succeed in:

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[3] "Artificial Intelligence (AI) applies advanced analysis and logic-based techniques, including machine learning, to interpret events, support and automate decisions, and take actions". Definition given by: Gartner Glossary.

[4] "The Internet of Things (IoT) is the network of physical objects that contain embedded technology to communicate and sense or interact with their internal states or the external environment". Definition given by: Gartner Glossary.

[5] "A blockchain is an expanding list of cryptographically signed, irrevocable transactional records shared by all participants in a network. Each record contains a time stamp and reference links to previous transactions. With this information, anyone with access rights can trace back a transactional event, at any point in its history, belonging to any participant. A blockchain is one architectural design of the broader concept of distributed ledgers". Definition given by: Gartner Glossary.

- **Creating the next-generation tech function:** It consists in pursuing digital maturity in order to create new technologies and having in the long run the possibility to improve efficiencies and costs.
- **Driving customer-centric digitization of the core:** Create value quickly requires digital initiatives capable of keeping the customer at the center, as digital customer journeys[6]. This attention increases customer satisfaction and simultaneously enhances product quality and time to market.
- **Focusing on new digital business opportunities:** Digitizing the core, while at the same time identifying new growth areas, grants new competitive advantage. Some potential opportunities can include startup collaboration or ecosystem expansion.

1.4.3 Digitalization in Italy

In compliance with the purpose of this thesis, once obtained a global overlook of the role of digitalization in our society and particularly its impact in corporate businesses, is absolutely helpful to analyze how Italy is dealing with this challenge.

According to Cedefop (2017), Italy is lagging behind many other countries in terms of digitalization, due to its weak digital infrastructure and low level of digital skills. To certify this lack has been conducted a research, aimed at identifying the proportion of the workforce aged between 25 and 64 with low digital qualification and taking as reference countries those part of the EU Member States. In 2015 out of these 28 states[7], Italy is only ranked better than Portugal, Malta and Spain with 32.2% of the previously mentioned population considered with low skills and far behind the average EU level of 18.1%. Moreover, the study presents even a forecast of how this data will evolve in the future, predicting a consistent decrease of the

[6] "The customer journey is the actual process which represents the formation of customer experience and facilitates the understanding of how customer goals, expectation and behaviours evolve over time" (Alamanos, Papagiannidis & Tueanrat, 2021)

[7] In this analysis the EU Member States are 28 because it has been conducted in 2015, prior to the Brexit process that led UK to leave the European Union. Actually the Member States are 27.

low skilled population by 2025 (22.6%), that however is not sufficient to scale up positions in the ranking (Cedefop, 2017).

If these findings are sufficiently worrying, a study conducted by Gasparri & Tassinari (2020), help to provide new concerns about the challenge of digitalization in Italy. In addition to the weak digital infrastructure and to the low level of digital skills of the workers is evidenced a consistent heterogeneity between sectors and regions in terms of technological innovation that makes the categorization of an overall level or the implementation of generalized policies even harder. Moreover, from a social perspective, all these problems arising in Italian context could lead even to an increase in unemployment, due to the automation of the works more practical and repetitive and the lack of possibility of low skilled employees to reinvent themselves in a more digitized environment (Arntz, Gregory & Zierahn, 2016).

Once observed these findings, emerged from studies willing to analyze in detail few specific characteristics of digitalization level in Italy, is now interesting to have a complete picture and in support of this need comes the Networked Readiness Index (NRI). The NRI, also known as Technology Readiness Index, is an indicator calculated, starting from 2002, by the World Economic Forum in collaboration with INSEAD[8], as part of its Global Information Technology Report (GITR). It measures the degree to which economies across the world leverage Information and Communication Technologies (ICT) for enhanced competitiveness. (Dutta & Osorio, 2012). In 2019 the name has been transformed in Network Readiness Index and the pillars have been revised in a way more focused to what future challenges of digitalization require, after which the final structure consists in 4 pillars and 12 sub-pillars, calculated from the analysis of 62 indicators.

According to this updated structure (Dutta & Lanvin, 2019) the four pillars are:

[8] Acronym of Institut Européen d'Administration des Affair. It is a private University located in Europe (France), Asia (Singapore), the Middle East (UAE) and North America (USA). Source: INSEAD website.

- **Technology:** First pillar has the duty to assess the level of technological advancement, believing it as an essential condition for a country's participation in the global economy. The three sub-pillars are: access, content and future technologies.
- **People:** Second pillar is ideated to measure the application of ICT by people, believing that having a good level of technology is only useful if the population and organizations have the access, resources and skills to use them properly. The three sub-pillars are: individuals, businesses and governments.
- **Governance:** Third pillar embeds the features of the national environment in order to understand if it is favorable for country's participation in the network economy. The three sub-pillars are: trust, regulation and inclusion.
- **Impact:** Fourth pillar is aimed to assess the economic, social and human impact of participation in the network economy. The three sub-pillars are: economy, quality of life and SDG[9] contribution.

The Network Readiness Index 2019 analyzes in depth, based on the abovementioned parameters, a total of 121 economies, ranking them based on the overall score obtained. The score achieved can range between 0 and 100, with the highest value obtained by Sweden with 82.65 and the lowest by Yemen with 12.33. In addition, the companies under observation have been subdivided based on four level of income (namely high, upper-middle, lower-middle and low), where income was calculated as GDP pro capita. This last choice is due to the evidence that countries with higher income have a higher NRI. (Dutta & Lanvin, 2019).

The figure below represents the Network Readiness Index 2019 for Italy, highlighting the score obtained in each of the 4 pillars and its relative sub-pillars and how the specific nation performs compared to the other with the same level of income thanks to a radar chart.

[9] Acronym for Sustainable Development Goals. Are the goals agreed by the United Nations for a better and more sustainable future for all (Dutta & Lanvin, 2019).

Italy

	Rank (out of 121)	Score
Network Readiness Index	**34**	**63.21**
A. Technology pillar	**33**	**61.06**
1st sub-pillar: Access	45	75.63
2nd sub-pillar: Content	35	61.17
3rd sub-pillar: Future Technologies	31	46.38
B. People pillar	**31**	**56.26**
1st sub-pillar: Individuals	45	60.11
2nd sub-pillar: Businesses	28	50.67
3rd sub-pillar: Governments	33	57.99
C. Governance pillar	**36**	**71.58**
1st sub-pillar: Trust	43	65.99
2nd sub-pillar: Regulation	43	71.05
3rd sub-pillar: Inclusion	25	77.70
D. Impact pillar	**34**	**63.93**
1st sub-pillar: Economy	31	35.16
2nd sub-pillar: Quality of Life	50	65.45
3rd sub-pillar: SDG Contribution	31	91.19

Figure 3: Network Readiness Index 2019 Composition for Italy (Dutta & Lanvin, 2019).

Looking at figure 3 is possible to notice that Italy's worst performance is obtained in the people pillar (56.26), result that is extremely compliant to what evidenced by Cedefop (2017), that is a high inadequacy of digital skills level for a relevant number of Italian workers. On the other hand, the best score is referred to the governance pillar (71.58), evidence showing that however Italian regulation and inclusion policy in the digital field are more advanced than other features.

While between pillars there are small misalignments, considering the sub-pillars categories are present huge differences. The positive aspect is undoubtedly in SDG contribution's score (91.19), highlighting that Italy is admirably able to cope with Sustainable Development Goals where ICT has an important role, as it is the case for health, education and environment. On the other side, the country is extremely laggard compared to the other developed economies in future technology (46.38) and economy (35.16). These two bad results paint Italy as not concretely prepared to deal with the future of network technology and new technological trends such as

Artificial Intelligence and Internet of Things, but neither capable of exploiting the economic impact deriving from participating at the network economy.

A further relevant aspect to assess Italian performance in terms of Network Readiness Index is granted by the radar chart positioned on the right of figure 3. From that classified between those with a high income, Italy results to be some steps back compared to the average of the nations ranked in the same income category, in every of the 4 pillars.

1.5 How to Measure Digitalization

While precedent paragraphs were principally interested in understanding what the digitalization process consisted of, its effects on business models and how to get advantage from it, this one has the objective to achieve a more practical perspective, analyzing how digitalization can be measured. The task is not easy and even in literature there aren't agreements on a unanimous way in order to measure it, however different perspectives can be presented.

Another differentiation that can be done for this measurement is between assessing it for countries and for corporations. In previous paragraph have been presented for instance the Network Readiness Index, but this is not the only possible renowned method used for assessing the digital capability of different countries. A methodology which is worth a mention is the Digital Density Index (DDI), created by Accenture in collaboration with Oxford Economics, and aimed at evaluating the level of adoption of digital technologies in terms of breadth and depth. The analysis started with the collection of observations that were possible to be consistently compared between hundreds of measures of digital technology from public and private sources. Once gathered the data the sample has been reduced to around 50 indicators in order to construct the Digital Density Index for the 33 most relevant economies across the world and testing statistically the outcome obtained. Finally, to use practically the index, some multivariate analysis have been conducted in order to estimate equations capable of highlighting relations between productivity factors and the DDI. (Accenture, 2015).

The composition of the DDI can be however simplified dividing the numerous indicators used in 4 macro areas:

- **Making Markets:** It consists in the level of recognition from governments that existing markets are becoming increasingly digital, with the predisposition of the necessary support to guide this transition.
- **Sourcing Inputs:** It starts evaluating to what extent factors of production are employed through digital technology and continues capturing the level to which these technologies change the way of sourcing these factors for the business.
- **Running Enterprises:** It relates to the extent to which companies are adopting digital technologies in fields like supply chain, strategy or research and development.
- **Fostering Enablers:** It requires to evaluate the impact of the institutional and socio-economic environment, that are important factors to enable digital technologies.

Once quoted for sake of completeness methodologies used to estimate digital maturity of countries, it’s time to focus the attention on the analysis of companies, which is more correlated with the purpose of the thesis. Given the subjectivity revealed by literature in dealing with digitalization measurement for corporations, many authors use surveys to estimate it in their papers.

An example is given by the paper published by Alford et al., (2020) on a panel of 193 companies part of the category of SMEs. In this case the authors prepared a survey to score the three independent variables that during the regression analysis have been used, with this choice dictated by the impossibility of getting data on them (namely IT, employee skills and digital strategy). The variables have been measured in the survey with the five-point Likert scale[10] ranging from the lowest value of 1 (strongly disagree) to the highest value of 5 (strongly agree).

A similar path was even followed by Joensuu-Salo et al., (2018) in a paper aimed at identifying the impact of digitalization and internationalization on corporate performance and, likewise the precedent study conducted by Alford et. al (2020), has been conducted a questionnaire distributed to 504 Finnish companies and completed by 101 of them.

In this research, to estimate the value of the independent variable ‘digitalization’, the authors developed appropriately a 7-item instrument in which the companies were asked to answer ‘yes’ or ‘no’ whether they used or not some specific technologies, which specifically were: web pages, social media, cloud services, digital communication with stakeholders, web commerce, industrial internet of things and big data. Then the study classified the digitalization level of the firms under observation based on the number of these technologies used by any of them, ranging so from 0 if none of them were adopted to 7 if all of them were used. To complete the estimation of the digital maturity the score obtained was converted using the natural logarithm to account for the relative change instead of the absolute change.

Although the survey is the most widespread methodology used to assess the level of digitalization of companies and practically almost the only one used when firms under observations are SMEs (for clear reasons of unavailability of data), this is not necessarily always the case.

Interesting is the research conducted by Domnicheva, Limonova & Manakhova (2018) to understand the overall level of digitalization between Russian companies, where the benchmark to understand it is the Biesiot Indicator (BI). This index suggests that the sustainable development of a certain organization is possible only

[10] Likert scale, conceived by the psychologist Rensis Likert in 1932, is a technique used to measure attitude in a scientifically and validated manner. The original Likert scale is composed by a series of statements offered for a real or hypothetical situation under study and in which participants are asked to show their level of agreement (from strongly disagree to strongly agree) to the given statement on a metric scale to denote the attitude for the issue (Chandel, Joshi, Kale & Pal, 2015).

if the response speed of the organization's protection system is higher than the speed of development of the external threat, meaning that the indicator should have a value higher than 1. (Domnicheva et al., 2018).

In the paper the Biesiot Indicator is calculated as BI = CPE/CPA, where CPE is the speed of response of the company and CPA the speed of threat. During the analysis conducted the CPA was the digitalization rate of the country (Russia in this specific case) and was composed based on data gathered by 'The ICT development index 2017' on four parameters: ICT development index, access to ICT, use of ICT and practical skills of using ICT.

For the CPE instead data were collected through an online dataset disclosing information about the level of digital economy in Russia and were oriented to evaluate the digital maturity of the companies under observation. For doing so the 8 categories chosen were: use of internet, use of broadband internet, companies having websites, companies using cloud services, companies using CRM-systems, companies using ERP-systems, companies using the internet to purchase goods, works and services and companies using the internet to sell goods, works and services.

Given that the paper aimed at evaluating the overall degree of digitalization of Russian firms, for each category has been reported the percentage of companies with that specific feature, but the result can even be completed case by case in order to estimate the indicator for different companies.

In conclusion the study evidenced a modest speed of digitalization of the country (CPA), but that of companies was even lower (CPE), resulting in an overall Biesiot Indicator of 0.46 for 2017, meaning that companies in Russia are far ahead from reaching a competitive advantage from digital technologies.

A different methodology of analysis has been proposed by Bistrova, Eremina & Lace (2019) in a study aimed at identifying the effect of digital maturity on corporate performance in the Baltic States.

The panel of companies under observation was that of the biggest Baltic companies listed on the Tallinn, Riga and Vilnius stock exchanges with at least three years of activity, more than 4 million euros of market capitalization and free float of minimum of 25% of free float or if this last requirement was not satisfied a market cap of at least 10 million euros. The researchers found 31 companies matching these constraints and managed to collect the data through nasdaqbaltic.com, firmas.Iv and the web pages of the firms under observation (Bistrova et al., 2019).

Specifically, to estimate their digital maturity, six major groups have been identified with many parameters composing each macro area:

- **General:** It includes twelve basic factors as computers and software, representing the general base of the digitalization process.
- **Internet of Things:** It includes thirteen concepts among which connectivity and connected objects.
- **Data science:** It incorporates eight factors among which predictive analytics or data management.
- **Process automation:** It comprise seven factors and refers to the integration of technologies in the operational processes of the business.
- **Artificial Intelligence:** It is estimated based on four factors among which machine learning and neural network.
- **Online:** It includes six factors referring to activities performed on the global network.

Completed the data collection for the five years (2013-2017) this partition in categories allowed the authors to understand even how the companies were evolving in each of the 6 fields composing digital maturity, evidencing for instance that the biggest increase refers to data science and process automation.

From the study emerged even a positive relationship between digital maturity and corporate performance, when the latter is calculated in terms of sales growth, ROE and gross profit/total assets, showing that on average companies with a higher digitalization had higher results in terms of these three parameters.

Another interesting case is presented by Banga (2019), who uses firm level digital capability to understand through a regression its effect on product sophistication for Indian manufacturing firms. During this work the author highlighted the impossibility of collecting data on the use of digital technologies, robotics and e-commerce for this kind of companies and for this reason he decided to look at an indicator capable of capturing the underlying potential of the firm to exploit them.

To measure digital capability have been constructed, using principal component analysis (PCA)[11], an index incorporating technology assets (including for instance computer and electrical installation) and software assets of the firm, because they were perceived as the voices of a corporate balance sheet more suitable as a proxy for underlying the potential of companies to exploit digital technologies.

If all the precedent examples were focused on dealing with methodologies suitable for measuring digitalization, a following step is provided by Egloffstein & Ifenthaler (2020). The most interesting part of their paper consists in, once assessed a maturity model to measure the degree of digital transformation, dividing the outcome in five ranges based on the level achieved in a scale from 0 to 100. The result is a continuous model with five maturity levels, namely: Minimalist (0-30 points), Conservative (31-50 points), Pragmatist (51-70), Advanced (71-90) and Trailblazing (91-100).

[11] Principal component analysis (PCA) is a multivariate technique that analyzes a data table in which observations are described by several inter-correlated quantitative dependent variables (Abdi & Williams, 2010).

CHAPTER 2 - PERFORMANCE AND RISK OF BANKRUPTCY

2.1 Contextualization of Performance

Measuring performance of companies and in general of business processes needs a set of indicators capable to represent in a single report the ability of the enterprise under observation to pursue its objectives both in short and medium to long term.

This necessity is provided by the fact that any organization, whether public or private, must comply with financial constraints and to grant a satisfying return to its stakeholders. On the other side, not being able to cope with these boundaries lead to financial distress and as conclusive step to bankruptcy (Neely, 2002).

However, is interesting to contextualize the discussion on performance inserting it into a wider field.

The figure below helps to understand a perspective on the macro area in which performance measurement can be collocated.

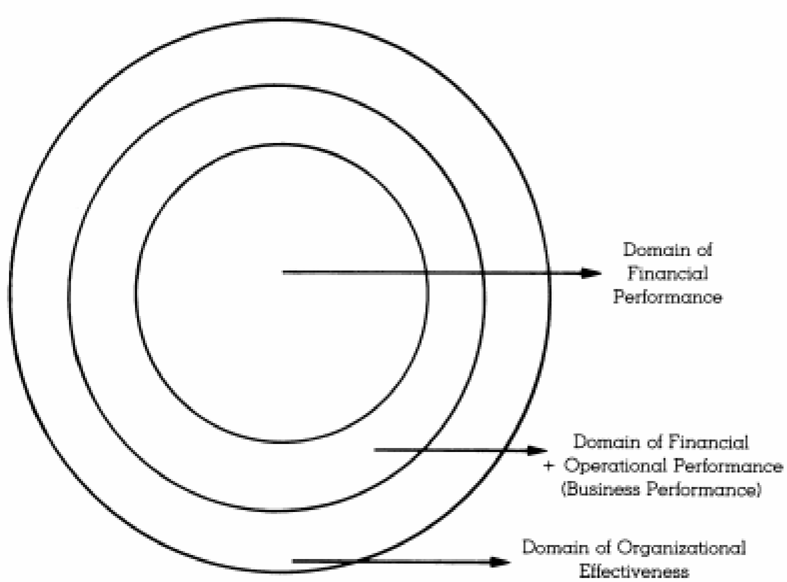

Figure 4: Circumscription of Performance Domain (Ramanujam & Venkatram, 1986).

According to Ramanujam & Venkatram (1986) financial and business performance are part of a broader framework, called organizational effectiveness.

Analyzing figure 4 emerges that financial performance, usually the final synthesis of the overall health of companies, is just the inner part. The authors in fact defines it as the ultimate mix of outcome-based indicators that are assumed to reflect the fulfillment of the economic goals of the firm and typical indicators to measure it are for instance sales growth, return on equity and return on investment.

Then is possible to notice that this deeper part is embedded into the business performance, whose peculiarity is to enlarge the domain even to the operational one. This typology includes nonfinancial indicators, such as market share, new product introduction, product quality, marketing effectiveness or manufacturing value-added (Ramanujam & Venkatram, 1986).

The larger circle that encloses all the types of performance is instead the one of organizational effectiveness, but this argument being particularly conceptual is afflicted by strong debates in literature on which are the models to measure it.

Cameron (2015) summarizes several models for organizational effectiveness that have been proposed by scholars, focusing on the interpretation of "effectiveness":

- **Bureaucratic model:** where effectiveness means matching the ideal characteristics of a bureaucratic organization.
- **Goal model:** where effectiveness signifies achieving the predetermined goals.
- **Natural systems model:** where effectiveness refers to obtain necessary resources.
- **Strategic constituencies model:** where effectiveness means satisfying relevant stakeholders.
- **Internal processes model:** where achieving effectiveness requires high quality internal processes.
- **Paradox model:** where effectiveness means presence of simultaneous opposites.
- **Abundance model:** where effectiveness signifies producing flourishing and virtuousness.

2.2 Models for Performance Measurement in Literature

This paragraph is willing to give an overview of the most successful models for performance measurement proposed in literature following a chronological order, but before passing to the core of this section the paper proposed by Sink & Tuttle (1989) can give an interesting overview of the argument.

According to them, performance of an organization is a complicated interrelation between various prospects of performance criteria and in the study they identified the following seven:

- **Effectiveness:** consisting in doing the right things, at the right time and with the right quality and practically calculated as a ratio of actual output to expected output.
- **Efficiency:** referring to do things properly and practically defined as ratio between expected resources to be consumed and resources effectively consumed.
- **Quality:** understood as a wide concept, but synthesized to be made more tangible through six measurable checkpoints (upstream systems, inputs, transformation value-adding process, outputs, downstream systems and quality management process).
- **Productivity:** calculated with a simple ratio of output to input.
- **Quality of work life:** seen as an essential, but often forgotten, element contributing to a well performing system.
- **Innovation:** believed a fundamental element for sustaining and improving performance.
- **Profitability or budget ability:** representing the ultimate goal for any organization.

According to Khan & Shah (2011), the performance measurement matrix proposed by Keagan et al., (1989) was the first performance measurement system widely accepted as a balanced and integrated frame.

The figure below shows the main features of the matrix.

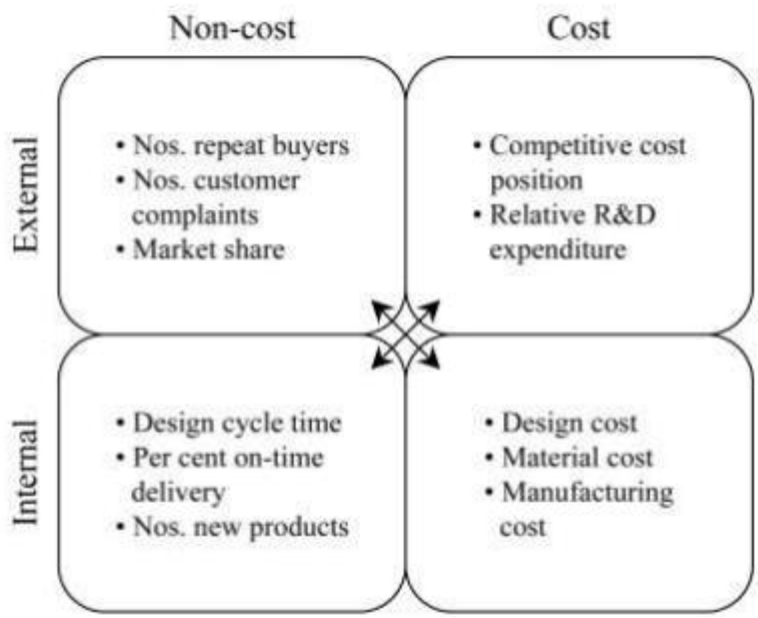

Figure 5: Performance Measurement Matrix (Keagan et al., 1989).

Figure 5 represents how performance measurement matrix is constructed, evidencing the presence of four different dimensions (cost, non-cost, internal and external) and in each combination box are described some particular features linked to performance to look at. The framework reveals the need for a balanced system, but due to its simplicity reflects its ability to accommodate any measure of performance. Moreover, the matrix serves as support and overview to evaluate strengths and weaknesses of the entity analyzed and to find collaboration patterns between these areas. (Dahal, 2019).

Although this first model resulted innovative and interesting, more developed and wider reasonings have been proposed by literature.

A different approach was indeed followed by Cross & Lynch (1992), believing necessary many new measures going beyond a simple analysis of profitability and cash flow generation. For doing so the authors proposed the so-called Performance Pyramid, shown in figure 6.

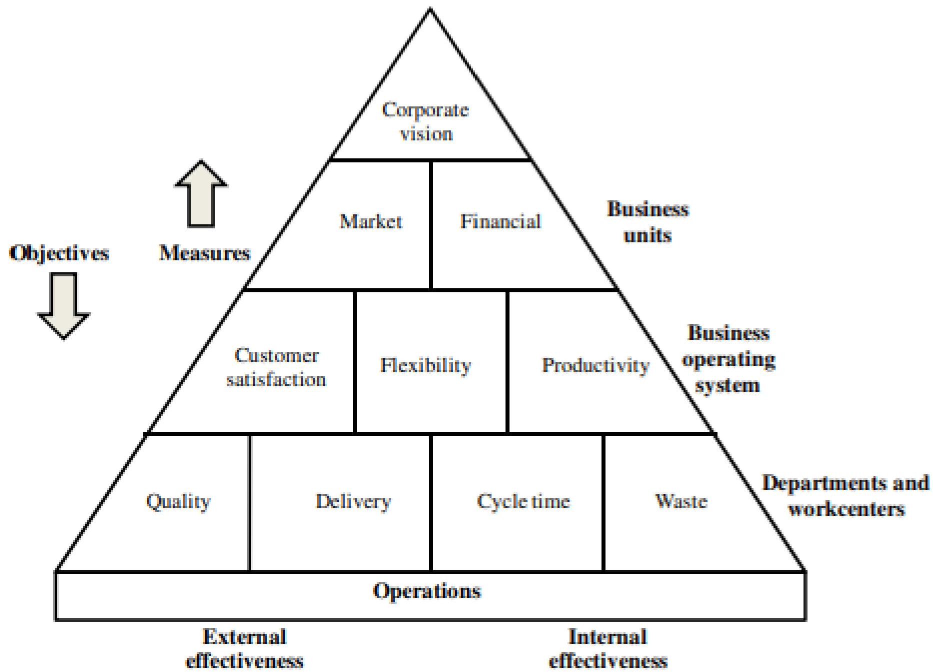

Figure 6: Performance Pyramid (Cross & Lynch, 1992).

The idea of representing the model using the pyramidal form of the above figure 6 comes from the idea that companies and in general organizations operate at different levels, each of them with a different focus.

To analyze the structure, a methodology can be to start from the middle, with those items characterizing the business operating system. In Cross & Lynch perspective instead the driving forces on which company objectives are based are customer satisfaction, flexibility and productivity. However, successful outcomes at this level, rely and can be monitored thanks to lower level indicators (those that in the figure are under the name "departments and workcenters"), so enhancing quality and delivery performance and reducing cycle time and waste.

Looking on the top of the pyramid is possible to see that a successful business operating system is necessary to get advantages in terms of market consideration (and practically to a potential higher market capitalization in the case of listed companies) and financial performance. With all the underlying structure working properly is then easier for the entity to achieve the so-called “corporate vision”.

In conclusion this pyramid behaves as a continuous interrelation between levels, connecting together the hierarchical perspective of business performance measurement with the review of the business process. In doing so it also evidences differences between measures of external effectiveness as quality, delivery and customer satisfaction (on the left side of the pyramid) and measures of internal effectiveness as cycle time, waste and productivity (on the right side of the pyramid).

One of the most successful models is instead the one proposed by Kaplan & Norton (1992), that shifted the focus from single measures itself, as in a model as the one previously quoted, to a system of performance measurement with the aim of linking the company’s long-term strategy with its daily operations.

As stated by the authors, the balanced scorecard is a model with the purpose of not making necessary a choice between financial and operational measures, giving however a fast and comprehensive view of the business.

This framework rotates around four perspectives, each of them reflecting an important dimension of the company’s business, which are:

- **Customer perspective:** It answers to the question “How do customers see us?” and begin analyzing what are the usual customers’ concerns, classifying them in four categories (time, quality, performance and service and cost). In this perspective some of the major goals are the effectiveness of new products, responsive supply and customer partnership, while some potential measures are the percent of sales from new products or the punctuality level of shipment of orders.
- **Internal business perspective:** It answers to the question “What must we excel at?” and the measures for this field should come from factors influencing quality, employee skills and productivity. In this perspective some of the major goals are technological capability, manufacturing excellence or design productivity, while some potential measures are the cycle time or the unit cost.

- **Innovation and learning perspective:** It answers to the question "Can we continue to improve and create value?", believing that every organization should undertake continuous processes of innovations and improvement, launching new products and penetrating new markets. In this perspective some of the major goals are technology leadership, product focus or time to market, while some potential measures are time to develop next generation or new product introduction versus competitors.
- **Financial perspective:** It answers to the question "How do we look to shareholders?", typically looking at profitability, growth and shareholder value. In this perspective some of the major goals are survival, success and prospering, while some potential measures are the cash flows, sales growth, market share growth or ROE.

"*The balanced scorecard is like the dials in an airplane cockpit: it gives managers complex information at a glance"* (Kaplan & Norton, 1992).

Between 1992 and 1996 another research program has been carried out in Norway, with the goal of analyzing productivity issues in Norwegian manufacturing companies and the framework proposed as outcome of the work is the TOPP model. For developing this structure, the authors dated back to the first two of the seven performance criteria exposed in 1989 by Sink & Tuttle (effectiveness and efficiency), considered in the sense proposed by them, and added a new dimension: the ability to change (Rolstadås, 1998). Being successful in these three variables is seen in the model as a good way to assure a good performance even in the long term, while simply the first two proposed by Sink & Tuttle tend to guarantee it in the short run.

According to Bredrup & Moseng (1993) the TOPP model allowed to develop two other sets of methodologies for measuring productivity in a company, namely:

- **Self-audit based on questionnaire answered by the companies:** Similar to TOPP, although this one has more focus on quality, rather than TOPP that focuses principally on the competitiveness of the whole company. This questionnaire consists in three parts, where the first analyzes facts about the company, production, costs, finance and more, the second provides an overall evaluation of different functions and system variables and the third gives a detailed evaluation of primary and support functions and system variables.

- **External audit performed by experts analyzing the companies:** In this methodology a team composed by external experts analyzes and scores indicators in a 1 to 7 scale. The analysis is done first at a company-level, using indicators of the overall performance and then using indicators specific of a limited area of business.

A further model, with an outstanding success between scholars, is the Performance Prism. In their paper Neely et al., (2001) recognized the pioneering role of the balanced scorecard proposed by Kaplan & Norton in 1992, highlighting their ability to cope with the need for a balance between financial and non-financial measures, but at the same time they pointed out the necessity for a new method focused on the necessity to face changed times.

The figure below represents the synthesis of the Performance Prism.

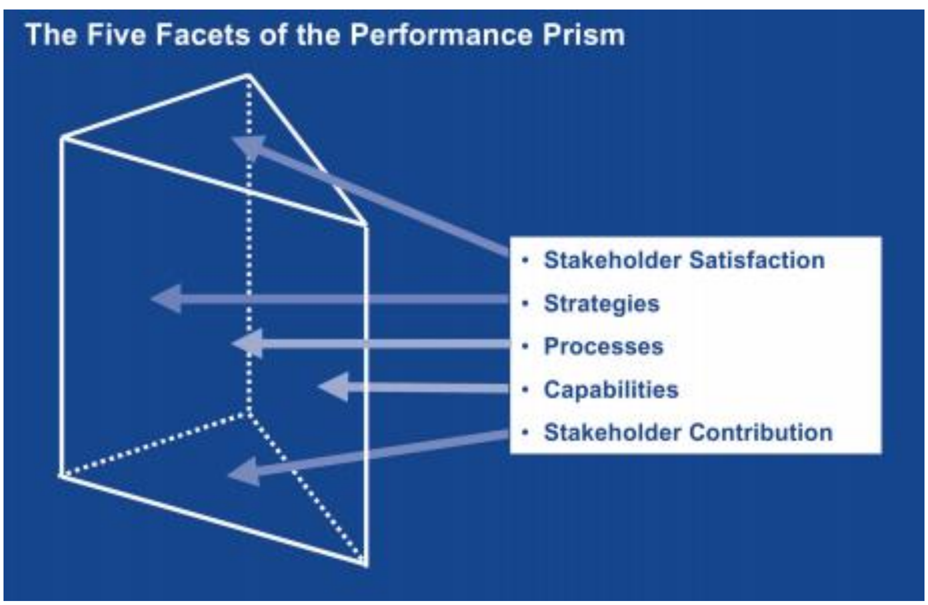

Figure 7: The Five Facets of the Performance Prism (Neely et al., 2001).

Figure 7 shows the structure of the model, consisting in five interrelated facets, which are described specifically by Neely et al., (2001) for a broader comprehension:

- **Stakeholder satisfaction:** It answers to the question: "Who are the stakeholders and what do they want and need?". This perspective is deliberately broader than the one proposed in the balanced scorecard view, where only customers and shareholders are considered, taking in consideration also employees, suppliers, intermediaries, governments, local community and pressure groups.
- **Strategies:** It answers to the question: "What are the strategies we require to ensure the wants and needs of our stakeholders are satisfied?". Referring to this point the authors deny the traditional idea that measures should be derived from strategy, stating that the only reason companies have strategies is to deliver value to stakeholders. In the light of this evidence the only moment in which is possible to start to analyze the issue of what strategy to follow is after having assessed the needs of the stakeholders.
- **Process:** It answers to the question: "What are the processes we have to put in place in order to allow our strategies to be delivered?". The processes described in this stage are generic business processes as developing new products and services or generating and responding to the demand, for each of which should be possible to identify specific measures allowing management to address targeted questions related to each one.
- **Capabilities:** It answers to the question: "What are the capabilities we require to operate our processes?". Capabilities refer to a combination of people, practices, technologies and infrastructures enabling together the execution of organization's business processes, without which is not possible to advance and compete.
- **Stakeholder contribution:** This last feature is seen as a separate component into the analysis and it recognizes the evidence that not just organizations have to deliver value to their stakeholders, but also the latter have to contribute to the organization. Neely et al., (2001) in this perspective quote the example of employees, requiring a

good salary, recognition and opportunities to influence the organization, while in return the company needs back good ideas and suggestions, expertise, loyalty and continuous knowledge update by them. The recognition of this symbiotic environment, as declared by the authors, is true for all classes of stakeholders and is a critical and unique characteristic brought by the Performance Prism and never considered before.

A further interesting model is the Triple-P proposed by Tangen in 2005, where the author admits that his research question was effectively related to an issue revealed by Sink & Tuttle (1989), synthesized by the latter in the following statement: "*The field is filled with practitioners with no conceptual models and weak operational definitions; the field is filled with academicians with weak conceptual models and no operational definitions. The result has been confusion in the literature and in practice with no respect to performance measurement and improvement".*

The aim of the Triple-P model is so to reduce the confusion in terminology, by explaining the basic meaning of frequently used terms into the field of productivity and performance management (Tangen, 2005).

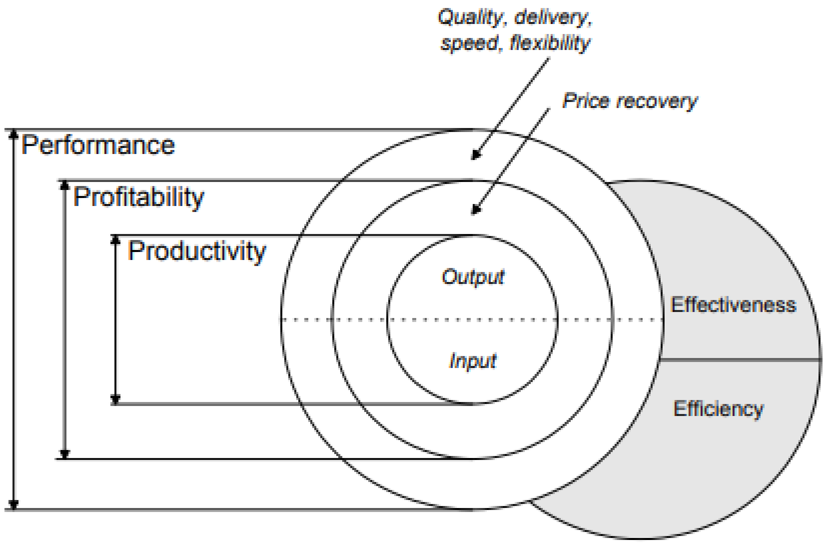

Figure 8: The Triple-P Model (Tangen, 2005).

Figure 8 depicts the Triple-P described by Tangen (2005), highlighting productivity as the core of the model. To the latter is given a straightforward definition, identified as the relation between output quantity (correctly produced products which fulfill their specifications) and input quantity (all resources used to deal with the transformation process). Above it, there is the term profitability, which is still seen as a relationship between input and output, but this time is a monetary relationship in which the influences of price-factors are embedded. Performance is instead the umbrella term of excellence, including productivity and profitability as well as other non-cost factors as quality, speed, delivery and flexibility. Effectiveness and efficiency are instead cross-functional when referring to the other three terms, where the first represents the degree to which desired results are obtained and the second describes how well the resources of the transformation process are utilized (Tangen, 2005).

2.3 Most Common Indicators to Measure Performance in Literature

Differently from the previous, this paragraph is going to take a much more practical perspective, looking at which are effectively the most common indicators used by practitioners in the literature to measure the performance of an entity.

From a deep analysis of previous studies emerge that the majority of scholars focuses principally on two ratios to evaluate performance of companies, namely ROE and ROA.

Between the literature for instance Chaghadari & Chaleshtori (2011) used firstly ROE as the variable indicating firm performance and afterwards to perform a robustness check they utilized ROA instead of ROE as dependent variable for the same regression.

Even Gan, Nadeem & Nguyen (2017) used as performance parameters ROE and ROA, but in addition considered also the asset turnover (ATO) and the price to book ratio (P/B), while in the study conducted by Bhagat & Bolton (2008) to measure the abovementioned variable has been used just the ROA.

$$\boldsymbol{ROE = \frac{Net\ Income}{Equity}}$$

Return On Equity (ROE) is a ratio indicating the capability of the company to repay its shareholders, used to verify concretely the rate of return of the capital conferred as equity.

This measure is usually compared with the expected return obtained through the Capital Asset Pricing Model (CAPM)[12], described by the following formula:

$$\boldsymbol{E(r) = r_f + \beta * (Er_m - r_f)}$$

[12] The Capital Asset Pricing Model is described by Sharpe in 1964 in his paper "Capital Asset Prices: A theory of market equilibrium under conditions of risk". As stated by the author the mathematical framework used to derive the model is the portfolio theory of Markowitz. The CAPM has the purpose to determine a relation between the yield of a security and its riskiness, through the beta factor.

The CAPM formula is composed by the following three elements:

- **Risk-free rate**: is the return obtained for investing in an activity with no risk and is an important variable of the model given that is straightforward that, under the assumption that investors behave rationally, higher is this rate and higher will be the return required to invest. Notwithstanding the unassailable theoretical framework, is impossible to find in practice an investment that is effectively risk free and for this reason when computing this calculation in real circumstances is taken as reference value that of the 10-year government bond. For instance, in the Eurozone, practitioners tend to suggest that the reference rate is that of the 10-year German bonds, considered the safest.
- **Beta**: is the coefficient that measures the behavior of a security compared to that of the market. It is in fact calculated as the covariance between the expected returns of the security and that of the market, divided by the variance of the expected return of the market ($\beta = \frac{cov\ (r_i, r_m)}{var\ (r_m)}$). To estimate the beta for listed companies is common practice to compare returns of the specific security and of the market, looking at the past. In this perspective the time horizon is crucial because there are different time horizons and length of observations to take into account, looking for instance at daily returns of the previous year, weekly returns of the previous two years or monthly returns of the previous five years. Practitioners, as reference, agree to the second option, believing daily returns to be potentially influenced by the so-called 'non-trading issue' and a five years horizon to be too far back in the past and no more reliable for the actual situation of the market, but however the perspective changes case to case.
- **Market Risk Premium (MRP):** it consists in the return that an investor believes to obtain from a risky portfolio of securities. Market risk premium is obtained subtracting from the expected return of the market the risk-free rate, letting in fact just the additional risk borne by investing in the activity more dangerous. To calculate MRP is necessary the observation of a long historical series of market returns and risk-free rate, but a general reference can be even Damodaran's webpage.

Coming back to the principal topic of understanding how to deal with ROE, a practical way to understand if that obtained by the company under observation is a good one, is to compare it with the expected return calculated through the CAPM, obviously using the specific beta of the firm (where a value higher of 1 means that the entity is riskier than the average of the market, leading also the expected return to rise, the other way around if beta is lower than 1).

Once obtained the outcome from CAPM, this value is compared with the ROE and if this last ratio is higher the company has "beaten the market" and its appeal will be higher, given that it has been already able to provide a return higher than the "fair" return for that type of investment.

The observation of ROE is then a very important comparison parameter between firms of the same sector to understand which of them is better rewarding shareholders.

However, with this measure alone, it can't be effectively said that a company is performing better than a competitor because firms that rely heavily on debt, having a high financial leverage, will tend to have a ROE very high if they have a positive net income. On the other hand, if this last parameter is negative the impact even of a small loss can be extremely disruptive for shareholders' equity.

For this reason, in support of this performance measure can come another ratio that overcome some of these previously quoted issues: the ROA.

$$\boldsymbol{ROA} = \frac{\boldsymbol{Net\ Income}^{13}}{\boldsymbol{Total\ Assets}}$$

[13] In ROA formula there are some disagreements whether to use as numerator the Net Income or the Earnings Before Interest and Taxes (EBIT). In accordance with the choices done even for the other indicators of taking as reference the website of Borsa Italiana is used the Net Income, being the measure suggested by them.

This ratio, as the ROE, is an indicator of profitability, but differently from the previous, interested in understanding the return obtained by shareholders, has a wider perspective analyzing how much net income is created compared to the overall assets.

Even for this reason instead ROE and ROA are usually used together as performance parameters in literature. One more feature that makes these two variables extremely connected and important when analyzed together, is that while ROE can be manipulated by a company deciding to embrace a higher financial leverage, that's not possible for ROA because this operation would be reflected in the ratio with an increasing denominator, resulting so, maintaining constant the numerator, in a lower value.

If these last two indicators are widely the most used the previously quoted research conducted by Gan et al., (2017) highlights other two suitable indexes: Asset Turnover and the price to book ratio.

$$\boldsymbol{Asset\ Turnover = \frac{Sales}{Net\ Operating\ Assets}}$$

Asset turnover (ATO) is an indicator helpful to state the effectiveness of the company, going to investigate whether the net operating assets (calculated as operating assets minus operating liabilities) were effective at generating sales.

The value obtained through this ratio is a number in absolute value and not to look in percentage, for which the minimum value to consider a company effective is 1, meaning that the amount of sales must be at least equal to the capital invested in operating activities. An asset turnover with a value higher than 1 can be interpretated as a sound capability of the firm to invest in the right operating assets, while if the ratio is lower than 1 it should be ready to analyze assets one by one to grasp the issue.

However, in two specific cases even an asset turnover lower than 1 can be physiological, specifically:

- At the beginning (first three years of activity).
- For companies active within a capital-intensive business. In this case, given the high investment required can't be possible every year to have a value higher than 1, but if the firm is healthy this will be covered by higher Return On Sales (ROS).

$$\boldsymbol{Price\ to\ Book = \frac{Market\ Capitalization}{Book\ Value}}$$

The price to book ratio (P/B) is a very interesting parameters to have a complete perspective of the performance of the company, taking as reference the market (with all its strengths and weaknesses). It is calculated dividing the market capitalization (calculated as the number of outstanding shares multiplied by the share price) for the book value of the firm (assessed through the balance sheet from the sum of share capital, reserves and retained earnings).

According to Borsa Italiana, the following are the advantages of using the P/B:

- Book value provides a measure relatively stable and intuitive of the value that can be easily compared with market price.
- Starting from a presumption of uniformity of accounting measures between companies, P/B ratios of similar entities are easily comparable in order to identify an overvaluation or undervaluation of the latter. In addition, from benchmarking this measure with that of the most highly comparable companies of the same sector, is possible to have at least a raw measure of market capitalization of the one examined simply observing book value.

The same source provides also a set of drawbacks to consider when using the P/B ratio:

- Time lag from numerator and denominator, representing relatively market data (more fluid) and accounting values (more static).
- Effects on denominator can be determined by accounting policies decided by companies' management.
- Weakness of accounting data to assess economic value of companies.

Some different factors to evaluate performance of companies in the literature are instead used by Hartono & Santhanam (2003), that use ROA, but even other interesting measures as Return On Sales (ROS) and Operating Income to employees.

$$\boldsymbol{Return\ On\ Sales = \frac{Earnings\ Before\ Interest\ and\ Taxes}{Sales}}$$

ROS is an indicator that tells us about the efficiency of the organization under analysis, showing what percentage of sales become operating profit, with the reciprocal (1-ROS), that represents the part of sales "eaten" by operating costs.

Depending on the sector of analysis ROS inevitably changes, suggesting as minimum acceptable threshold 10% for manufacturing companies and between 15% and 20% for services firms.

$$\boldsymbol{Operating\ Income\ to\ Employees = \frac{Operating\ Income}{Number\ of\ Employees}}$$

Operating income measures are widely adopted in the literature to measure performance of companies and although the one above is not between the most used, is undoubtedly interesting.

This ratio is suitable to identify management's ability to employ its workforce effectively in order to create profits for the company. Sometimes this calculation is even performed as revenues to employees, however practitioners tend to agree that considering the operating income is more correct, because it also considers labor costs.

To sum up, this measure is assessed to get a perspective of the efficiency of the company, believing that on average those capable of obtaining a higher operating income with the same number of employees are performing better. In this case, differently from other ratios, there is not a benchmark value considered acceptable, but is necessary to compare the result obtained with competitors in the same industry.

A study conducted by Lakhal, Limam & Pasin (2006), aimed at identifying the relationship between management practices and performance measurement, further expands the methodologies used in literature to calculate performance, considering in addition to the widely quoted ROA, the Return On Investment (ROI) and the growth rate of sales.

$$\boldsymbol{Return\ On\ Investment = \frac{Earnings\ Before\ Interest\ and\ Taxes}{Net\ Operating\ Assets}}$$

ROI is a very famous and adopted indicator, investigating how much EBIT has been obtained exploiting the operating assets.

Looking at ROI from the perspective of the Managerial Pyramid[14], it is investigated during the first level breakdown as the factor representing operating profitability. Continuing to use the pyramid with the second level breakdown we can investigate the composition of this indicator, acknowledging that it is in turn obtained through

[14] The Managerial Pyramid is, together with the Analyst Pyramid, one of the possible ways to look at performance of a company. This pyramid has three levels and starting from ROE investigates the impact of all the factors influencing it. This topic has been covered and analyzed during the course of Financial Statement Analysis.

a simple multiplication between ROS and asset turnover (this is clear from the formula already quoted of these ratios, that simplified result in that of ROI).

In this perspective is so possible to state that through this measure is feasible to evaluate both effectiveness (through the asset turnover) and efficiency (through the ROS) and depending in the business ROI can be obtained with a different impact of these two components.

To understand if the yearly ROI is a good result is, similarly to other indicators, necessary to look at previous years and competitors' value.

$$\boldsymbol{Growth\ Rate\ of\ Sales} = \frac{\boldsymbol{Sales_t - Sales_{t-1}}}{\boldsymbol{Sales_{t-1}}}$$

This measure has the aim of identifying whether the sales increased from previous year and how much. In accordance with the ratios previously quoted, even this one is more purposeful if analyzed in parallel with competitors, but another suitable comparison to be made is with the overall state of the economy.

In this perspective is straightforward that a great increase in the growth rate of sales can be both due to a solid business conducted by the firm or simply by a higher customer confidence in the economy, making interesting a joint study of the variables before stating how the company effectively performed in this fundamental.

Another extremely interesting research is the one conducted by Fu, Parkash & Singhal (2016). In this paper the authors were focused on investigating whether existed a relation between Tobin's q and firm performance, finding a concrete correlation between the two factors, calculating in such a case performance as EBITDA margin.

$$\boldsymbol{EBITDA\ Margin} = \frac{\boldsymbol{EBITDA}}{\boldsymbol{Sales}}$$

This margin investigates the Earning Before Interest, Taxes, Depreciation and Amortization, seen as a raw measure to understand what is left after all the operating costs have been paid, which is expressed in percentage of sales.

EBITDA margin is interesting because gives a quick overview of the operating performance of companies, suggesting immediately how much operating cash is obtained for each unit of sales and a good characteristic of this ratio is that it is not much influenced by accounting policies as could be the case when using the net income.

In addition, another thing to consider when analyzing this ratio is that a negative value means that the company has remarkable operating problems, not even being able to cover operating costs with sales. Different is the situation when talking of net income, because in that case problems are not necessarily operational, but they can be even due to a bad financial situation, with interests on debt too heavy to bear.

Further to the previous paper wrote by Fu, Parkash & Singhal (2016) aimed at identifying a relation between Tobin's q and firm performance, another research, conducted by Abdi, Càmara-Turull & Li (2020), has followed a similar path. In this case however the authors used exactly this ratio as company's performance measure.

Tobin's q was ideated in 1966 by Nicholas Kaldor in its paper "Marginal Productivity and the Macro-Economic Theories of Distribution: Comment on Samuelson and Modigliani" and has been effectively made known by James Tobin in 1978 (from which it takes the name). According to Tobin (1978), many uses of this ratio can be done, ranging from the q for specific incremental investments, the average q of the firm, the market q or that of the whole economy.

$$Tobin's\ q = \frac{Total\ Market\ Value\ of\ the\ Firm}{Total\ Asset\ Value\ of\ the\ Firm}$$

The above formula represents the way to look at Tobin's q for the firm, however due to strong difficulties to assess the total asset value of the firm (defined by Tobin as their replacement cost) some practitioners refer to their book value.

The classification of results gathered through this ratio can be divided between two outcomes:

- If Tobin's q is between 0 and 1, the replacement cost of the assets is higher than the market value of the firm, meaning that the stock is undervalued or alternatively that the company is not sufficiently able to exploit its assets.
- If Tobin's q is higher than 1, the replacement cost of the assets is lower than the market value of the firm, meaning that the stock is overvalued or alternatively that the company is capable of correctly exploiting its assets.

While previously quoted indicators refer principally to a profitability analysis, is fair for a wider perspective of companies' performance to look even at some liquidity ratios.

Neely (2002) proposed some ratios based on the working capital, of which the most important are the current ratio and the quick ratio (alternatively called acid test).

$$Current\ Ratio = \frac{Current\ Assets}{Current\ Liabilities}$$

Current ratio serves to detect the capability of the company to face current liabilities through current assets. In this perspective "current" refers to those items that are expected to be liquidated or turned into cash within twelve months.

To look from a numeric perspective the safety threshold is 1, meaning that if current liabilities are greater than current assets the mismatch is problematic, however to be considered a healthy situation this ratio should be higher than 1.5-1.8.

$$\boldsymbol{Quick\ Ratio} = \frac{\boldsymbol{Current\ Assets - Inventories}}{\boldsymbol{Current\ Liabilities}}$$

Quick ratio investigates whether company's most liquid assets are able to cover short term obligations. Differently from the current ratio, this one subtracts from the numerator inventories, because they are the less liquid items of the current assets.

This indicator, due to its construction, is so strictly dependent in the type of business that companies are conducting, in the sense that those with a high inventory needed will perform physiologically lower than service companies.

Due to the impact of inventories in the calculation, the value allowing to state that the company is in a healthy short term liquidity position is 1.

2.4 Understanding Bankruptcy: What is and its Spread since 2008 Crisis

According to Oxford dictionary bankruptcy is a term that can be referred both to a person or to an organization declared by the law as unable to pay its debts.

Around the definition of bankruptcy and the similar of failure there has been a wide debate from which emerged that many authors in their papers used interchangeably these two words, although bankruptcy legally is a process beginning financially and concluded legally, while financial failure is a necessary but not sufficient condition for the previous term (Karels & Prakash, 1987).

Starting from the evidence sorted out by Karels & Prakash (1987) where different practitioners resorted to these two terms for the same purpose (for instance Altman, Elam and Tamari used bankruptcy while Beaver, Blum and Edminster accounted for similar issues with the term failure) this thesis will proceed using bankruptcy as reference term for the purpose.

Referring at a worldwide definition is however pretty difficult due to widespread differences in legislation. In some countries indeed if a company declares to be bankrupt must stop operating immediately, while in others even after the filing of this status is allowed, with particular constraints, to continue operating (OECD, 2015).

Notwithstanding this issue a 2015 OECD study tried to identify the trend level of bankruptcies from 2007 until 2015.

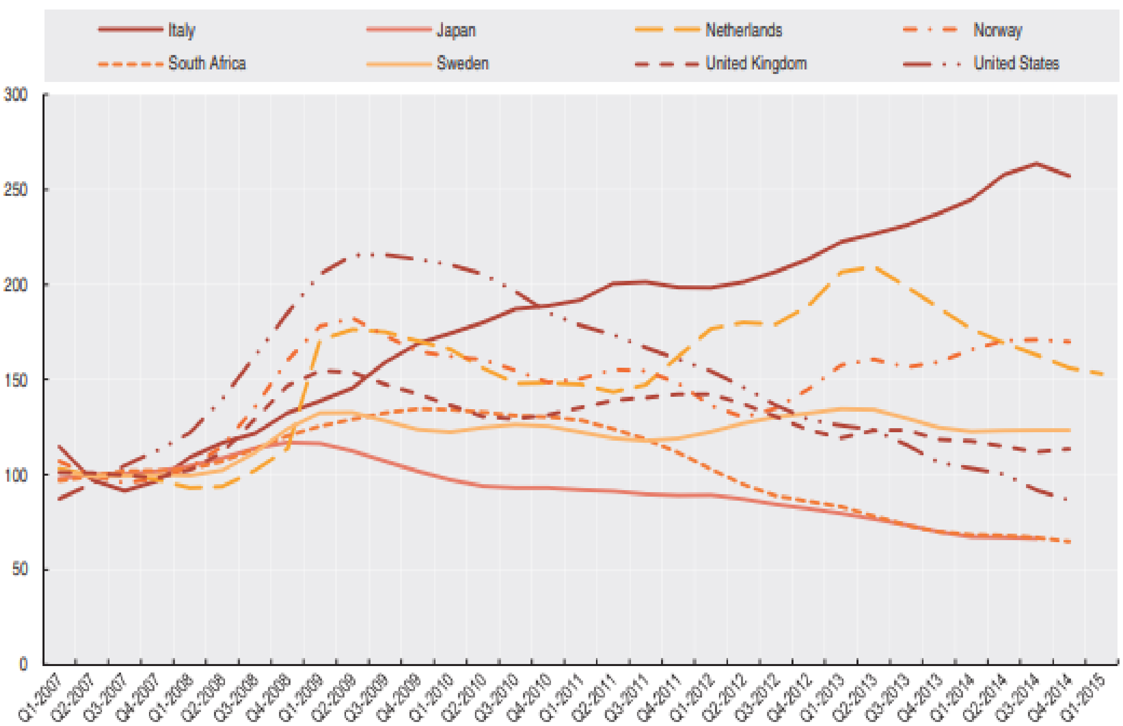

Figure 9: Bankruptcies Trend between 2007 and 2015 (OECD, 2015).

What figure 9 shows is a drastic increase of bankruptcies during 2008 crisis, displaying as easily perceptible, the United States as the country where this increase has been sharper. Starting from 2010 instead the situation began a downward trend for all the nations, with a temporary increase during 2013 for some of them, reverting quickly back to the previous decreasing path.

Notwithstanding this general trajectory, evidence shows that Italy had a very difficult and worrying behavior, moving similarly to other countries just during 2008-2009, where the spread in bankruptcy cases have been high everywhere. The problematic situation emerged instead from 2010 onwards, where Italy maintained a continuous upward trend, with first signals of decrease during the second half of 2014, when the level reached was already much higher than any other country considered in the analysis.

2.5 Models for Predciting Bankruptcy

The situation portraited in the previous paragraph demonstrates how some historical periods are extremely full of bankruptcies and many of them are due to external factors that can’t be predicted in any way.

Notwithstanding the unpredictability that has always characterized the market, in the literature have been proposed some models for trying to forecast the risk of bankruptcies of companies.

The most famous model attempting to address this issue has been the Altman Z Score.

First model of the Altman Z Score has been proposed in 1968 in Altman’s paper “Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy”, with the author performing an analysis of a sample composed by sixty-six corporations divided in two groups of thirty-three firms each.

The first group was composed by manufacturing companies that filed a bankruptcy petition under Chapter X of the National Bankruptcy Act during the period 1946-

1965, while the second consisted of an equal number of manufacturing companies selected on a stratified random basis (Altman, 1968).

The choice of the size of the companies has been another central issue, with Altman deciding to exclude from the analysis those with a too high or too low level of total assets.

Once concretely detailed and justified the panel of companies under observation, the author selected a range of twenty-two potentially helpful variables retained to be significant indicators of corporate problems in past studies. The choice of these indicators has been dictated even by their popularity in the literature and by their potential relevance to the study.

From the original list Altman selected the five most suitable variables analyzing the statistical significance of all of them, evaluating their inter-correlations, observing the predictive accuracy of the previous profiles and concluding with the final judgement of the author.

From this process the formula derived is the following:

$$\boldsymbol{z = 1.2x_1 + 1.4x_2 + 3.3x_3 + 0.6x_4 + 0.999x_5}$$

Below is explained the meaning of the parameters as stated by Altman (1968):

- x_1 stands for Working Capital / Total Assets. This ratio is a measure of the net liquid assets of the firm, defined as the difference between current assets and current liabilities. For the purpose of the study and according to other researches conducted in the period this one proved to be the most valuable between the three liquidity ratios analyzed.
- x_2 stands for Retained Earnings / Total Assets. This ratio is a measure of cumulative profitability over time and it has not been grasped from previous studies. This indicator performs a sort of discrimination between young and old firms because in the former the possibility of having a higher amount of retained earnings is certainly

lower than that of another already established and mature. In such a perspective the author is aware that due to this ratio the possibility of being classified as bankrupt is higher in newer companies, believing it representative of reality.

- x_3 stands for Earnings Before Interest and Taxes / Total Assets. This ratio is a measure of the true productivity of the firm's assets, abstracted from any tax or leverage factors. Given that a firm's existence is based on the earning power of its assets and that insolvency in a bankruptcy sense occurs when total liabilities exceed a fair valuation of the firm's assets with the value determined by the earning power of these assets, this ratio appears extremely suitable for studies dealing with corporate failure.
- x_4 stands for Market Value of Equity / Book Value of Total Debt. This ratio, measured combining market value of all the shares preferred and common and total debt both current and long-term, shows how much the firm's assets (measured as market value of equity plus debt) can decline in value before the liabilities exceed the assets and the firm become insolvent. This indicator seems so particularly interesting, considering a dimension that similar studies did not consider.
- x_5 stands for Sales / Total Assets. This ratio is a measure of management's capability to deal with competitive conditions. This last indicator is considered quite important because despite being the least significant ratio on an individual basis, it is uniquely related to the other variables used, ranking second in terms of contribution to the overall discriminating ability of the model.

The abovementioned analysis leads so to a classification, in terms of risk of bankruptcy, of the firms studied, dividing the values obtained in three ranges:

- **z > 2.99:** Firms falling in this area clearly resulted between those that didn't go bankrupt.
- **1.81 ≥ z ≥ 2.99:** Firms falling in this range were considered in a "*zone of ignorance*", not being possible to estimate with the necessary accuracy whether they were susceptible of a high risk of bankruptcy or not.
- **z < 1.81:** Firms falling in this area resulted as those bankrupted.

Notwithstanding the relevance of this model, a concrete problem would have arisen if the company under observation would have been a private company. This contingency has been however tackled by Altman (1993), with a new model specific for firms not listed on the market.

The framework used in this case has been very similar to the one adopted in Altman (1968) and the formula obtained is:

$$\boldsymbol{z' = 0.717x_1 + 0.847x_2 + 3.107x_3 + 0.420x_4 + 0.998x_5}$$

The above formula is calculated with coefficients pretty different from those used in the original one, while the ratios used are identical except for the fourth.

This edit has been necessary for the fact that market value of equity, appearing at the numerator of the formula, is not possible to be found for private companies. In accordance with this limitation that ratio has been substituted with "Book Value of Equity / Total Equity".

After all these changes also the three ranges have been modified, suggesting the safe zone with a value higher than 2.90, the grey area between 1.23 and 2.90 and the distress zone under 1.23.

In the same paper another revision has been suggested by Altman (1993), in order to account for non-manufacturing companies, with the following formula:

$$\boldsymbol{z'' = 6.56x_1 + 3.26x_2 + 6.72x_3 + 1.05x_4}$$

This ulterior modification of the z-score removes the Sales / Total Assets ratio (x_5) in order to minimize the potential industry effect, which is more likely to take place when such an industry-sensitive variable is included.

In such a case the three ranges suggest that the safe zone is reached with a value higher than 2.60, the grey zone between 1.1 and 2.6 and below the threshold of 1.1 the company is into the distress zone.

A further study aimed at identifying the risk of bankruptcy is the one conducted by Ohlson (1980).

In its paper the author criticized previous studies of the same field, stating that the number of firms analyzed by Altman (1968) and later Moyer (1977) were an extremely limited sample.

In contrast Ohlson highlights the wider range of companies adopted for his research, comprehensive of 105 bankrupt firms and 2058 nonbankrupt firms between 1970 and 1976, as an ulterior feature for its reliability. Further specifications for the restriction of the boundaries of the study refer to the necessity that the equity of the firm has been traded on some stock exchange or over-the-counter and that the company could be classified near the industrial perimeter.

These constraints make this study appearing pretty similar to the one conducted by Altman (1968), however a concrete difference consisted in the choice of the econometric methodology of conditional logit analysis to avoid recurrent problems with the Multivariate Discriminant Analysis (MDA).

Once completed this part Ohlson was able to create the following formula, deciding to embed more variables than the predecessor Altman did, believing this increased number capable to foster accuracy and, still in contrast with him, to assign different signs to the various coefficients:

$$\boldsymbol{O\ Score = -1.32 - 0.407x_1 + 6.03x_2 - 1.43x_3 + 0.076x_4 - 2.37x_5 - 1.83x_6 + 0.285x_7 - 1.72x_8 - 0.521x_9}$$

Below are describes the ratios used by Ohlson (1980):

- x_1 stands for log (Total Assets / GNP price-level index). In this first ratio the author specifies to consider the index at the denominator with a base value of 100 for 1968, in order to compare the future values with this reference year.
- x_2 stands for Total Liabilities / Total Assets.
- x_3 stands for Working Capital / Total Assets.
- x_4 stands for Current Liabilities / Current Assets.
- x_5 stands for Net Income / Total Assets.
- x_6 stands for Funds provided by Operations / Total Liabilities
- x_7 is a dummy variable with value one if net income was negative for the last two years and zero otherwise.
- x_8 is a dummy variable with value one if total liabilities exceeds total assets and zero otherwise.
- x_9 represents a formula with numerator the difference between net income the year analyzed minus that of the previous year, while as denominator the absolute value of net income of the year plus the absolute value of net income for previous year. In this case the author justifies the denominator as a level indicator.

In conclusion Ohlson (1980) estimates the probability of default of the companies with the following formula:

$$\boldsymbol{Probability\ of\ Default} = \frac{\boldsymbol{Exp\ (O\ Score)}}{\boldsymbol{(1 + Exp(O\ Score))}}$$

With this calculation the author had the chance to pass from a simple number obtained through the O Score formula to a measure that predicts, according to

Ohlson (1980), the probability of bankruptcy of the examined company within a year.

A further study of this topic is provided by Zmijewski (1984).

In its research the author selected as sample all firms listed on the American and New York Stock Exchanges between 1972 and 1978 except those operating in the financial sector, obtaining a population range between 2082 and 2241 firms in the various years.

Zmijevski (1984) defined in its study financial distress as the act of filing a petition for bankruptcy and identifies a firm as bankrupt if it filed a bankruptcy petition during the period.

From the panel analyzed is derived the following formula:

$$\textbf{Zmijewski Formula} = -\mathbf{4.336} - \mathbf{4.513}\boldsymbol{x_1} + \mathbf{5.679}\boldsymbol{x_2} + \mathbf{0.004}\boldsymbol{x_3}$$

The three parameters defined by Zmijevski (1984) are:

- x_1 stands for Net Income / Total Assets (ROA)
- x_2 stands for Total Debt / Total Assets (Financial Leverage)
- x_3 stands for Current Assets / Current Liabilities (Current Ratio)

The probability of default is then defined through a probit model with cutoff level of 0.5, meaning so that firms with probabilities greater or equal than 0.5 were classified as bankrupt and nonbankrupt if this value was lower than 0.5.

CHAPTER 3 - EMPIRICAL ANALYSYS

This section has the aim to bring a worthy contribution to the previous literature on the field of digitalization. This theme is a very new phenomenon with whom companies have to deal daily and without which surviving in a highly competitive environment is becoming merely impossible.

As it is easily intuitive from the early age of the process, very few studies have been published compared to other widely covered topics, reason why treating such a field appeared to be highly valuable.

In this perspective the chapter is willing to analyze the impact that the level of digitalization of Italian listed companies has on their performance and in a second moment if this level can have even an effect in their risk of bankruptcy.

3.1 Research Questions

In order to achieve the abovementioned goals some research questions had to be stated.

From previous studies emerged that digitalization used to have a positive impact on companies' performance, leading on average firms capable to deal and manage this process to more impressive outcomes than laggard peers.

In this field Alford et al., (2020) highlighted this connection using a panel of Austrians SMEs, Banga (2019) did it with reference to a panel of Indian manufacturing companies, Bistrova et al., (2019) got the same evidence from a list of Baltic firms divided between Estonia, Latvia and Lithuania and Joensuu-Salo et al., (2018) showed the significance of this cause-effect relationship for a set of widely internationalized Finnish corporations.

Although some papers already attempted to answer the abovementioned question, they all analyzed the effect on companies operating in other countries. This thesis tries so to position itself in a field widely uncovered, that of Italian listed companies.

For the part dealing with the impact of digitalization on performance the procedure followed is pretty similar to the one proposed by Chaghadari & Chaleshtori (2011).

In accordance with them, two indicators have been reputed to be those more compliant for the analysis: ROE and ROA.

Another peculiarity that makes these two indicators extremely suitable to be analyzed together for such a goal is their complementarity. ROE indeed allows to identify the percentual return obtained by shareholders for a single unit invested in the company, being extremely accurate for the perspective of the owners, but not sufficiently indicative for the concrete operating performance of the firm.

ROA however can help to overcome such drawback. While ROE just considers at the denominator shareholders' equity, this other ratio considers total assets. Given the changed variables, the effect of a higher indebtedness using leverage to foster the return for shareholders and consequently widening the ROE, is no more a value-added in ROA, because this last indicator takes into account also this eventuality, increasing the denominator if additional debt is underwritten.

Chaghadari & Chaleshtori (2011) decision to prepare two different regressions embedding in the first ROE as dependent variable, while ROA for the second, seems to be a wise idea in order to perform even a robustness check.

The above discussion leads to the following hypothesis:

Hypothesis 1: *Companies with a greater level of digitalization obtain a higher ROE.*

Hypothesis 2: *Companies with a greater level of digitalization obtain a higher ROA.*

The third and last hypothesis is connected with the assessment of the impact of digitalization on risk of bankruptcy. This idea is very ambitious, given that there are not clear evidences of a study that tried to link directly these two phenomena, but has the desire to be a relevant value-added contribution for the literature.

With this goal, in the previous chapter have been purposefully shown some of the most important studies dealing with the estimation of the risk of bankruptcy of companies. From their analysis the most interesting resulted to be Altman Z Score and Ohlson O Score, believing the model proposed by Zmijevski (1984) less suitable for this study due to the low number of variables considered in its construction.

The other two proposed by Altman and Ohlson seem instead more accurate for the purpose and their use in the analysis will be presented in following paragraphs.

In the meantime, the last hypothesis formulated to assess the impact of digitalization on risk of bankruptcy is:

Hypothesis 3: *Companies with a greater level of digitalization have a lower risk of getting bankrupt.*

3.2 Data Collection

This section will explain in detail the data gathered and the sources from which they have been extracted, revealing in addition the reasonings behind the choice of each indicator.

In the last paragraph of this part will be shown some descriptive statistics in order to start obtaining the first information about the data that will be analyzed through panel regressions in the following section.

3.2.1 Sample Selection and Sources

Given that the purpose of this study is to evaluate the impact of digitalization on performance and risk of bankruptcy of Italian listed companies, the first step of the selection has been pretty straightforward, completed extracting from Bureau Van Dijk database all the companies fulfilling the abovementioned prerequisite (that were more than 350).

Then, using as reference time horizon the five years since 2015 to 2019, have been collected all the data potentially suitable for the purpose in a wide dataset.

From this passage has been clear a concrete lack of data and even a difficult comparability between organizations operating in banking, insurance and business services sectors, that has been addressed, in order not to provide a biased analysis, with the removal of these entities from the database.

The hardest issue in data extraction and sample selection is however derived from the collection of an item used to measure the level of digitalization. Indeed, while all the other data were easily collected from Bureau Van Dijk Orbis, this was not the case for the "software assets"[15].

Given that neither this database nor Thomson Reuters Eikon were providing this sort of information for Italian listed companies, to identify it has been necessary to check all the annual reports of the Italian listed companies to gather the data.

This procedure has been rather successful, allowing to find the data in some cases. However, in many situations the field including the software assets of the firm was not disclosed (especially for smaller companies), leading to a reduction of the sample.

Notwithstanding this issue, the final database was composed by 122 companies and though many small firms had to be discarded due to the absence of "software assets" data, the panel of firms still maintained a wide heterogeneity even in terms of size.

[15] Motivations behind the choice of this item in the context of measuring the level of digitalization of companies will be explained in the following paragraph.

If the database for the analysis of the impact of digitalization on performance was composed by 122 entities, further steps have been necessary for preparing a sound one even for the part referring to risk of bankruptcy.

Given that to estimate this latter feature has been followed Altman procedure suggested for public companies, much more data compared to performance analysis were needed. One of the issues was for example due to the necessity of using the market capitalization of the companies to estimate the final “z score”, item that was not present for any of the year that this work is analyzing if the firm has been listed after this period.

If instead the listing process happened into the reference time horizon, the company simply lost the observations for the years in which it was not yet public.

A further step, that led to a consistent decrease of the sample, has been the size of the companies. As described by Altman et al. (2017), which provided also a recap of the first study proposed in 1968, the choice of the firms has followed a criterion based on eliminating from its research those too big or too small and for higher compliance a similar approach has been pursued even in this thesis. Altman (2017) suggested that the parameter adopted for assessing the size of the companies should have been the total assets.

In this perspective, from the sample constructed to measure the impact of digitalization on performance of Italian listed companies, were removed those that had at least in a year between 2015 and 2019 an amount of total assets lower than 1 million or higher than 5 billion euros.

Another issue referred to be as much reliable as possible to the panel selected by Altman (1968), deals with his choice of considering just a panel of manufacturing companies.

To be as close as possible to Altman’s reasoning, the range of firms has been further diminished, taking off completely firms operating within public administration and computer services sectors and dividing those operating in construction and property services[16], including in the dataset just those companies dealing with construction activity. In addition, those remaining have been studied in terms of business model in order to discard even single firms too far from the aim of this classification.

At the end of this further screening the firms under observation decreased until 71, however this sacrifice in terms of sample size turned out to be important for increasing the reliability and accuracy of the study.

3.2.2 Selection of the Variables to use during Regression Analysis

This paragraph is aimed at describing the reasoning behind the selection of the variables.

For the regression analyzing the effect of digitalization on performance, ROE and ROA were the indicators representing this last feature. The choice of these two ratios, as explained before, is due to their effectiveness and complementarity but even to their predominance in similar measurements in the literature.

The principal issue was instead due to the research of a way through which assessing the level of digitalization of companies. For this purpose, similarly to the approach followed by Banga (2019), the methodology prosecuted has been to look at the software assets of the firm (net of depreciation and amortization), believing them as a reliable proxy for digital maturity.

Although this measure was perceived potentially as an accurate predictor for the level of digitalization, their total amount alone was not sufficient to give this information.

The final decision regarding such a digitalization's indicator has however embedded the necessity of comparing this value to a measure suitable to represent the size of the company. In this perspective the software assets of the firm have

[16] The division of companies into sectors as public administration, computer services and construction and property services is done relying on the classification performed by Bureau Van Dijk Orbis.

been scaled for the total assets, considered as the most appropriate item to estimate the dimension of the firm under evaluation.

With this adjustment, the relative value obtained results in a concrete measure to understand how much relevance is given by each company to the digitalization process and can be seen as a proxy for the level of digital maturity.

Once identified the items suitable to represent the dependent variables of my regressions (ROE and ROA) and that appropriate to act as independent (software assets / total assets), has been necessary to identify the control variables.

Introduction of the latter, and in particular multiple control variables, allow to obtain a safer and more statistically conservative approach for econometric models (Aguinis & Bernerth, 2016), however, identifying those more suitable for the specific regression that has to be performed is crucial.

For this analysis, interested in evaluating the effect of digitalization on performance with reference to a panel of Italian listed companies, a wide attention to previous similar studies can be valuable.

According to a similar research aimed at interpreting the impact of IT capability as a moderator between IT investment and firm performance, the most suitable variables to take into account for this role are: time period, industry type and firm size (Hu, Liu, Lu, 2008).

For the purpose of the thesis, as representation of the time period have been obviously used the years of our analysis (2015-2019).

For the industry type have been taken the sector as suggested by Bureau Van Dijk Orbis, merging those most similar to achieve a reduction of the variables and diminishing for instance the number of sectors with just one or two companies, which have been consequently converted in an identification number. For this reason, the variable has been called “sectorID”.

While the choice was pretty easy for the previous two control variables, accounting for firm size is much more discretionary. In this field the final decision has been to follow a measure based on the number of employees as suggested by Baumann, Becker-Blease, Etebari, & Kaen (2010) and Banga (2019), despite other practitioners suggest total assets as another reliable indicator (Wang, 2011).

Obviously, uniformly to what done even in these other studies, the variable used is the natural logarithm of the number of employees, choice necessary to normalize the values.

Moreover, a further interesting variable widely used in the literature, cope with the riskiness of the company and many indicators as the financial leverage are embedded as control variables in these models, as done by Naimah (2017) or Wang (2011).

In this perspective the indicator used is the solvency ratio, which looks at the shareholders' equity over the total assets, and due to its construction has a very similar role to the most common debt to equity ratio.

The choice of the last control variable is instead suggested by the paper provided by Gasparri & Tassinari (2020), that evidences a problematic pretty linked to Italy, that is the considerable heterogeneity even between the different regions.

To deal with this issue, Italian regions are divided in three macro-areas, namely north, center and south, to which have been assigned an identifying number from one to three, calling the variable "regionID".

For the regression concerning the risk of bankruptcy some more data were needed in order to obtain the dependent variable, based on the z score. For the construction of the formula, further data needed were: total assets, working capital, retained earnings, EBIT, market capitalization, book value of total debt and sales.

3.3 Descriptive Statistics

This paragraph has the aim of highlighting trends deriving from the data gathered, in order to grasp some intuitions that should be confirmed by the following regression analysis.

As first analysis, data referring to ROE, ROA and software assets over total assets have been categorized by year to give an understanding of the evolution in time.

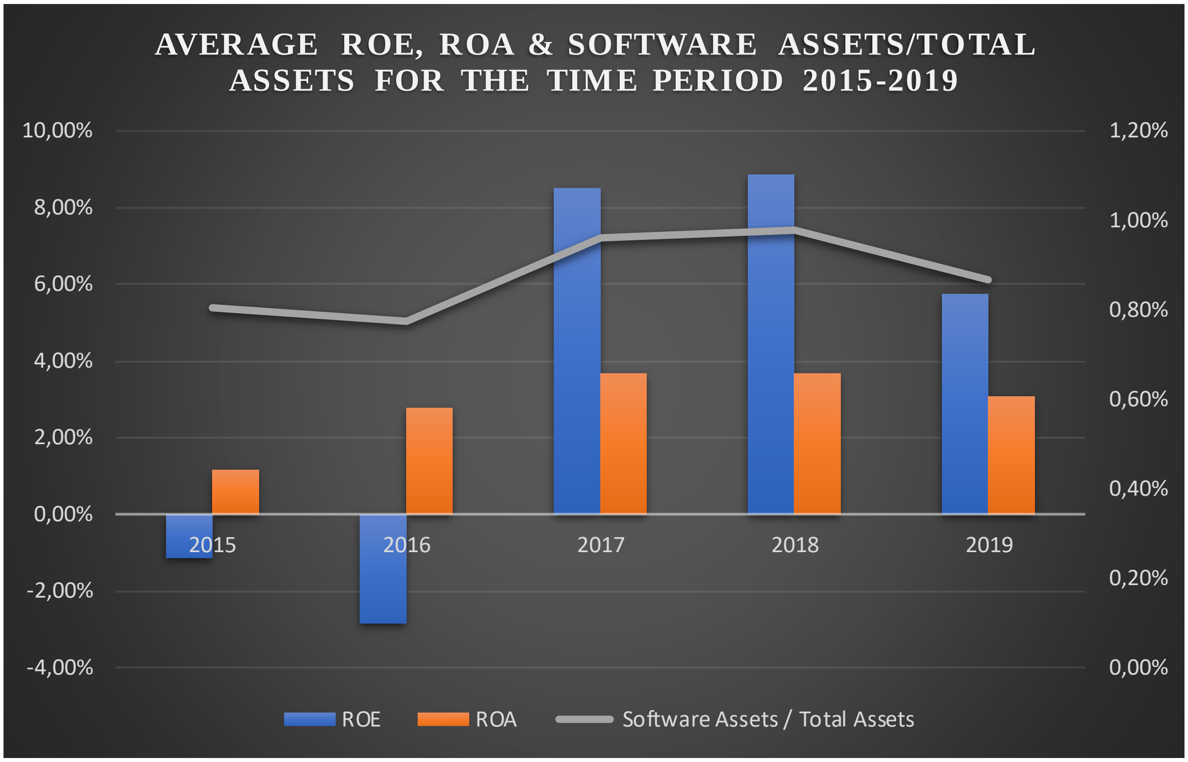

Figure 10: Average ROE, ROA & Software Assets / Total Assets Evolution in Time (Source: Own Elaboration).

Figure 10 shows the trend of the average ROE and ROA from 2015 to 2019 of the abovementioned panel of 122 companies. These values, referring to the left vertical axis, are then evaluated in relation with the evolution of the average digitalization, represented by the grey line, with values referring to the right vertical axis.

The choice of this type of graph is due to the important differences in absolute value between ROE or ROA and software assets / total assets, that would have made the movements of this last ratio not clear from the figure without the different scaling of the two vertical axis.

Analyzing the data depicted in figure 10, emerges a concrete relationship between the digital maturity and the performance.

For digitalization, is possible to notice how the lowest average level pertains to the year 2015-2016, which even match with the time-period with lower average ROE and ROA.

The year crucial for the change of pace is instead 2017, where the digital maturity sharply increased, leading especially ROE, but even ROA, to a dizzying increase. The level reached in 2017 has been maintained pretty constant even in 2018, with a very small increase of software assets over total assets from 0.96% to 0.98% and in ROE from 8.51% to 8.86% (with ROA barely constant).

In 2019, however, average digital maturity took a consistent step back, resulting in a concrete repercussion even in ROE (from 8.86% to 5.74%) and ROA (from 3.67% to 3.07%).

For a complete overview of the evidence just mentioned and to have confirmation of the values stated, is however possible to refer to the Appendix with the summary statistics carried out through the software Stata.

If the precedent figure is already quite representative of the potential effect of digitalization on the performance of companies, a further classification could give a better intuition of the trend.

For this part has been necessary a categorization of the firms in different ladders of a digital maturity scale, in order to understand the average ROE and ROA for each level of digitalization. This partition will be even helpful to perform descriptive statistics referred to the risk of bankruptcy.

The model used to rank digital maturity traces the one used by Egloffstein & Ifenthaler (2020), in which companies were divided in five ranges from the least to the most digitized, namely: minimalist, conservative, pragmatist, advanced and trailblazing.

To adapt the previous framework to the scope of this thesis and specifically to the measure of digitalization adopted, the following are the criteria to insert the observations in each of the abovementioned categories:

- **Minimalist:** Are part of this category the observations that report a software assets/ total assets ratio lower than 0.05%.
- **Conservative:** Are part of this category the observations that report a software assets /total assets ratio between 0.05%(included) and 0.30% (excluded).
- **Pragmatist:** Are part of this category the observations that report a software assets / total assets ratio between 0.30% (included) to 0.70% (excluded).
- **Advanced:** Are part of this category the observations that report a software assets / total assets ratio between 0.70% (included) to 1% (excluded).
- **Trailblazing:** Are part of this category the observations that report a software assets / total assets ratio of at least 1%.

The following figure will give an overview of how companies falling within a certain range of digital maturity perform on average in terms of ROE and ROA.

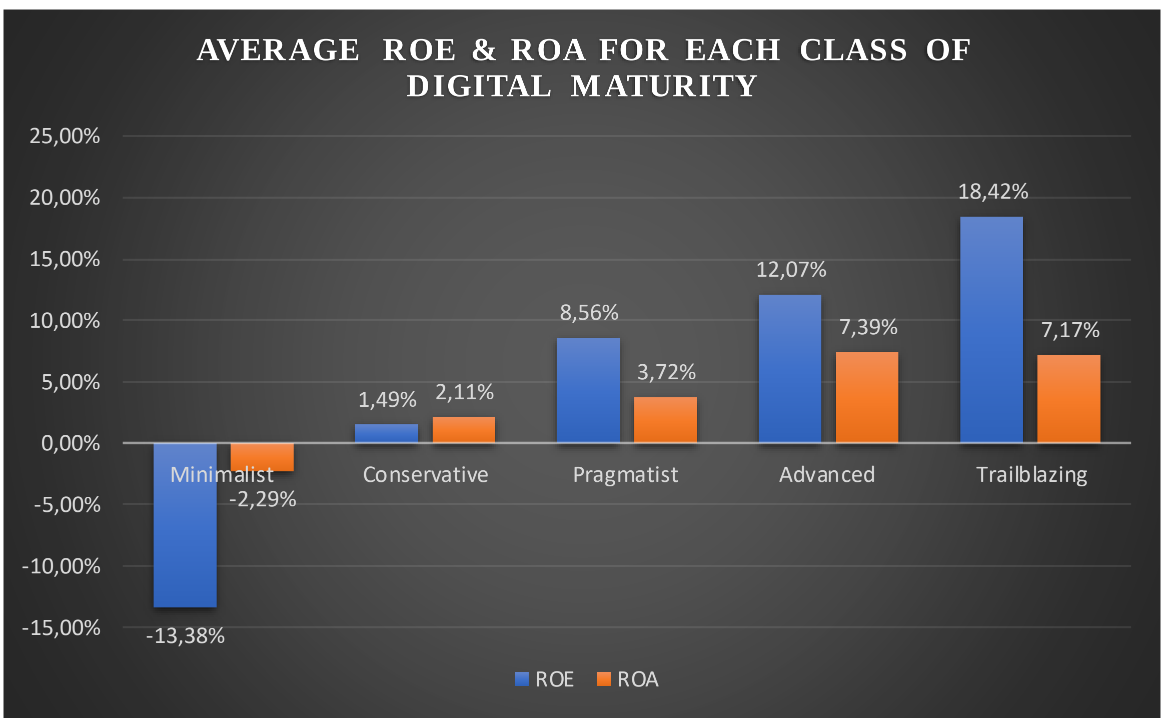

Figure 11: Average ROE & ROA for Each Class of Digital Maturity (Source: Own Elaboration).

Figure 11 gives a deeper perception of how much digitalization is crucial to achieve a consistent performance, with a path absolutely indisputable.

What emerges is in fact that ROE and ROA rise constantly and heavily, passing from a lower to a higher level of digital maturity, with only exception ROA from the categories "Advanced" and "Trailblazing", although this reduction is undoubtedly tiny. ROE instead maintains a very linear upward trend.

Another feature that can be derived from figure 11 is the shattering performance of companies belonging to the class of "Minimalist", in which both average ROE and ROA are negative. This characteristic does not shows up neither for any of the other categories, nor for even just one of the two indicators.

Moreover, is possible to notice that the value-added in terms of performance that is gathered passing from the lowest category of "Minimalist" to the following of "Conservative" is the wider, both in terms of ROE and ROA (increase of 14.87% in terms of ROE with the second largest of just 7.07% and increase in ROA of 4.40% with the second largest of 3.67%).

This outcome provides the interesting insight that, notwithstanding to an increase in digitalization corresponds a general increase in performance, the major problems arise for companies extremely poor in this field. Having just a small level of digitalization, but not practically nil as those firms pertaining to "Minimalist", permits in fact to achieve a result much higher than those entities pertaining to the initial class, showing that the first basic step of digitalization seems to be the one with major contribution in terms of increase in performance.

Once proposed some effective descriptive statistics aimed at analyzing the existing relationship between digitalization and performance, is interesting to look even at the impact of risk of bankruptcy: also for this reason the partition in five ranges depending in the level of digital maturity can be important and purposeful for the will of the thesis.

Due to the change of objective and keeping in mind the premises done in the paragraph "Selection of the variables to use during regression analysis", the number of companies in our dataset shrink to 71, maintaining however the five-year time horizon (2015-2019).

In the following graph, the various observations are divided with the purpose of understanding to which of the five groups each company pertained in a certain year (as done even in figure 11) and for each class have been calculated the average "z score".

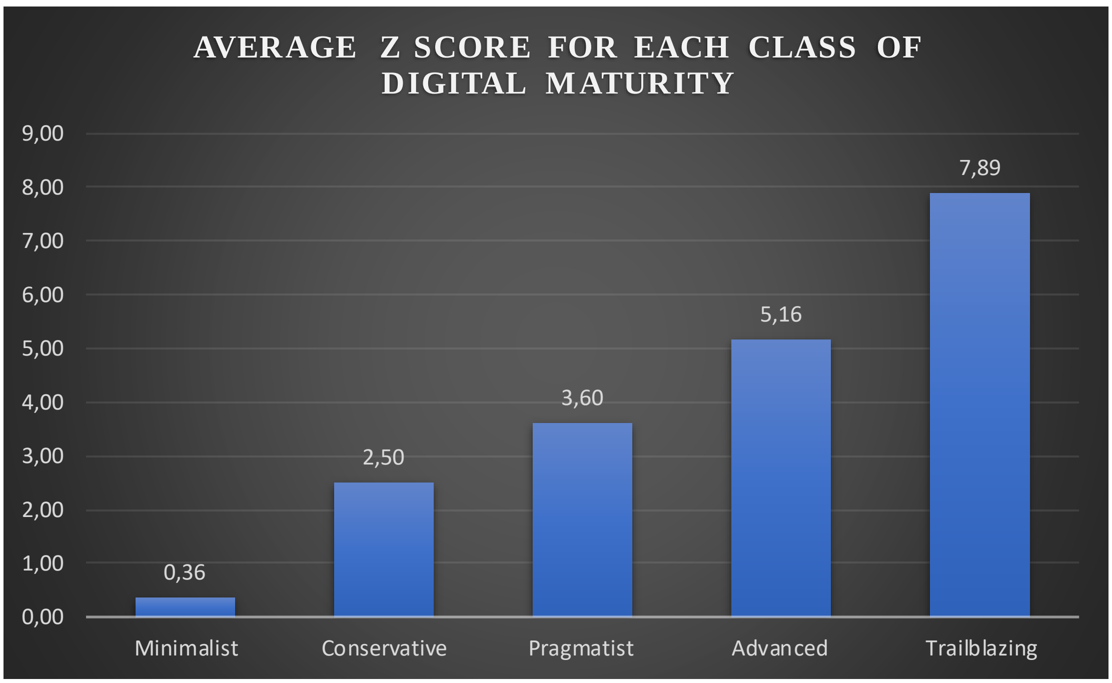

Figure 12: Average Z Score for Each Class of Digital Maturity (Source: Own Elaboration).

Figure 12 has the purpose of highlighting the impact of digitalization on the risk of bankruptcy, assessed through Altman's formula for public companies. Similar to what happened for performance analysis, even in this case the interpretation is straightforward and the impact of digitalization indisputable.

Calling back the theory below the "z score" proposed by Altman, if its value was higher than 2.99, the firm under observation pertained to the "safe zone" with a risk of bankruptcy practically inexistent, if the value ranged between 1.81 and 2.99 (both included), the company was in the “grey area”, meaning that a sound prediction was not possible, while with an outcome lower than 1.81 there was the “distress zone”, with a high probability of bankruptcy.

From the graph in figure 12 is possible to infer that the risk of bankruptcy rapidly decreases passing from one class to another (given that the z score increases).

As evidenced in figure 11 for performance, even in this case the hardest problems pertain to those companies belonging to “Minimalist”. In this section instead the average z score is absolutely low and well below the threshold of 1.81, meaning that their risk of bankruptcy in the next two years[17] is very high.

Passing from the first to the second class, named “Conservative”, is obtained a consistent increase in the z score, which allows to overcome the “distress zone”. In such a case the overall value obtained is 2.50, that falls precisely into the “grey area”, suggesting that no sound prediction could be done for these companies.

Then, from the third range onwards, with values respectively of 3.60, 5.16 and 7.89 for “Pragmatist”, “Advanced” and “Trailblazing”, the firms have on average a score that easily suggest that they incur in an extremely low and barely negligible risk of bankruptcy.

3.4 Preparation of Regression Analysis

This paragraph has the aim to explain the procedure followed to prepare the three regressions aimed at identifying the effect of digitalization on performance and risk of bankruptcy of Italian listed companies.

Once prepared the database with the appropriate data, as described in the previous paragraphs and prepared some descriptive statistics to have an overall picture of what to expect from the regression analysis, has been the moment to decide precisely the statistical technique most suitable for the scope of the study.

[17] The evidence that the z score predicts the risk of bankruptcy in the following two years is suggested by Altman (1968)

The analysis has been conducted over a sample of Italian listed companies and the parameters used for this study have been collected for a period ranging from 2015 to 2019.

This type of dataset is called “panel”, a definition of which is given by Hsiao (2014):

“A longitudinal, or panel, dataset is one that follows a given sample of individuals over time, and thus provides multiple observations on each individual in the sample”.

According to Torres-Reyna (2007), there are two principal techniques used to analyze panel data: fixed effects and random effects. The choice of the adoption of one or the other methodology has then been the necessary step prior to the effective use of the model.

Below are reported the major features of each of the two techniques as described by Torres-Reyna (2007).

Fixed effects model explores the relationship between predictor and outcome variables within an entity, where each entity has its own characteristics that may or may not influence the predictor variables (where predictor variable stands for independent variable and outcome variable for dependent variable). Through this technique is also assumed that something within the individual may impact or bias the predictor or outcome variable, that has to be accounted for. In the fixed effects model the effect of the time-invariant characteristics is removed, so that is possible to assess the net effect of predictors on the outcome variable.

A further assumption pertains to the fact that time-invariant characteristics are unique to the individual and should not be correlated with other individual characteristics. Each entity is then different from the entity’s error term and the constant (capturing individual characteristics), should not be correlated with the others. If error terms are alternatively correlated, fixed effects model is not suitable.

Torres-Reyna (2007) then describes the mathematical equation underlying the fixed effects model as:

$$\boldsymbol{Y_{it} = \beta_1 X_{it} + \alpha_i + u_{it}}$$

The variables used in the formula are:

- Y_{it} is the dependent variable, where i represents the entity and t the time of the observation.
- β_1 is the coefficient for the specific independent variable.
- X_{it} represents an independent variable, where i represents the entity and t the time of the observation.
- α_i is the unknown intercept for each entity.
- u_{it} is the error term.

Differently from the fixed effects model, the rationale behind the one with random effects is that the variation across entities is assumed to be random and uncorrelated with the independent variables included in the model.

In addition, Torres-Reyna (2007) states that if there are reasons to believe that differences across entities have some influence on the dependent variable, random effects model is the right choice, suggesting even that another advantage of this framework is the possibility of including time-invariant variables (like in our case can be the sector), that in the fixed effects model are absorbed by the intercept.

Torres-Reyna (2007) then describes the mathematical equation underlying the random effects model as:

$$\boldsymbol{Y_{it} = \beta X_{it} + \alpha + u_{it} + \varepsilon_{it}}$$

The crucial difference that can be deduced from the formula refers to the presence of two error terms, between-entity and within-entity.

After an overview of these two applicable models and the application of an Hausman test[18] in order to confirm which of them was the best choice, the decision has been to use a random effects framework.

3.5 Empirical Results of Regression Analysis and Discussion

Once the decision of using the random effects model has been taken, the following step has been to perform the various regressions.

The first one has the aim to answer to the initial hypothesis: "*Companies with a greater level of digitalization obtain a higher ROE*".

[18] The Hausman test is useful to decide between a fixed or random effects model, basically testing whether the unique errors (u_i) are correlated with the regressors, against the null hypothesis that they are not (Torres-Reyna, 2007).

	ROE Coef.	Std. err.
SOFTWARE/TOT.ASSETS	1.323+	0.702
LN EMPLOYEES	0.022*	0.010
SOLVENCY RATIO	0.004***	0.001
SECTOR ID=1	0.000	.
SECTOR ID=2	0.113	0.111
SECTOR ID=3	0.030	0.114
SECTOR ID=4	0.073	0.090
SECTOR ID=5	0.075	0.107
SECTOR ID=6	0.077	0.075
SECTOR ID=7	0.055	0.114
SECTOR ID=8	0.201	0.126
SECTOR ID=9	-0.105	0.128
SECTOR ID=10	0.001	0.094
SECTOR ID=11	0.126	0.150
SECTOR ID=12	0.084	0.082
SECTOR ID=13	0.067	0.084
SECTOR ID=14	0.209*	0.100
SECTOR ID=15	0.171+	0.092
SECTOR ID=16	-0.040	0.102
REGION ID=1	0.000	.
REGION ID=2	0.039	0.047
REGION ID=3	-0.041	0.120
YEAR=2015	0.000	.
YEAR=2016	0.046+	0.026
YEAR=2017	0.048+	0.025
YEAR=2018	0.069**	0.026
YEAR=2019	0.069**	0.026
Constant	-0.385***	0.104
R-squared		
N. of cases	528.000	

+ $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 1: Summary Table of the First Regression (Source: Own Elaboration through Stata).

The regression showed in table 1 is performed as described in the paragraph “Selection of the variables to use during regression analysis”.

In this framework the dependent variable is the ROE, as indicator describing performance of companies, while the independent variable is the level of software assets over total assets, that represents the digital maturity of the firms.

Five control variables are included which are: natural logarithm of the number of employees, solvency ratio, sector, region and year.

For last three variables the reasoning has been similar, controlling the effect for each of the sixteen identified sectors, the three macro-areas of Italy and the five years from 2015 to 2019.

Analyzing the outcome of the regression, emerges that digitalization has a concrete positive impact on performance, with a significance level of 0.1. The positive coefficient of 1.323 evidences also a more than proportional increase in ROE with an increase of one unit in the independent variable, confirming what even descriptive statistics have evidenced.

ROE seems to be in fact highly sensitive to an increase in digital maturity of companies and this evidence consistently confirms the first hypothesis of the thesis.

A further interesting feature derivable from table 1, is the impact of the year of the observations. According to this table indeed is evidenced that, compared to operate in 2015, just being in the business in the following years gave a value-added in terms of ROE.

Obviously, this phenomenon has not an outstanding impact in terms of absolute value, but the positive effect is guaranteed at a significance level of 0.1 for 2016 and 2017 and even of 0.01 for 2018 and 2019.

Moreover, the upward trend has been evident, increasing year by year the coefficients, with values of 0.046 in 2016, 0.048 in 2017 and 0.069 in 2018 and 2019.

Once acknowledged that digitalization has a positive effect on performance (measured in such a case through the ROE), confirming the first hypothesis, the outcome of the second regression is synthesized in table 2.

	ROA Coef.	Std. err.
SOFTWARE/TOT.ASSETS	0.310+	0.177
LN EMPLOYEES	0.005+	0.003
SOLVENCY RATIO	0.001***	0.000
SECTOR ID=1	0.000	.
SECTOR ID=2	0.048	0.032
SECTOR ID=3	-0.007	0.032
SECTOR ID=4	0.012	0.025
SECTOR ID=5	0.027	0.030
SECTOR ID=6	0.030	0.021
SECTOR ID=7	0.019	0.033
SECTOR ID=8	0.079*	0.036
SECTOR ID=9	-0.037	0.037
SECTOR ID=10	0.003	0.027
SECTOR ID=11	0.030	0.043
SECTOR ID=12	0.044+	0.023
SECTOR ID=13	0.028	0.024
SECTOR ID=14	0.057*	0.028
SECTOR ID=15	0.036	0.026
SECTOR ID=16	0.018	0.029
REGION ID=1	0.000	.
REGION ID=2	0.010	0.013
REGION ID=3	-0.007	0.034
YEAR=2015	0.000	.
YEAR=2016	0.020***	0.006
YEAR=2017	0.023***	0.006
YEAR=2018	0.026***	0.006
YEAR=2019	0.023***	0.006
Constant	-0.105***	0.025
R-squared		
N. of cases	540.000	

+ $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 2: Summary Table of the Second Regression (Source: Own Elaboration through Stata).

This second regression is still aimed at assessing the impact of digitalization on performance of Italian listed companies, but in this case the only difference with the previous is given by the dependent variable, represented by the ROA.

As previously exposed, the choice of preparing these two akin regressions with the same purpose, is due to the intention of performing a robustness check, similarly to the approach followed by Chaghadari & Chaleshtori (2011).

In accordance with the results achieved through the first regression, table 2 shows that an increase in the software assets over total assets ratio generates an increase in ROA. This evidence confirms even the second hypothesis stating: "*Companies with a greater level of digitalization obtain a higher ROA".*

This statement is justified by the coefficient of 0.310, with significance level of 0.1, depicting a positive relationship between the abovementioned measure used to assess digital maturity and the dependent variable.

Akin to the regression in table 1, even in this case emerges that operating in years after 2015 is an added value. This is justified by the coefficients of 0.020 for 2016, 0.023 for 2017, 0.026 for 2018 and 0.023 for 2019, all positive and with a significance level of 0.001.

If the two previously proposed regressions have been helpful to demonstrate the positive effect of digitalization on performance of Italian listed companies, the third one is aimed at understanding its impact on risk of bankruptcy.

For this analysis, the first necessity encountered was relative to the shrinking of the panel of companies under observation for the reasons evidenced in the paragraph "Sample selection and sources", with 71 remaining firms out of the 122 used for studying performance.

For the effective regression, however, the difference pertained to the dependent variable used, connected with the z score for publicly listed companies proposed by Altman. Although the indicator pertained to it, due to its construction the values achieved through the z score calculation have been converted into three potential outcomes, respectively 0 if the score obtained assigned the observation into the "distress zone", 1 if it pertained to the "grey area" and 2 if it reached the "safe zone".

The variable achieved with this passage has been called "result" and used as dependent variable in the regression.

The underlying table 3 shows the findings of this analysis.

	RESULT Coef.	Std. err.
SOFTWARE/TOT.ASSETS	7.663**	2.967
LN EMPLOYEES	0.064	0.043
SOLVENCY RATIO	2.156***	0.246
SECTOR ID=1	0.000	.
SECTOR ID=2	0.615	0.436
SECTOR ID=3	-0.385	0.304
SECTOR ID=4	-0.038	0.335
SECTOR ID=5	-0.161	0.247
SECTOR ID=6	-0.458	0.381
SECTOR ID=7	0.513	0.381
SECTOR ID=8	-0.593+	0.337
SECTOR ID=9	0.080	0.262
SECTOR ID=10	0.088	0.292
SECTOR ID=11	0.723+	0.374
SECTOR ID=12	-0.425	0.428
SECTOR ID=13	0.480	0.382
REGION ID=1	0.000	.
REGION ID=2	-0.195	0.199
REGION ID=3	0.141	0.427
YEAR=2015	0.000	.
YEAR=2016	0.001	0.065
YEAR=2017	0.112+	0.063
YEAR=2018	-0.067	0.063
YEAR=2019	-0.032	0.064
Constant	-0.372	0.371
R-squared		
N. of cases	298.000	

+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Table 3: Summary Table of the Third Regression (Source: Own Elaboration through Stata).

The regression in table 3 justifies even the third hypothesis stating: "*Companies with a greater level of digitalization have a lower risk of getting bankrupt*".

In such a case emerges that digitalization has also a positive effect on the variable "result", suggesting so an increase in the dependent variable with a higher digital maturity (still measured as software assets over total assets). This phenomenon has a significance level of 0.01.

A difference emerging from the analysis conducted for performance, refers to the fact that in this regression the effect of operating in one year instead of another does not affect the risk of bankruptcy or, at least, the results achieved are not statistically significant except for 2017 (significance level of 0.1).

Once assessed through the regression that an increase in digitalization has a positive effect in the z score measured through the variable "result", is interesting to foster the discussion on the topic having a look even at the probability of default.

In this perspective the choice has been to calculate the Ohlson O Score through the formula suggested by Ohlson (1980), for the companies that pertained for the last 4 years (2016-2019), always to the class with the highest level of digitalization ("Trailblazing") and to that with the lowest level ("Minimalist").

Given the high number of variables required in the calculation, not all the firms fulfilling these requirements had all the necessary data for the computation available for all the years and due to that have been just possible to pick eight companies representing the upper segment and nine representing the lower.

Once obtained the score, has been derived the probability of default for each observation through the formula, described in the paragraph relative to Ohlson O Score explanation.

For its construction with data on the companies available for last five years, just four scores have been assigned to each company because some variables needed observations both of the reference year and that before to be calculated.

For the calculation, a peculiarity of the formula provided by Ohlson (1980) consisted in the scaling due to the GNP price level index in variable x_1. In its paper the author gave an important hint to consider this effect in the years following the research, stating that the year taken as reference in this computation was 1968 (with value of 100). From this assumption and through the estimations of the Federal Reserve Bank of St. Louise, has been so easily possible to draw the values referring to the year of interests of the research, obtaining 539.5 for 2016, 549.8 for 2017, 562.9 for 2018 and 573.1 for 2019.

A further adjustment occurred for the variable x_6, where the numerator "funds provided by operations" has been substituted with a concrete proxy, EBITDA, for a matter of availability of data.

The suggestion of using the EBITDA in the abovementioned formula instead of the item suggested by Ohlson (1980) is provided by Vulpiani (2014).

To simplify the reading, the probabilities of default of the seventeen firms have been clustered in the two segments of digital maturity previously stated and has been computed an average between all the observations.

From this procedure the final outcome consisted in two percentages, saying the average probability of default for the period analyzed of the studied companies within a year (where the fact that the probability of default obtained is that within a year is suggested directly by Ohlson (1980)).

Concluded the process, the intuitions grasped from the regressions and by previous descriptive statistics on the Altman Z Score have been confirmed, with an average probability of default of 1.51% for the companies pertaining to the class of "Trailblazing" and 20.60% for that of "Minimalist".

3.6 Limits of the Analysis

Notwithstanding the successful results achieved is fair mentioning some of the limits of this study and the hardest problematic to overcome during the process.

The first limit that has to be stated undoubtedly refers to the choice of the variable representing digitalization. Choosing one ratio, whatever it is, can not obviously be exhaustive and comprehensive of all the features that digitalization embeds and in general, compared for instance to performance, this phenomenon is much more hardly possible to represent through such types of factors.

In this perspective is instead not completely sufficient saying that a company has a higher digital maturity because it invests more, but is even necessary that the workforce and especially the management team has a wide perspective on how to exploit these potential advantages.

However, notwithstanding this evidence, is assumed that a higher investment refers even to a greater knowledge and competence on the digital field.

In terms of data mining the principal issue that arose referred to the software assets of the firm. Given the absence of such information on some of the most reliable databases as Bureau Van Dijk Orbis and Thomson Reuters, they have been collected from the annual report of the companies under observation. This procedure has led to a big reduction of the sample with the purpose of keeping into the panel just the firms with this data well identifiable, but of course some differences in terms of policies of the firms should have slightly altered the analysis.

A further issue pertains to the selection of the variables used in the regression analysis. Although those used have been accurately selected from similar studies in the literature and carefully controlled can not be stated with absolute certainty that were the most appropriate, with outcomes even more precise.

An ulterior limit can be then identified in the panel of companies used to estimate the risk of bankruptcy, through the Altman Z Score.

Although the formula results, similarly to the one provided by Ohlson (1980), considerably old, it is still widely accepted in the literature and suggested by many books (as that of Vulpiani (2014)), making this not a considerable issue to worry about, but the problem matches with the selection of the companies under analysis.

As previously stated, the panel considered by Altman (1968) for his study was totally composed by listed manufacturing firms. In this perspective to maintain the reliability of the study all the passages done by Altman has been followed (as the elimination from the sample of those companies extremely small or extremely big, that as suggested in his paper could have jeopardized the analysis), but however adapting to the definition of "manufacturing firm" is not trivial.

Due even to the changed times is not so easy identifying many firms with this definition provided by Altman in 1968 and in this perspective a similar procedure was undertaken. In this work, to comply as much as possible to the original study without reducing the sample in an unsustainable way, the decision has been, more than relying only on completely manufacturing firms, to eliminate those too far from this definition, as it is the case for service companies or those of public administration.

A final concern refers to the sample size. Although that used is not too small, to comply with all the issues relative to data availability and maximum compliance with Altman study (with this last limit only referred to risk of bankruptcy analysis) a huge number of observations were lost, from the initial panel of more than 350 firms.

A larger sample would have undoubtedly helped to gather a wider perspective, but, however, the preferred solution has been to limit the numerosity to achieve a higher quality of data, as demonstrated in the abovementioned part relative to the identification of the software assets of the firm.

3.7 Suggestions for Future Research

This work, especially this last chapter, had the purpose to evaluate the impact of digitalization on performance and risk of bankruptcy of Italian listed companies.

Notwithstanding the satisfying results obtained, this thesis has not the presumption of being considered as definitive and unassailable and in this perspective is fair and interesting giving suggestions to widen the scope of this paper.

As previously stated, the argument of the digitalization of Italy is a topic that still not have the due attention and relevant works are still missing. In this perspective, an interesting study to be conducted is relative to the analysis of the impact of the level of digital maturity on performance and risk of bankruptcy of non-listed companies and specifically to the SMEs in Italy.

For doing so, is however to take into account that data referring to these types of companies are generally not publicly available, contrary to what happens for those listed (although for this specific topic the research has not been easy even for them), highlighting that the most suitable procedure to follow in this case is a survey conducted over the firms under evaluation.

Similar studies have in fact been published for other countries, at least for what concern the part on performance, by Alford (2020) for Austrians SMEs and by Joensuu-Salo (2018) for Finnish SMEs, while something comparable seems to lag for Italy.

A further interesting expansion of this research could be a similar investigation embedding the analysis of companies of different countries, because literature lacks studies of this kind, expanding their perspective to a broader horizon.

Obviously, in this kind of analysis, some differences in terms of accounting standards, regulations and general comparability could arise for some national contexts, leading the selection of the panel of firms under observation to be a crucial moment.

Noteworthy would also be a research conducted dividing the companies by sector instead of in terms of countries. This would help to understand in which sectors embracing a sound process of digitalization is crucial and if there are sectors in which the sufficient level of digital maturity is nil or very low.

For the specific case of this thesis, the sample size was not sufficient to perform an effective comparison within all the sixteen identified sectors, given that many of them had just few observations. However, between the eight sectors with at least thirty observations, that with the highest average software assets over total assets (1.46%) was also that with the highest average ROE (second in terms of ROA), while the one with the lowest average of digital maturity ratio (0.08%) has the worst average ROA (second worst in terms of ROE).

In this case the sector with the best results was Personal, Travel & Leisure while the one with the worst was Construction, but such a low level of observations can't be held as an absolutely reliable outcome.

In this perspective, a future research with this goal would carry a relevant value added to the literature in terms of impact of digitalization between sectors and could be even helpful to the companies to have a clearer perspective of the type of environment they are going to challenge in a certain field.

Analyzed some possible implementations in terms of choice of the entities under observation, other noteworthy changes could pertain to the choice of the variables to embed in the empirical analysis. In this perspective, it might turn to be an added value the addition of more methodologies to estimate the digital maturity, where one could be the share of online turnover in percentage of the total turnover.

Even for the part relative to the estimation of risk of bankruptcy some alternatives can be valuable. Notwithstanding the classical methodologies pertaining to the Altman Z Score and Ohlson O Score are widely accepted by practitioners, the usage of alternative frameworks should be adopted in order to account even for financial firms like banks or simply to update the knowledge on evidence of more recent bankruptcy events.

Conclusions

The purpose of this thesis was to shed light on the phenomenon of digitalization, with the objective of highlighting how this process is capable to impact performance and risk of bankruptcy of Italian listed companies.

From the study conducted is pointed out that an increase of digitalization, leads to a consistent increase in ROE and ROA, taken in this research as the two ratios representing performance. In support of the consistent results obtained through the regression analysis, descriptive statistics confirmed the trend.

With this different analysis, arose in addition that the wider impact on performance, both in terms of ROE and ROA is achieved passing from the category enclosing all the companies with the lowest levels of digital maturity to the following one (so passing from "Minimalist" to "Conservative"). This evidence suggests the intuition that just being a bit digitized can overcome the toughest inconveniences, as being barely ousted or inefficient on the market.

Notwithstanding this first crucial step, good advantages arise passing from a lower category of digital maturity to a higher one. While in terms of ROE this statement is always justified by data, for ROA there is just a small decrease passing from "Advanced" to "Trailblazing", however, the general upward trend is indisputable.

Similar path is demonstrated by the graph depicting ROE, ROA and Software Assets over Total Assets on a yearly basis, where the highest average results of the first two ratios are in the same years in which the average of the third is greater (2017-2018).

The initial hypothesis is confirmed even for the effect of digitalization on risk of bankruptcy. The relative regression shows indeed a positive relation between the increase of the Software Assets over Total Assets ratio and the variable "result", constructed on the basis of the Altman Z Score for publicly listed companies. An increase in this parameter suggests a lower risk of bankruptcy in the short term (two years is what Altman (1968) suggested).

Even in this case, clustering the Altman Z Score in the same five classes used for performance analysis, the hardest troubles emerge for the class of “Minimalist”. On average, companies pertaining to this category fall widely within the “distress zone”, meaning that the risk of bankruptcy is undoubtedly high.

While this is the case for the less digitized firms, those into “Conservative” pertain to the “grey area”, where no sound predictions in terms of risk of bankruptcy in the next two years can be addressed, while on average all the other categories reach the “safe zone”.

Finally, the evidence that companies with a higher level of digital maturity have a lower possibility of being bankrupt has been confirmed even by a study of Ohlson O Score. The computation of this score has been performed just for the firms that for the years 2016-2019 guaranteed their stay into the “Minimalist” or “Trailblazing” category.

The Ohlson O Score, for its construction, allowed to be easily converted in a probability of default (1-year probability of default according to Ohlson (1980)), showing that in the period observed, the companies pertaining to “Trailblazing” had an average probability of default of 1.51% and the “Minimalist” an average of 20.60%.

Keeping in mind all the results achieved, is possible to state that the research conducted produced the outcome expected, justifying the choice of those companies caring about adapting to this noteworthy digital revolution.

In this perspective is interesting to notice that even in a country as Italy, that between the most developed economies is not one of those that exploited more consistently the opportunities provided by digitalization (as demonstrated even by the 2019 Network Readiness Index), having the strength, or at least the willingness, to embrace these changes, provide an undisputable value added in terms of increased performance and lower risk of bankruptcy.

References

Abdi, H., & Williams, L. J. (2010). Principal component analysis. *Wiley interdisciplinary reviews: computational statistics, 2*(4), 433-459.

Accenture (2015). Digital Density Index. *Accenture Strategy*, 1-16.

Aguinis, H., & Bernerth, J. B. (2016). A critical review and best-practice recommendations for control variable usage. *Personnel Psychology*, *69*(1), 229-283.

Ahmed, H.M.S., Alraja, M.N., & Hussein, A.M. (2021). What affects digitalization process in developing economies? An evidence from SMEs sector in Oman. *Bulletin of Electrical Engineering and Informatics Vol. 10, No. 1, February 2021,* 441-448.

Alamanos, E., Papagiannidis, S., & Tueanrat, Y. (2021). Going on a journey: A review of the customer journey literature. *Journal of Business Research*, *125*, 336-353.

Alford, P., Eller, R., Kallmünzer, A., & Peters, M. (2020). Antecedents, consequences, and challenges of small and medium-sized enterprise digitalization. *Journal of Business Research*, *112*, 119-127.

Alibage, A., & Weber, C. (2018). Nokia Phones: From a Total Success to a Total Fiasco: A Study on Why Nokia Eventually Failed to Connect People, and an Analysis of What the New Home of Nokia Phones Must Do to Succeed. *Portland International Conference on Management of Engineering and Technology (PICMET), Honolulu, HI, 2018,* 1-15.

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The journal of finance*, *23*(4), 589-609.

Altman, E. I. (1993). Corporate financial distress and bankruptcy. *Wiley Finance,* 233-264.

Altman, E. I., Iwanicz-Drozdowska, M., Laitinen, E. K., & Suvas, A. (2017). Financial distress prediction in an international context: A review and empirical analysis of Altman's Z-score model. *Journal of International Financial Management & Accounting*, *28*(2), 131-171.

Arntz, M., Gregory, T., & Zierahn, U. (2016), "The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis", *OECD Social, Employment and Migration Working Papers, No. 189, OECD Publishing, Paris,* 12-20.

Bain & Company. (2018). Digital Transformation Roadmap: Enablers. *Bain & Company*, 1-3.

Banga, K. (2019). Digital technologies and" value" capture in global value chains: Empirical evidence from Indian manufacturing firms (No. 2019/43). *WIDER Working Paper,* 1-29.

Baumann, H., Becker-Blease, J. R., Etebari, A., & Kaen, F. R. (2010). Employees, firm size and profitability of US manufacturing industries. *Investment Management and Financial Innovations*, 7-23.

Berners-Lee, T. J. (1992). The World-Wide Web. *Computer networks and ISDN systems*, *25*(4-5), 454-459.

Bhagat, S., & Bolton, B. (2008). Corporate governance and firm performance. *Journal of corporate finance*, *14*(3), 257-273.

Bican P.M., & Brem, A. (2020) Digital Business Model, Digital Transformation, Digital Entrepreneurship: Is There A Sustainable "Digital"? *Sustainability, 12(13), 5239*, 1-15.

Bistrova, J., Eremina, Y., & Lace, N.(2019). Digital maturity and corporate performance: The case of the Baltic states. *Journal of Open Innovation: Technology, Market, and Complexity*, *5*(3), 54, 1-13.

Boardman, L., Schallmo, D., & Williams, C.A.(2017). Digital Transformation of Business Models – Best Practice, Enablers and Roadmap. *International Journal of Innovation Management Vol. 21, No.8, December 2017*, 1-17.

Bouée, C.E., & Schaible, S. (2015). The Digital Transformation of Industry. *Roland Berger,* 9-44.

Bredrup, H., & Moseng, B. (1993), "A methodology for industrial studies of productivity performance". *Production Planning and Control, Vol. 4 No. 3,* 198-206.

Cameron, K. (2015). Organizational effectiveness. *Wiley Encyclopedia of Management,* 1-4.

Cedefop (2017). Investing in skills pays off: the economic and social cost of low-skilled adults in the EU. *Luxembourg: Publications Office. Cedefop research paper; No 60,* 29-55.

Chaghadari, F. M., & Chaleshtori, G.N. (2011). Corporate governance and firm performance. In *International Conference on Sociality and Economics Development (ICSED 2011), Kuala Lumpur, Malaysia, June*, 484-489.

Chandel, S., Joshi, A., Kale, S., & Pal, D. K. (2015). Likert Scale: Explored and Explained. *Current Journal of Applied Science and Technology*, *7*(4), 396-403.

Cross, K.F., Lynch, R.L. (1992), "For good measure". *CMA Magazine,* 20-23.

Dahal, R.K. (2019). Towards Business Performance Measurement Systems. *International Journal of Business Case Studies*, 1-16.

Domnicheva, A., Limonova, E., & Manakhova, I. (2018). Digitalization of companies-the basis of regions' competitive development. In *International Scientific Conference" Competitive, Sustainable and Secure Development of the Regional Economy: Response to Global Challenges"(CSSDRE 2018). Atlantis Press,* 659-662.

Dutta, S., & Lanvin, B. (2019). The Network Readiness Index. *Portulans Insititute*, 12-32, 99.

Dutta, S., & Osorio, B.B. (2012). The Global Information Technology Report 2012. *World Economic Forum*, 3-9.

Eckerson, W. W. (2007). Predictive analytics. *Extending the Value of Your Data Warehousing Investment. TDWI Best Practices Report*, *1*, 1-36.

Egloffstein, M., & Ifenthaler, D. (2020). Development and implementation of a maturity model of digital transformation. *TechTrends*, *64*(2), 302-309.

El-Darwiche, B., Friedrich, R., Ganediwalla, S., Katz, R., Sabbagh, K., & Singh, M. (2012). Maximizing the Impact of Digitization. *The global information technology report*, *2012*, 121-133.

Elgendy, N., & Elragal, A. (2014). Big data analytics: a literature review paper. *Industrial conference on data mining*, 214-227.

Elliott, T., Noga, M., & Wellers, D. (2017). 8 Ways Machine Learning Is Improving Companies' Work Processes. *Harvard Business Review*, 1-5.

Federal Reserve Bank of St. Louis (2020). Gross National Product.

Franke, M.R., Grebe, M., Leyh, M., & Rüßmann , M. (2018). Digital Maturity is paying off. *Boston Consulting Group,* 1-7.

Franke, M.R., Grebe, M., Leyh, M., & Rüßmann , M. (2019). How digital champions invest. *Boston Consulting Group,* 1-7.

Fu, L., Singhal, R., & Parkash, M. (2016). Tobin's q ratio and firm performance. *International research journal of applied finance*, *7*(4), 1-10.

Gan, C., Nadeem, M., & Nguyen, C. (2017). Does intellectual capital efficiency improve firm performance in BRICS economies? A dynamic panel estimation. *Measuring Business Excellence*, 65-85.

Gasparri, S., & Tassinari, A. (2020). 'Smart'Industrial Relations in the Making? Insights from Analysis of Union Responses to Digitalization in Italy. *Relations industrielles/Industrial Relations*, *75*(4), 796-817.

Gerhardt, C.I. (1849). Die mathematische schriften von Gottfried Wilhelm Leibniz, vol. VII, 223-227.

Gray, J., & Rumpe, B. (2015). Models for digitalization. *Software & Systems Modeling* 14**,** 1319-1320.

Härting, R. C., Jozinovic, P., & Reichstein, C. (2017). The Potential Value of Digitization for Business. *INFORMATIK 2017*, 1647-1656.

Hartono, E., & Santhanam, R. (2003). Issues in linking information technology capability to firm performance. *MIS quarterly*, 125-153.

Hsiao, C. (2014). Analysis of panel data (No. 54). *Cambridge university press*, 1-13.

Hu, J., & Liu, Y., Lu, H. (2008). IT capability as moderator between IT investment and firm performance. *Tsinghua Science and Technology*, *13*(3), 329-336.

Joensuu-Salo, S., Sorama, K., Varamäki, E., & Viljamaa, A. (2018). Firm performance among internationalized SMEs: The interplay of market orientation, marketing capability and digitalization. *Administrative sciences*, *8*(3), 31, 1-13.

Joshi, V., & Panigrahi, A. (2020). Failure of Nokia. Lessons from losers. *Emerging Issues in Business Management,* 155-160.

Kääriäinen, J., Parviainen, P., Teppola, S., & Tihinen, M. (2017). Tackling the digitalization challenge: how to benefit from digitalization in practice. *International journal of information systems and project management*, *5*(1), 63-77.

Kaldor, N. (1966). Marginal productivity and the macro-economic theories of distribution: Comment on Samuelson and Modigliani. *The Review of Economic Studies*, *33*(4), 309-319.

Kaplan, R.S., & Norton, D.P. (1992). The Balanced Scorecard — measures that drive performance. *Harvard Business Review*, 71–79.

Karels, G. V., & Prakash, A. J. (1987). Multivariate normality and forecasting of business bankruptcy. *Journal of Business Finance & Accounting*, *14*(4), 573-593.

Keegan, D.P., Eiler, R.G., & Jones, C.R. (1989). Are your performance measures obsolete? *Manage. Account., 70(12),* 45-50.

Khan, K., & Shah, A. (2011). Understanding performance measurement through the literature. *African Journal of Business Management Vol. 5(35),* 13410-13418.

Khanna, S., Manyika, J., Pinkus, G., Ramaswamy, S., Sarrazin, H., Sethupathy, G., & Yaffe, A. (2015). Digital America : a tale of the haves and have-mores. *McKinsey Global Institute*, 19-34.

Khoshgoftaar, T. M., Najafabadi, M. M., Muharemagic, E., Seliya, N., Villanustre, F., & Wald, R. (2015). Deep learning applications and challenges in big data analytics. *Journal of big data*, *2*(1), 1-21.

Kulkarni, S., Liu, S., Muro, M., & Whiton, J. (2017). Digitalization and the American workforce. *Brookings Institution*, 6-10.

Lakhal, L., Limam, M., & Pasin, F. (2006). Quality management practices and their impact on performance. *International Journal of Quality & Reliability Management*, 625-646.

Mitchell, T. M. (2006). The discipline of machine learning (Vol. 9). *Pittsburgh, PA: Carnegie Mellon University, School of Computer Science, Machine Learning Department*, 1-8.

Mohri, M., Rostamizadeh, A., & Talwalkar, A. (2018). Foundations of machine learning. *MIT press,* 1-7.

Moyer, R. C. (1977). Forecasting financial failure: a re-examination. *Financial Management (pre-1986), 6*(1), 11-17.

Naimah, Z. (2017). The role of corporate governance in firm performance. In *SHS Web of Conferences, Vol. 34*, 1-6.

Neely, A., Adams, C., & Crowe, P. (2001). The performance prism in practice. *Measuring business excellence*, 6-12.

Neely, A. (2002). Business performance measurement. *Cambridge university press, 40*, 42, 4-6.

OECD (2015). Bankruptcies. *Entrepreneurship at a Glance 2015, OECD Publishing, Paris*, 18-19.

OECD (2017). Key issues for digital transformation in the G20. *OECD Publishing, Berlin*, 35-46

Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of accounting research*, 109-131.

Press, G. (2015). A very short history of digitization. *Forbes.*

Ramanujam, V., & Venkatraman, N. (1986). Measurement of business performance in strategy research: A comparison of approaches. *Academy of management review*, *11*(4), 801-814.

Rolstadås, A. (1998). Enterprise performance measurement. *International Journal of Operations & Production Management*, 989-999.

Russom, P. (2011). Big data analytics. *TDWI best practices report, fourth quarter, 19*(4), 1-34.

Sagiroglu, S., & Sinanc, D. (2013). Big data: A review. *2013 International Conference on Collaboration Technologies and Systems (CTS), San Diego, CA, 2013*, 42-47.

Schwab, K. (2017). The fourth industrial revolution. *Currency*, 1-8.

Scott, S., & Thomas, C. T. (1989). Planning and measurement of in your organisation of the future. *Inst of Industrial Engineers and Management Press, USA*, 237-244.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The journal of finance*, *19*(3), 425-442.

Tangen, S. (2005). Demystifying productivity and performance. *International Journal of Productivity and performance management*, 34-46.

Torres-Reyna, O. (2007). Panel data analysis fixed and random effects using Stata. *Princeton University*, 1-40.

Tobin, J. (1978). Monetary policies and the economy: the transmission mechanism. *Southern economic journal*, 421-431.

Vulpiani, M. (2014). Special cases of Business Valuation. *McGraw-Hill*, 268-273.

Wang, M. S. (2011). Intellectual capital and firm performance. In *Annual Conference on Innovations in Business & Management. London, UK: The Center for Innovations in Business and Management, Practice,* 1-26.

Zmijewski, M. E. (1984). Methodological issues related to the estimation of financial distress prediction models. *Journal of Accounting research*, 59-82.

Appendix

Legend

Sector ID for Performance Regressions:

1. Chemicals, Petroleum, Rubber & Plastic
2. Communications
3. Computer Services
4. Construction & Property Services
5. Food & Tobacco Manufacturing
6. Industrial, Electric & Electronic Machinery
7. Leather, Stone, Clay & Glass Products
8. Media & Broadcasting
9. Mining, Extraction & Metal Products
10. Printing, Publishing & Wood Manufacturing
11. Public Administration, Education & Health Social Services
12. Textiles & Clothing Manufacturing
13. Transport, Transport Manufacturing, Freight & Storage
14. Travel, Personal & Leisure
15. Utilities
16. Wholesale

Sector ID for Risk of Bankruptcy Regression:

1. Chemicals, Petroleum, Rubber & Plastic
2. Communications
3. Construction[19]
4. Food & Tobacco Manufacturing
5. Industrial, Electric & Electronic Machinery

[19] Compared to "Construction & Property Services" sector identified for Performance regressions, here are removed those companies pertaining more to the Property Services segment, with the purpose to comply as much as possible to Altman's study.

6. Leather, Stone, Clay & Glass Products
7. Media & Broadcasting
8. Printing, Publishing & Wood Manufacturing
9. Textiles & Clothing Manufacturing
10. Transport, Transport Manufacturing, Freight & Storage
11. Travel, Personal & Leisure
12. Utilities
13. Wholesale

Region ID:

1. North: Valle D'Aosta, Lombardia, Piemonte, Trentino-Alto Adige, Veneto, Friuli-Venezia Giulia, Liguria, Emilia-Romagna.
2. Center: Toscana, Umbria, Marche, Lazio.
3. South: Abruzzo, Molise, Campania, Puglia, Basilicata, Calabria, Sardegna, Sicilia.

Appendix 1: Data for Regressions on Performance

ID	NAME	YEAR	SECTOR ID	REGION ID	LN EMPLOYEES	SOLVENCY RATIO	ROE	ROA	SOFTWARE/TOT.ASSETS
1	ENEL	2019	15	2	11.13	27.38%	4.63%	1.27%	0.34%
1	ENEL	2018	15	2	11.15	28.93%	10.01%	2.90%	0.22%
1	ENEL	2017	15	2	11.05	33.51%	7.25%	2.43%	0.20%
1	ENEL	2016	15	2	11.04	33.79%	4.89%	1.65%	0.40%
1	ENEL	2015	15	2	11.13	32.11%	4.24%	1.36%	0.36%
2	ENI	2019	9	2	10.38	38.80%	0.31%	0.12%	0.16%
2	ENI	2018	9	2	10.36	43.15%	8.08%	3.49%	0.19%
2	ENI	2017	9	2	10.40	41.83%	7.02%	2.94%	0.09%
2	ENI	2016	9	2	10.42	42.62%	-2.76%	-1.18%	0.19%
2	ENI	2015	9	2	10.28	39.82%	-16.37%	-6.52%	0.19%
3	ATLANTIA	2019	13	2	10.27	18.26%	2.40%	0.44%	0.00%
3	ATLANTIA	2018	13	2	10.28	20.50%	5.01%	1.03%	0.00%
3	ATLANTIA	2017	13	2	9.64	29.37%	9.96%	2.93%	0.00%
3	ATLANTIA	2016	13	2	9.59	25.81%	11.21%	2.89%	0.00%
3	ATLANTIA	2015	13	2	9.58	24.86%	10.05%	2.50%	0.00%
4	SNAM	2019	13	1	8.01	26.03%	17.42%	4.53%	0.70%
4	SNAM	2018	13	1	8.01	26.50%	16.04%	4.25%	0.62%
4	SNAM	2017	13	1	7.98	28.37%	14.50%	4.11%	0.60%
4	SNAM	2016	13	1	7.97	32.28%	13.25%	4.28%	0.64%
4	SNAM	2015	13	1	8.75	30.49%	16.32%	4.98%	0.73%
5	TERNA	2019	15	2	8.36	23.51%	17.90%	4.21%	0.51%
5	TERNA	2018	15	2	8.36	23.67%	17.43%	4.13%	0.52%
5	TERNA	2017	15	2	8.27	22.63%	17.98%	4.07%	0.41%
5	TERNA	2016	15	2	8.26	22.16%	17.81%	3.95%	0.44%
5	TERNA	2015	15	2	8.23	21.65%	17.80%	3.85%	0.45%
6	MONCLER	2019	12	1	8.43	50.92%	27.46%	13.98%	1.07%
6	MONCLER	2018	12	1	8.33	65.75%	31.10%	20.45%	0.94%
6	MONCLER	2017	12	1	8.16	66.92%	27.04%	18.09%	0.93%
6	MONCLER	2016	12	1	8.08	61.09%	27.86%	17.02%	0.95%
6	MONCLER	2015	12	1	7.72	54.03%	30.70%	16.59%	0.92%
7	PRADA	2019	12	1	9.53	42.46%	8.56%	3.63%	0.83%
7	PRADA	2018	12	1	9.51	61.92%	7.09%	4.39%	0.96%
7	PRADA	2017	12	1	9.40	60.48%	7.60%	5.01%	0.74%
7	PRADA	2016	12	1	9.42	66.67%	8.97%	5.98%	0.54%
7	PRADA	2015	12	1	9.43	65.12%	10.68%	6.96%	0.23%
8	RECORDATI	2019	1	1	8.37	42.68%	30.77%	13.13%	5.70%
8	RECORDATI	2018	1	1	8.33	44.54%	32.42%	14.44%	7.87%
8	RECORDATI	2017	1	1	8.34	49.95%	28.11%	14.04%	8.76%
8	RECORDATI	2016	1	1	8.32	57.92%	26.26%	15.21%	0.23%
8	RECORDATI	2015	1	1	8.28	59.23%	22.85%	13.53%	0.27%
9	DIASORIN	2019	1	1	7.57	79.79%	20.71%	16.52%	2.80%
9	DIASORIN	2018	1	1	7.59	77.79%	22.44%	17.46%	3.21%
9	DIASORIN	2017	1	1	7.55	78.45%	18.85%	14.79%	3.01%
9	DIASORIN	2016	1	1	7.52	76.37%	16.94%	12.94%	3.24%
9	DIASORIN	2015	1	1	7.41	82.94%	17.10%	14.19%	3.85%
10	LEONARDO	2019	13	2	10.81	19.83%	15.39%	3.05%	0.29%
10	LEONARDO	2018	13	2	10.75	17.67%	11.29%	2.00%	0.27%
10	LEONARDO	2017	13	2	10.72	17.92%	6.07%	1.09%	0.31%
10	LEONARDO	2016	13	2	10.73	17.23%	11.55%	1.99%	0.39%
10	LEONARDO	2015	13	2	10.76	16.40%	11.32%	1.86%	0.01%
11	AMPLIFON	2019	6	1		24.41%	15.61%	3.81%	1.79%
11	AMPLIFON	2018	6	1	9.25	26.88%	16.84%	4.53%	1.74%
11	AMPLIFON	2017	6	1	9.00	40.15%	17.09%	6.86%	2.20%
11	AMPLIFON	2016	6	1	8.88	39.66%	11.41%	4.53%	2.18%
11	AMPLIFON	2015	6	1	8.75	38.86%	9.36%	3.64%	1.78%
12	PRYSMIAN	2019	2	1		24.81%	11.22%	2.79%	0.38%
12	PRYSMIAN	2018	2	1	10.28	24.12%	5.32%	1.28%	0.35%
12	PRYSMIAN	2017	2	1	9.95	24.84%	13.55%	3.37%	0.46%
12	PRYSMIAN	2016	2	1	9.95	26.54%	14.69%	3.90%	0.49%
12	PRYSMIAN	2015	2	1	9.87	23.29%	15.03%	3.50%	0.46%
13	A2A	2019	15	1	9.41	34.04%	10.66%	3.63%	0.29%
13	A2A	2018	15	1	9.40	34.10%	9.76%	3.33%	0.23%
13	A2A	2017	15	1	9.34	30.28%	9.73%	2.95%	0.19%
13	A2A	2016	15	1	9.51	31.52%	6.85%	2.16%	0.20%
13	A2A	2015	15	1	9.42	33.25%	2.24%	0.75%	0.27%
14	INWIT	2019	2	1	4.80	60.22%	8.92%	5.37%	2.50%
14	INWIT	2018	2	1	4.76	80.12%	9.09%	7.28%	3.22%
14	INWIT	2017	2	1	4.57	84.09%	8.32%	7.00%	3.06%
14	INWIT	2016	2	1	4.48	83.66%	6.60%	5.52%	1.99%
14	INWIT	2015	2	1	4.25	83.61%	4.36%	3.65%	0.73%
15	SAIPEM	2019	9	1	10.39	31.71%	0.29%	0.09%	0.16%
15	SAIPEM	2018	9	1	10.36	34.56%	-11.70%	-4.04%	0.18%
15	SAIPEM	2017	9	1	10.38	36.53%	-7.13%	-2.61%	0.12%
15	SAIPEM	2016	9	1	10.51	34.19%	-42.72%	-14.61%	0.09%
15	SAIPEM	2015	9	1	10.66	21.56%	-22.90%	-4.94%	0.10%
16	ACEA	2019	15	2		23.53%	13.47%	3.17%	0.18%
16	ACEA	2018	15	2	6.49	23.34%	14.24%	3.32%	0.11%
16	ACEA	2017	15	2	6.38	24.68%	9.98%	2.46%	0.15%
16	ACEA	2016	15	2		25.46%	14.92%	3.80%	0.19%
16	ACEA	2015	15	2	8.51	23.80%	10.96%	2.61%	0.14%

17	BUZZI	2019	7	1		57.65%	10.45%	6.02%	0.05%
17	BUZZI	2018	7	1	9.21	55.40%	12.16%	6.74%	0.05%
17	BUZZI	2017	7	1	9.23	49.32%	13.73%	6.77%	0.06%
17	BUZZI	2016	7	1	9.22	48.32%	5.20%	2.51%	0.05%
17	BUZZI	2015	7	1		46.72%	4.86%	2.27%	0.07%
18	BREMBO	2019	13	1	9.29	50.61%	16.66%	8.43%	0.36%
18	BREMBO	2018	13	1	9.27	48.55%	19.40%	9.42%	0.31%
18	BREMBO	2017	13	1	9.19	46.29%	24.75%	11.46%	0.20%
18	BREMBO	2016	13	1	9.11	44.91%	27.27%	12.25%	0.15%
18	BREMBO	2015	13	1	8.97	43.39%	26.76%	11.61%	0.16%
19	IREN	2019	15	1	9.00	30.13%	8.92%	2.69%	0.47%
19	IREN	2018	15	1	8.86	29.91%	9.45%	2.83%	0.38%
19	IREN	2017	15	1	8.75	31.65%	9.51%	3.01%	0.43%
19	IREN	2016	15	1	8.74	29.35%	7.60%	2.23%	0.31%
19	IREN	2015	15	1	8.72	29.93%	5.73%	1.72%	0.11%
20	FERRAGAMO	2019	12	2	8.32	42.59%	11.12%	4.73%	0.11%
20	FERRAGAMO	2018	12	2	8.35	65.73%	11.32%	7.44%	0.22%
20	FERRAGAMO	2017	12	2	8.34	63.29%	15.85%	10.03%	0.24%
20	FERRAGAMO	2016	12	2	8.32	60.46%	27.95%	16.90%	0.12%
20	FERRAGAMO	2015	12	2	8.30	54.17%	28.38%	15.37%	0.14%
21	INTERPUMP	2019	6	1	8.84	52.01%	16.98%	8.83%	0.09%
21	INTERPUMP	2018	6	1	8.78	52.62%	19.90%	10.47%	0.07%
21	INTERPUMP	2017	6	1	8.66	50.39%	17.58%	8.86%	0.09%
21	INTERPUMP	2016	6	1	8.52	47.57%	13.85%	6.59%	0.12%
21	INTERPUMP	2015	6	1	8.48	49.02%	18.89%	9.26%	0.16%
22	ENAV	2019	13	2	8.34	54.76%	10.25%	5.61%	1.18%
22	ENAV	2018	13	2	8.32	55.61%	10.06%	5.59%	0.77%
22	ENAV	2017	13	2	8.34	55.90%	9.06%	5.07%	0.74%
22	ENAV	2016	13	2	8.35	55.82%	6.82%	3.81%	0.60%
22	ENAV	2015	13	2					
23	HERA	2019	15	1	9.10	29.05%	12.81%	3.72%	0.46%
23	HERA	2018	15	1	9.06	31.24%	9.90%	3.09%	0.47%
23	HERA	2017	15	1	9.07	30.79%	9.29%	2.86%	0.40%
23	HERA	2016	15	1	9.03	30.92%	8.09%	2.50%	0.50%
23	HERA	2015	15	1	9.04	30.32%	7.19%	2.18%	0.45%
24	ASTM	2019	13	1	8.53	38.96%	2.58%	1.00%	0.10%
24	ASTM	2018	13	1	8.35	42.88%	5.41%	2.32%	0.04%
24	ASTM	2017	13	1	8.18	46.40%	5.23%	2.43%	0.01%
24	ASTM	2016	13	1	8.15	41.79%	3.48%	1.46%	0.02%
24	ASTM	2015	13	1	7.96	40.06%	4.43%	1.78%	0.02%
25	REPLY	2019	8	1	8.98	44.89%	19.40%	8.71%	0.41%
25	REPLY	2018	8	1	8.86	45.22%	20.53%	9.29%	0.35%
25	REPLY	2017	8	1	8.77	46.15%	19.37%	8.94%	0.37%
25	REPLY	2016	8	1	8.70	43.80%	20.01%	8.77%	0.49%
25	REPLY	2015	8	1	8.57	42.25%	19.17%	8.10%	0.53%
26	IMA	2019	6	1	8.69	21.94%	33.52%	7.36%	8.44%
26	IMA	2018	6	1	8.63	25.36%	24.72%	6.27%	6.21%
26	IMA	2017	6	1	8.63	25.91%	21.92%	5.68%	4.14%
26	IMA	2016	6	1	8.57	19.63%	34.62%	6.80%	4.75%
26	IMA	2015	6	1	8.47	14.96%	37.21%	5.57%	5.96%
27	AUTOGRILL	2019	14	1	10.63	17.69%	21.92%	3.88%	0.31%
27	AUTOGRILL	2018	14	1	10.65	28.11%	9.27%	2.60%	0.85%
27	AUTOGRILL	2017	14	1	10.62	29.60%	13.83%	4.10%	0.92%
27	AUTOGRILL	2016	14	1	10.58	28.42%	14.29%	4.06%	0.53%
27	AUTOGRILL	2015	14	1	10.61	24.98%	10.69%	2.67%	0.38%
28	TECHNOGYM	2019	14	1	7.66	40.73%	31.99%	13.03%	2.62%
28	TECHNOGYM	2018	14	1	7.67	34.60%	44.45%	15.38%	2.49%
28	TECHNOGYM	2017	14	1	7.57	26.90%	45.43%	12.22%	3.06%
28	TECHNOGYM	2016	14	1	7.53	19.15%	49.16%	9.42%	1.90%
28	TECHNOGYM	2015	14	1	7.54	12.33%	65.16%	8.03%	1.96%
29	CUCINELLI	2019	12	2	7.54	30.03%	17.56%	5.27%	1.02%
29	CUCINELLI	2018	12	2	7.46	57.97%	17.64%	10.23%	1.89%
29	CUCINELLI	2017	12	2	7.38	58.48%	19.42%	11.36%	1.42%
29	CUCINELLI	2016	12	2	7.27	52.54%	16.11%	8.47%	1.29%
29	CUCINELLI	2015	12	2	7.22	47.87%	16.94%	8.11%	0.75%
30	CERVED	2019	11	1	7.85	32.73%	10.53%	3.45%	2.24%
30	CERVED	2018	11	1	7.75	36.60%	15.42%	5.65%	2.11%
30	CERVED	2017	11	1	7.59	38.15%	10.21%	3.90%	1.86%
30	CERVED	2016	11	1	7.57	38.57%	8.69%	3.35%	1.64%
30	CERVED	2015	11	1	7.49	40.16%	0.25%	0.10%	1.28%
31	RAI WAY	2019	8	2	6.42	53.65%	34.40%	18.45%	1.58%
31	RAI WAY	2018	8	2	6.42	61.51%	33.04%	20.32%	0.93%
31	RAI WAY	2017	8	2	6.40	52.39%	31.90%	16.71%	0.63%
31	RAI WAY	2016	8	2	6.43	44.02%	25.89%	11.40%	0.29%
31	RAI WAY	2015	8	2	6.46	41.17%	24.45%	10.07%	0.19%
32	FALCK	2019	15	1	6.15	33.97%	7.97%	2.71%	0.32%
32	FALCK	2018	15	1	5.97	34.53%	7.94%	2.74%	0.07%
32	FALCK	2017	15	1	5.85	31.27%	4.09%	1.28%	0.08%
32	FALCK	2016	15	1	5.77	31.88%	-0.83%	-0.26%	0.07%
32	FALCK	2015	15	1	5.70	36.23%	1.02%	0.37%	0.04%

33	MARR	2019	16	1	6.71	30.66%	19.60%	6.01%	0.22%
33	MARR	2018	16	1	6.74	31.58%	21.13%	6.67%	0.21%
33	MARR	2017	16	1	6.70	30.76%	21.50%	6.61%	0.18%
33	MARR	2016	16	1	6.74	30.48%	20.49%	6.25%	0.12%
33	MARR	2015	16	1	6.69	31.66%	21.37%	6.77%	0.09%
34	CEMENTIR	2019	7	2	8.02	52.14%	7.07%	3.69%	0.22%
34	CEMENTIR	2018	7	2	8.03	52.92%	11.27%	5.97%	0.19%
34	CEMENTIR	2017	7	2	8.01	43.09%	7.04%	3.03%	0.18%
34	CEMENTIR	2016	7	2	8.21	43.54%	6.34%	2.76%	0.11%
34	CEMENTIR	2015	7	2	8.02	61.16%	5.97%	3.65%	0.11%
35	DATALOGIC	2019	6	1	8.03	50.23%	12.39%	6.22%	1.01%
35	DATALOGIC	2018	6	1	8.06	45.27%	16.55%	7.49%	0.90%
35	DATALOGIC	2017	6	1	7.98	42.19%	17.02%	7.18%	0.46%
35	DATALOGIC	2016	6	1	7.90	45.28%	13.63%	6.17%	0.37%
35	DATALOGIC	2015	6	1	7.85	43.28%	13.60%	5.88%	0.37%
36	PIAGGIO	2019	13	2	8.74	23.60%	12.18%	2.87%	1.52%
36	PIAGGIO	2018	13	2	8.78	24.72%	9.20%	2.28%	1.23%
36	PIAGGIO	2017	13	2	8.80	25.50%	5.19%	1.32%	1.05%
36	PIAGGIO	2016	13	2	8.81	24.14%	3.57%	0.86%	0.97%
36	PIAGGIO	2015	13	2	8.86	26.06%	2.94%	0.77%	0.94%
37	ASCOPIAVE	2019	15	1	6.18	67.28%	56.47%	37.99%	0.31%
37	ASCOPIAVE	2018	15	1	6.52	52.97%	9.96%	5.28%	0.16%
37	ASCOPIAVE	2017	15	1	6.51	56.89%	10.46%	5.95%	0.78%
37	ASCOPIAVE	2016	15	1	6.43	60.58%	12.07%	7.31%	0.44%
37	ASCOPIAVE	2015	15	1	6.42	53.70%	10.24%	5.50%	0.03%
38	WEBUILD	2019	4	1	9.60	18.30%	-1.47%	-0.27%	0.02%
38	WEBUILD	2018	4	1	9.81	12.51%	5.82%	0.73%	0.01%
38	WEBUILD	2017	4	1	9.88	12.41%	-9.85%	-1.22%	0.01%
38	WEBUILD	2016	4	1	9.95	14.58%	4.40%	0.64%	0.01%
38	WEBUILD	2015	4	1	9.73	16.66%	4.98%	0.83%	0.01%
39	SESA	2019	4	2	7.84	23.11%	14.94%	3.45%	0.75%
39	SESA	2018	4	2	7.55	26.16%	12.59%	3.29%	0.69%
39	SESA	2017	4	2	7.40	26.83%	12.44%	3.34%	0.38%
39	SESA	2016	4	2	7.26	28.81%	12.58%	3.63%	0.31%
39	SESA	2015	4	2	7.10	29.01%	13.36%	3.88%	0.30%
40	IGD	2019	4	1	5.18	46.48%	1.04%	0.48%	0.00%
40	IGD	2018	4	1	5.19	50.86%	3.70%	1.88%	0.00%
40	IGD	2017	4	1	5.17	48.97%	7.75%	3.80%	0.00%
40	IGD	2016	4	1	5.14	47.76%	6.39%	3.05%	0.00%
40	IGD	2015	4	1	5.11	47.47%	4.42%	2.10%	0.00%
41	EL.EN.	2019	6	2	7.31	56.58%	10.81%	6.12%	0.42%
41	EL.EN.	2018	6	2	7.22	60.92%	7.66%	4.67%	0.40%
41	EL.EN.	2017	6	2	7.10	60.99%	7.65%	4.67%	0.36%
41	EL.EN.	2016	6	2	7.00	64.09%	20.97%	13.44%	0.29%
41	EL.EN.	2015	6	2	6.87	63.85%	8.01%	5.11%	0.29%
42	FILA	2019	1	1	9.22	31.05%	6.72%	2.09%	0.00%
42	FILA	2018	1	1	9.17	29.24%	2.58%	0.76%	0.00%
42	FILA	2017	1	1	9.04	35.44%	6.58%	2.33%	0.01%
42	FILA	2016	1	1	8.96	35.12%	8.79%	3.09%	0.01%
42	FILA	2015	1	1	8.71	55.07%	-7.87%	-4.33%	0.02%
43	RCS	2019	10	1	7.38	26.94%	24.41%	6.58%	0.10%
43	RCS	2018	10	1	8.10	28.85%	33.52%	9.67%	0.11%
43	RCS	2017	10	1	8.13	18.00%	41.46%	7.46%	0.19%
43	RCS	2016	10	1	8.18	9.72%	3.49%	0.34%	0.29%
43	RCS	2015	10	1	8.30	7.69%	-167.02%	-12.85%	0.23%
44	MONDADORI	2019	10	1	7.61	18.20%	16.58%	3.02%	1.02%
44	MONDADORI	2018	10	1	7.66	15.37%	-103.77%	-15.95%	0.27%
44	MONDADORI	2017	10	1	8.01	25.83%	9.54%	2.46%	0.54%
44	MONDADORI	2016	10	1	8.09	22.34%	7.09%	1.59%	0.54%
44	MONDADORI	2015	10	1	8.03	24.76%	2.15%	0.53%	0.34%
45	DANIELI	2019	6	1	9.13	38.16%	3.25%	1.24%	0.02%
45	DANIELI	2018	6	1	9.16	37.45%	3.53%	1.32%	0.02%
45	DANIELI	2017	6	1	9.14	39.53%	3.15%	1.25%	0.03%
45	DANIELI	2016	6	1	9.15	37.78%	2.78%	1.05%	0.04%
45	DANIELI	2015	6	1	9.15	33.32%	4.97%	1.66%	0.03%
46	AEROPORTO MARCONI	2019	13	1	6.31	66.24%	11.70%	7.75%	0.65%
46	AEROPORTO MARCONI	2018	13	1	6.27	66.61%	10.32%	6.87%	0.62%
46	AEROPORTO MARCONI	2017	13	1	6.16	66.08%	9.27%	6.12%	0.42%
46	AEROPORTO MARCONI	2016	13	1	6.08	63.88%	6.81%	4.35%	0.34%
46	AEROPORTO MARCONI	2015	13	1	6.05	61.58%	4.32%	2.66%	0.26%
47	CEMBRE	2019	6	1	6.18	78.90%	13.52%	10.67%	0.77%
47	CEMBRE	2018	6	1	6.61	78.46%	14.87%	11.67%	0.59%
47	CEMBRE	2017	6	1	6.16	83.86%	15.89%	13.32%	0.50%
47	CEMBRE	2016	6	1		84.10%	12.30%	10.34%	0.34%
47	CEMBRE	2015	6	1	6.44	84.22%	12.15%	10.23%	0.44%
48	FIERA MILANO	2019	14	1	6.56	14.69%	31.92%	4.69%	0.20%
48	FIERA MILANO	2018	14	1	6.55	36.41%	22.95%	8.36%	0.42%
48	FIERA MILANO	2017	14	1	6.54	28.39%	2.60%	0.74%	0.48%
48	FIERA MILANO	2016	14	1	6.59	25.12%	-36.96%	-9.28%	0.66%
48	FIERA MILANO	2015	14	1	6.72	28.03%	1.19%	0.33%	0.71%

49	OVS	2019	12	1	8.62	27.78%	-19.26%	-5.35%	0.00%
49	OVS	2018	12	1	8.77	44.35%	2.94%	1.31%	0.00%
49	OVS	2017	12	1	8.76	42.28%	0.61%	0.26%	0.00%
49	OVS	2016	12	1	8.80	45.02%	8.95%	4.03%	0.00%
49	OVS	2015	12	1	8.78	43.38%	10.50%	4.56%	0.00%
50	AVIO	2019	13	2	6.80	29.89%	8.62%	2.58%	0.16%
50	AVIO	2018	13	2	6.70	35.58%	8.22%	2.93%	0.06%
50	AVIO	2017	13	2		33.49%	6.51%	2.18%	0.06%
50	AVIO	2016	13	2		38.05%	0.43%	0.16%	0.09%
50	AVIO	2015	13	2		41.44%	1.49%	0.62%	0.08%
51	BASICNET	2019	12	1	6.70	41.52%	17.29%	7.18%	1.27%
51	BASICNET	2018	12	1	6.39	47.95%	18.61%	8.92%	1.49%
51	BASICNET	2017	12	1	6.34	44.19%	10.97%	4.85%	1.86%
51	BASICNET	2016	12	1	6.30	44.51%	10.86%	4.83%	2.14%
51	BASICNET	2015	12	1	6.23	45.09%	18.12%	8.17%	2.20%
52	RENO DE MEDICI	2019	10	1	7.47	39.86%	7.59%	3.03%	0.81%
52	RENO DE MEDICI	2018	10	1	7.46	38.61%	13.95%	5.38%	0.66%
52	RENO DE MEDICI	2017	10	1	7.30	41.13%	8.65%	3.56%	0.13%
52	RENO DE MEDICI	2016	10	1	7.34	38.53%	2.02%	0.78%	0.16%
52	RENO DE MEDICI	2015	10	1	7.06	41.35%	6.42%	2.66%	0.23%
53	DIGITAL BROS	2019	14	1	5.39	51.35%	18.73%	9.62%	1.25%
53	DIGITAL BROS	2018	14	1	5.27	52.95%	-2.36%	-1.25%	1.41%
53	DIGITAL BROS	2017	14	1	5.18	67.44%	13.77%	9.29%	2.32%
53	DIGITAL BROS	2016	14	1		58.78%	19.22%	11.30%	1.66%
53	DIGITAL BROS	2015	14	1		44.45%	25.94%	11.53%	4.17%
54	EUROTECH	2019	3	1	5.74	73.11%	15.42%	11.27%	1.41%
54	EUROTECH	2018	3	1	5.71	71.09%	5.57%	3.96%	1.57%
54	EUROTECH	2017	3	1	5.68	71.28%	-5.15%	-3.67%	1.70%
54	EUROTECH	2016	3	1	5.77	72.94%	-4.90%	-3.57%	1.33%
54	EUROTECH	2015	3	1	5.83	72.42%	-5.91%	-4.28%	1.34%
55	LA DORIA	2019	5	3	6.68	37.90%	7.83%	2.97%	0.10%
55	LA DORIA	2018	5	3	6.63	37.86%	11.33%	4.29%	0.16%
55	LA DORIA	2017	5	3	6.61	39.52%	13.40%	5.30%	0.22%
55	LA DORIA	2016	5	3	6.46	37.77%	16.15%	6.10%	0.24%
55	LA DORIA	2015	5	3	6.63	34.18%	22.60%	7.72%	0.18%
56	LU-VE	2019	6	1	8.06	29.04%	11.05%	3.21%	0.48%
56	LU-VE	2018	6	1	7.87	32.26%	10.60%	3.42%	0.60%
56	LU-VE	2017	6	1	7.82	35.07%	4.03%	1.41%	0.55%
56	LU-VE	2016	6	1	7.78	36.21%	11.79%	4.27%	0.28%
56	LU-VE	2015	6	1		39.80%	7.23%	2.88%	0.43%
57	RETELIT	2019	2	1	4.53	60.22%	6.68%	4.02%	1.04%
57	RETELIT	2018	2	1	4.51	58.82%	6.05%	3.56%	0.56%
57	RETELIT	2017	2	1	3.43	53.27%	7.77%	4.14%	0.41%
57	RETELIT	2016	2	1	4.30	60.46%	2.12%	1.28%	0.46%
57	RETELIT	2015	2	1	4.34	65.82%	2.62%	1.73%	0.45%
58	NEWLAT	2019	5	1		34.98%	7.84%	2.74%	0.45%
58	NEWLAT	2018	5	1	6.93	26.83%	9.37%	2.51%	7.19%
58	NEWLAT	2017	5	1					
58	NEWLAT	2016	5	1					
58	NEWLAT	2015	5	1					
59	CALTAGIRONE ED.	2019	10	2	6.42	75.85%	-7.51%	-5.70%	0.00%
59	CALTAGIRONE ED.	2018	10	2	6.46	76.32%	-2.00%	-1.53%	0.00%
59	CALTAGIRONE ED.	2017	10	2	6.51	77.22%	-6.60%	-5.10%	0.00%
59	CALTAGIRONE ED.	2016	10	2	6.61	75.18%	-13.22%	-9.94%	0.00%
59	CALTAGIRONE ED.	2015	10	2	6.69	75.70%	-3.44%	-2.61%	0.00%
60	PHARMANUTRA	2019	1	2	3.99	57.58%	30.05%	17.30%	2.75%
60	PHARMANUTRA	2018	1	2	3.87	58.94%	35.01%	20.63%	3.27%
60	PHARMANUTRA	2017	1	2	3.74	57.17%	31.57%	18.05%	3.29%
60	PHARMANUTRA	2016	1	2	3.56	35.06%	57.88%	20.29%	5.91%
60	PHARMANUTRA	2015	1	2		26.73%	62.92%	16.82%	7.81%
61	UNIEURO	2019	16	1	8.45	6.97%	26.62%	1.86%	1.13%
61	UNIEURO	2018	16	1	8.45	10.83%	31.80%	3.44%	1.53%
61	UNIEURO	2017	16	1	8.42	10.42%	14.19%	1.48%	1.61%
61	UNIEURO	2016	16	1	8.27	13.73%	13.64%	1.87%	1.46%
61	UNIEURO	2015	16	1		12.19%	14.49%	1.77%	1.44%
62	AEFFE	2019	12	1	7.20	40.44%	5.73%	2.32%	0.23%
62	AEFFE	2018	12	1	7.15	48.89%	8.47%	4.14%	0.35%
62	AEFFE	2017	12	1	7.18	46.19%	6.44%	2.98%	0.35%
62	AEFFE	2016	12	1	7.17	44.90%	-7.35%	-3.30%	0.38%
62	AEFFE	2015	12	1	7.15	39.63%	1.02%	0.40%	0.55%
63	MASSIMO ZANETTI	2019	5	1	8.18	36.01%	4.50%	1.62%	0.41%
63	MASSIMO ZANETTI	2018	5	1	8.12	39.37%	6.21%	2.45%	0.26%
63	MASSIMO ZANETTI	2017	5	1	8.10	37.67%	5.96%	2.25%	0.15%
63	MASSIMO ZANETTI	2016	5	1	8.09	39.81%	5.35%	2.13%	0.22%
63	MASSIMO ZANETTI	2015	5	1	8.01	44.91%	3.91%	1.76%	0.24%
64	IMMSI	2019	13	1	8.79	17.75%	4.03%	0.72%	0.01%
64	IMMSI	2018	13	1	8.83	17.97%	3.39%	0.61%	0.00%
64	IMMSI	2017	13	1	8.85	18.16%	2.21%	0.40%	0.00%
64	IMMSI	2016	13	1	8.86	18.13%	-2.21%	-0.40%	0.00%
64	IMMSI	2015	13	1	8.91	19.86%	-2.23%	-0.44%	0.00%

65	CARRARO	2019	13	1		13.54%	11.08%	1.50%	0.03%
65	CARRARO	2018	13	1	8.09	14.77%	15.81%	2.34%	0.03%
65	CARRARO	2017	13	1	8.06	15.10%	16.66%	2.51%	0.02%
65	CARRARO	2016	13	1	8.00	9.61%	-19.45%	-1.87%	0.00%
65	CARRARO	2015	13	1	8.09	5.35%	-28.74%	-1.54%	0.00%
66	SOMEC	2019	16	1	6.54	20.66%	16.24%	3.36%	0.00%
66	SOMEC	2018	16	1	6.22	23.71%	5.67%	1.34%	0.04%
66	SOMEC	2017	16	1	5.57	11.13%	-1.08%	-0.12%	0.23%
66	SOMEC	2016	16	1					
66	SOMEC	2015	16	1					
67	PRIMA INDUSTRIE	2019	6	1	7.48	33.67%	5.17%	1.74%	0.20%
67	PRIMA INDUSTRIE	2018	6	1	7.53	31.26%	14.17%	4.43%	0.19%
67	PRIMA INDUSTRIE	2017	6	1	7.48	29.01%	12.43%	3.61%	0.16%
67	PRIMA INDUSTRIE	2016	6	1		29.82%	7.27%	2.17%	0.19%
67	PRIMA INDUSTRIE	2015	6	1	7.40	30.07%	4.60%	1.38%	0.18%
68	TOSCANA AEROPORTI	2019	13	2		44.64%	11.84%	5.28%	0.33%
68	TOSCANA AEROPORTI	2018	13	2		46.69%	12.31%	5.75%	0.49%
68	TOSCANA AEROPORTI	2017	13	2	6.58	45.55%	9.29%	4.23%	0.57%
68	TOSCANA AEROPORTI	2016	13	2	6.56	47.18%	8.74%	4.13%	0.13%
68	TOSCANA AEROPORTI	2015	13	2		45.13%	7.69%	3.47%	0.13%
69	TAS	2019	3	2	6.17	39.44%	18.04%	7.12%	4.90%
69	TAS	2018	3	2	6.25	37.80%	0.81%	0.31%	6.21%
69	TAS	2017	3	2	5.93	33.61%	6.24%	2.10%	6.63%
69	TAS	2016	3	2	6.00	43.44%	-13.14%	-5.71%	7.33%
69	TAS	2015	3	2	5.97	0.97%		-16.29%	7.52%
70	ROSETTI MARINO	2019	4	1	7.14	48.87%	2.25%	1.10%	0.11%
70	ROSETTI MARINO	2018	4	1		47.77%	2.99%	1.43%	0.05%
70	ROSETTI MARINO	2017	4	1	6.94	49.50%	-3.25%	-1.61%	0.12%
70	ROSETTI MARINO	2016	4	1	6.97	49.30%	0.94%	0.47%	0.07%
70	ROSETTI MARINO	2015	4	1	6.70	53.68%	0.89%	0.48%	0.08%
71	B&C SPEAKERS	2019	2	2	5.23	52.60%	31.88%	16.77%	0.75%
71	B&C SPEAKERS	2018	2	2	5.16	49.99%	41.07%	20.53%	1.00%
71	B&C SPEAKERS	2017	2	2	5.09	41.38%	34.97%	14.47%	1.95%
71	B&C SPEAKERS	2016	2	2		69.70%	27.96%	19.49%	1.11%
71	B&C SPEAKERS	2015	2	2	4.74	64.84%	27.75%	17.99%	0.98%
72	SABAF	2019	6	1	6.94	49.10%	8.19%	4.02%	0.32%
72	SABAF	2018	6	1	6.68	52.21%	13.08%	6.83%	0.28%
72	SABAF	2017	6	1	6.63	62.29%	12.89%	8.03%	0.33%
72	SABAF	2016	6	1	6.63	62.74%	8.02%	5.03%	0.26%
72	SABAF	2015	6	1	6.62	64.47%	8.10%	5.23%	0.29%
73	EMAK	2019	6	1	6.04	40.29%	6.12%	2.47%	0.22%
73	EMAK	2018	6	1	6.07	40.22%	12.34%	4.96%	0.22%
73	EMAK	2017	6	1	6.11	37.96%	8.62%	3.27%	0.21%
73	EMAK	2016	6	1	6.11	44.73%	9.69%	4.33%	0.26%
73	EMAK	2015	6	1	6.10	39.89%	5.25%	2.09%	0.11%
74	RATTI	2019	12	1	6.72	42.61%	21.47%	9.15%	1.07%
74	RATTI	2018	12	1	6.67	40.48%	19.83%	8.03%	0.78%
74	RATTI	2017	12	1	6.59	41.56%	13.07%	5.43%	0.68%
74	RATTI	2016	12	1	6.53	40.81%	8.60%	3.51%	0.59%
74	RATTI	2015	12	1	6.51	42.24%	7.96%	3.36%	0.65%
75	CAREL	2019	6	1	7.43	40.88%	24.45%	10.00%	0.93%
75	CAREL	2018	6	1	7.36	37.29%	25.94%	9.67%	0.78%
75	CAREL	2017	6	1	7.22	51.43%	26.36%	13.56%	0.87%
75	CAREL	2016	6	1					
75	CAREL	2015	6	1					
76	BASTOGI	2019	4	1	5.71	17.25%	-5.05%	-0.87%	0.06%
76	BASTOGI	2018	4	1	5.60	18.97%	22.26%	4.22%	0.09%
76	BASTOGI	2017	4	1	5.56	10.52%	17.45%	1.84%	0.07%
76	BASTOGI	2016	4	1	5.58	9.31%	-21.99%	-2.05%	0.08%
76	BASTOGI	2015	4	1	5.69	11.75%	-7.26%	-0.85%	0.09%
77	GPI	2019	11	1	8.58	21.06%	12.98%	2.73%	0.14%
77	GPI	2018	11	1	8.38	23.69%	13.45%	3.19%	0.10%
77	GPI	2017	11	1	8.27	24.91%	12.24%	3.05%	0.07%
77	GPI	2016	11	1					
77	GPI	2015	11	1					
78	VALSOIA	2019	5	1	4.80	72.74%	10.19%	7.41%	2.28%
78	VALSOIA	2018	5	1	4.84	72.03%	14.99%	10.80%	2.61%
78	VALSOIA	2017	5	1	4.81	72.34%	11.51%	8.33%	3.31%
78	VALSOIA	2016	5	1	4.78	72.98%	15.46%	11.29%	0.61%
78	VALSOIA	2015	5	1	4.73	64.78%	22.40%	14.51%	0.72%
79	PITECO	2019	6	1		43.14%	9.60%	4.14%	15.64%
79	PITECO	2018	6	1	4.74	43.21%	16.91%	7.31%	17.56%
79	PITECO	2017	6	1	4.63	61.21%	11.32%	6.93%	17.48%
79	PITECO	2016	6	1	4.45	70.19%	14.06%	9.87%	2.05%
79	PITECO	2015	6	1	4.39	65.43%	11.66%	7.63%	1.85%
80	GAS PLUS	2019	1	1	5.08	39.08%	-0.29%	-0.11%	0.02%
80	GAS PLUS	2018	1	1	5.07	40.68%	-0.87%	-0.35%	0.01%
80	GAS PLUS	2017	1	1	5.20	40.54%	0.36%	0.15%	0.01%
80	GAS PLUS	2016	1	1	5.26	40.30%	-1.99%	-0.80%	0.01%
80	GAS PLUS	2015	1	1	5.23	41.06%	3.19%	1.31%	0.02%

81	NEWRON	2019	1	1	3.26	61.04%	-54.91%	-33.52%	0.03%
81	NEWRON	2018	1	1	3.18	91.82%	-27.41%	-25.17%	0.05%
81	NEWRON	2017	1	1	3.14	92.74%	-7.80%	-7.23%	0.05%
81	NEWRON	2016	1	1	3.14	87.91%	-30.63%	-26.93%	0.02%
81	NEWRON	2015	1	1	3.14	83.62%	-61.48%	-51.41%	0.03%
82	LANDI RENZO	2019	1	1	6.35	30.44%	9.12%	2.78%	0.18%
82	LANDI RENZO	2018	1	1	6.22	30.07%	7.84%	2.36%	0.15%
82	LANDI RENZO	2017	1	1	6.64	29.21%	7.30%	2.13%	0.21%
82	LANDI RENZO	2016	1	1	6.66	21.24%	-56.00%	-11.90%	0.23%
82	LANDI RENZO	2015	1	1	6.74	27.64%	-49.14%	-13.58%	0.33%
83	MASI AGRICOLA	2019	5	1	4.93	75.95%	3.39%	2.57%	0.07%
83	MASI AGRICOLA	2018	5	1	4.88	80.95%	5.57%	4.51%	0.12%
83	MASI AGRICOLA	2017	5	1	4.90	79.11%	5.51%	4.36%	0.13%
83	MASI AGRICOLA	2016	5	1		79.14%	5.43%	4.30%	0.17%
83	MASI AGRICOLA	2015	5	1		77.07%	5.89%	4.54%	0.17%
84	GEFRAN	2019	6	1	6.72	47.57%	9.38%	4.46%	0.20%
84	GEFRAN	2018	6	1	6.65	53.08%	11.19%	5.94%	0.19%
84	GEFRAN	2017	6	1	6.59	49.75%	9.82%	4.89%	0.17%
84	GEFRAN	2016	6	1		47.88%	5.90%	2.83%	0.20%
84	GEFRAN	2015	6	1	6.72	42.18%	-7.57%	-3.19%	0.24%
85	ITALIAN WINE	2019	16	1	5.04	45.76%	8.86%	4.05%	0.50%
85	ITALIAN WINE	2018	16	1	5.04	44.86%	7.53%	3.38%	0.49%
85	ITALIAN WINE	2017	16	1	5.08	45.56%	8.25%	3.76%	0.03%
85	ITALIAN WINE	2016	16	1	5.36	43.28%	5.70%	2.47%	0.03%
85	ITALIAN WINE	2015	16	1	5.91	42.06%	4.99%	2.10%	0.07%
86	PININFARINA	2019	13	1	6.51	32.10%	-59.16%	-18.99%	0.01%
86	PININFARINA	2018	13	1	6.45	47.00%	3.52%	1.65%	0.50%
86	PININFARINA	2017	13	1	6.38	46.70%	2.23%	1.04%	0.56%
86	PININFARINA	2016	13	1	6.36	30.07%	67.39%	20.27%	0.78%
86	PININFARINA	2015	13	1	6.43	8.15%	-184.84%	-15.06%	0.83%
87	PIQUADRO	2019	7	1	7.01	29.74%	-12.46%	-3.71%	0.89%
87	PIQUADRO	2018	7	1	7.06	47.19%	47.01%	22.18%	1.14%
87	PIQUADRO	2017	7	1	6.69	40.59%	11.99%	4.87%	1.81%
87	PIQUADRO	2016	7	1	6.63	42.28%	8.97%	3.79%	2.11%
87	PIQUADRO	2015	7	1	6.53	51.68%	10.73%	5.54%	0.50%
88	MAILUP	2019	3	1	5.04	31.58%	6.78%	2.14%	6.26%
88	MAILUP	2018	3	1	5.00	37.05%	7.88%	2.92%	7.28%
88	MAILUP	2017	3	1	4.94	43.39%	3.93%	1.71%	10.81%
88	MAILUP	2016	3	1	4.96	27.63%	11.11%	3.07%	14.13%
88	MAILUP	2015	3	1	4.88	37.57%	-0.17%	-0.06%	15.50%
89	RISANAMENTO	2019	4	1	3.37	20.07%	2.71%	0.54%	0.01%
89	RISANAMENTO	2018	4	1	3.40	14.96%	-17.59%	-2.63%	0.00%
89	RISANAMENTO	2017	4	1	3.40	17.15%	-14.28%	-2.45%	0.00%
89	RISANAMENTO	2016	4	1	3.47	18.93%	-34.18%	-6.47%	0.00%
89	RISANAMENTO	2015	4	1	3.56	23.71%	-18.84%	-4.47%	0.00%
90	LEONE FILM	2019	8	2	3.78	25.22%	2.40%	0.61%	0.00%
90	LEONE FILM	2018	8	2	3.69	28.26%	15.57%	4.40%	0.01%
90	LEONE FILM	2017	8	2	3.37	26.34%	10.91%	2.87%	0.01%
90	LEONE FILM	2016	8	2	3.04	30.71%	5.51%	1.69%	0.02%
90	LEONE FILM	2015	8	2	2.89	37.11%	10.95%	4.06%	0.04%
91	ENERVIT	2019	1	1	5.45	41.72%	3.47%	1.45%	0.99%
91	ENERVIT	2018	1	1	5.31	54.02%	15.80%	8.54%	1.05%
91	ENERVIT	2017	1	1	5.29	50.61%	11.81%	5.98%	1.21%
91	ENERVIT	2016	1	1	5.30	51.45%	10.69%	5.50%	1.41%
91	ENERVIT	2015	1	1		53.41%	-0.64%	-0.34%	1.57%
92	IRCE	2019	9	1	6.56	62.29%	1.48%	0.92%	0.00%
92	IRCE	2018	9	1	6.58	56.35%	4.48%	2.52%	0.00%
92	IRCE	2017	9	1	6.58	55.24%	3.54%	1.96%	0.02%
92	IRCE	2016	9	1	6.60	61.15%	0.04%	0.03%	0.01%
92	IRCE	2015	9	1	6.61	60.31%	2.25%	1.36%	0.01%
93	FOPE	2019	14	1	4.03	52.46%	23.21%	12.18%	3.03%
93	FOPE	2018	14	1	3.26	49.53%	20.95%	10.38%	1.50%
93	FOPE	2017	14	1	3.14	49.34%	19.58%	9.66%	1.82%
93	FOPE	2016	14	1		45.95%	11.15%	5.13%	2.45%
93	FOPE	2015	14	1		35.39%	15.95%	5.65%	2.72%
94	BEGHELLI	2019	6	1	7.08	39.29%	-1.43%	-0.56%	0.11%
94	BEGHELLI	2018	6	1	7.27	35.85%	-9.75%	-3.50%	0.12%
94	BEGHELLI	2017	6	1	7.25	35.88%	3.31%	1.19%	0.10%
94	BEGHELLI	2016	6	1	7.23	34.80%	3.60%	1.25%	0.11%
94	BEGHELLI	2015	6	1	7.27	32.94%	0.47%	0.16%	0.11%
95	COVER 50	2019	12	1	4.08	77.93%	12.28%	9.57%	0.23%
95	COVER 51	2018	12	1	4.01	75.90%	16.07%	12.19%	0.27%
95	COVER 52	2017	12	1	3.93	76.32%	13.92%	10.62%	0.39%
95	COVER 53	2016	12	1		75.51%	17.52%	13.23%	0.37%
95	COVER 54	2015	12	1		76.29%	19.18%	14.63%	0.06%
96	TESMEC	2019	6	1	5.89	15.56%	6.43%	1.00%	0.06%
96	TESMEC	2018	6	1	5.84	15.74%	0.07%	0.01%	0.08%
96	TESMEC	2017	6	1	5.80	19.23%	-3.19%	-0.61%	0.12%
96	TESMEC	2016	6	1	5.75	21.31%	-7.90%	-1.68%	0.19%
96	TESMEC	2015	6	1	6.34	22.82%	12.40%	2.83%	0.24%

97	PIERREL	2019	1	3	4.52	41.32%	16.69%	6.90%	0.14%
97	PIERREL	2018	1	3	4.51	32.81%	7.46%	2.45%	0.14%
97	PIERREL	2017	1	3	4.44	8.60%	-111.62%	-9.59%	0.19%
97	PIERREL	2016	1	3	4.47	-24.83%		7.80%	0.15%
97	PIERREL	2015	1	3	4.52	1.66%		-24.69%	0.03%
98	B&T GROUP	2019	6	1	6.39	33.44%	3.39%	1.13%	0.05%
98	B&T GROUP	2018	6	1	6.36	37.54%	7.83%	2.94%	0.05%
98	B&T GROUP	2017	6	1	6.35	34.01%	6.21%	2.11%	0.04%
98	B&T GROUP	2016	6	1	6.30	30.65%	12.22%	3.75%	0.03%
98	B&T GROUP	2015	6	1	6.32	23.01%	11.22%	2.58%	0.03%
99	SIRIO	2019	14	1	6.71	9.70%	-27.22%	-2.64%	0.10%
99	SIRIO	2018	14	1	6.52	15.23%	15.51%	2.36%	0.15%
99	SIRIO	2017	14	1	6.43	16.25%	24.16%	3.93%	0.49%
99	SIRIO	2016	14	1	6.30	8.60%	7.47%	0.64%	1.44%
99	SIRIO	2015	14	1	6.09	8.71%	6.07%	0.53%	1.82%
100	PLC	2019	4	1	6.03	37.75%	-9.96%	-3.76%	0.03%
100	PLC	2018	4	1	5.30	36.17%	20.38%	7.37%	0.01%
100	PLC	2017	4	1	4.84	40.35%	39.15%	15.80%	0.00%
100	PLC	2016	4	1	1.10	-77.95%		-7.92%	0.08%
100	PLC	2015	4	1	1.95	-17.99%		-27.44%	0.05%
101	VIANINI	2019	7	2		36.03%	2.13%	0.77%	0.00%
101	VIANINI	2018	7	2	1.79	38.18%	1.16%	0.44%	0.00%
101	VIANINI	2017	7	2	1.95	37.44%	1.84%	0.69%	0.01%
101	VIANINI	2016	7	2	3.43	33.42%	2.49%	0.83%	0.02%
101	VIANINI	2015	7	2	3.33	91.41%	0.45%	0.41%	0.04%
102	GIBUS	2019	12	1	5.22	51.92%	19.62%	10.19%	3.69%
102	GIBUS	2018	12	1	5.19	39.05%	28.38%	11.08%	4.95%
102	GIBUS	2017	12	1	5.06	41.95%	27.76%	11.65%	2.39%
102	GIBUS	2016	12	1					
102	GIBUS	2015	12	1					
103	TPS	2019	13	1	6.17	54.55%	12.35%	6.74%	1.24%
103	TPS	2018	13	1	6.05	61.13%	11.89%	7.27%	1.36%
103	TPS	2017	13	1	5.42	45.94%	26.31%	12.09%	1.73%
103	TPS	2016	13	1	4.90	35.95%	59.45%	21.38%	2.47%
103	TPS	2015	13	1	4.67	22.74%	40.21%	9.15%	2.34%
104	PRISMI	2019	16	1	4.98	6.74%	-153.37%	-10.34%	0.06%
104	PRISMI	2018	16	1		12.71%	-26.73%	-3.40%	0.00%
104	PRISMI	2017	16	1	4.76	7.07%	-138.33%	-9.78%	0.01%
104	PRISMI	2016	16	1		6.06%	-193.81%	-11.74%	0.03%
104	PRISMI	2015	16	1		6.88%	-400.92%	-27.56%	0.19%
105	TREVI	2019	4	1	8.68	-21.11%		-7.20%	0.01%
105	TREVI	2018	4	1	8.76	-13.19%		-12.84%	0.01%
105	TREVI	2017	4	1		-0.09%		-35.89%	0.01%
105	TREVI	2016	4	1	8.89	28.21%	-19.54%	-5.51%	0.01%
105	TREVI	2015	4	1	8.97	29.92%	-19.87%	-5.95%	0.01%
106	POLIGRAFICI EDITORIALE	2019	10	1	6.71	18.49%	-21.92%	-4.05%	0.19%
106	POLIGRAFICI EDITORIALE	2018	10	1	6.73	22.94%	1.62%	0.37%	0.26%
106	POLIGRAFICI EDITORIALE	2017	10	1	6.72	21.32%	3.95%	0.84%	0.34%
106	POLIGRAFICI EDITORIALE	2016	10	1	6.73	21.89%	2.33%	0.51%	0.34%
106	POLIGRAFICI EDITORIALE	2015	10	1	6.77	20.59%	-6.94%	-1.43%	0.43%
107	EUKEDOS	2019	6	2	6.93	20.09%	1.98%	0.40%	0.00%
107	EUKEDOS	2018	6	2	6.92	48.44%	3.46%	1.68%	0.00%
107	EUKEDOS	2017	6	2	6.89	46.12%	-7.54%	-3.48%	0.00%
107	EUKEDOS	2016	6	2	6.89	48.09%	0.43%	0.21%	0.00%
107	EUKEDOS	2015	6	2	6.77	40.09%	-2.75%	-1.10%	0.00%
108	CSP	2019	12	1		45.72%	-6.36%	-2.91%	0.21%
108	CSP	2018	12	1	6.61	48.92%	-20.27%	-9.91%	0.03%
108	CSP	2017	12	1	6.66	51.71%	1.41%	0.73%	0.30%
108	CSP	2016	12	1	6.71	51.75%	2.26%	1.17%	0.23%
108	CSP	2015	12	1	6.74	53.68%	2.62%	1.41%	0.27%
109	RESTART	2019	4	1	2.40	60.28%	0.53%	0.32%	0.00%
109	RESTART	2018	4	1	4.14	47.61%	1.57%	0.75%	0.23%
109	RESTART	2017	4	1	4.11	53.26%	2.91%	1.55%	0.01%
109	RESTART	2016	4	1	4.17	60.42%	9.60%	5.80%	0.01%
109	RESTART	2015	4	1	4.30	57.74%	1.88%	1.09%	0.01%
110	CALEFFI	2019	12	1	5.06	27.74%	-0.02%	0.00%	0.01%
110	CALEFFI	2018	12	1	5.09	29.39%	-6.69%	-1.97%	0.01%
110	CALEFFI	2017	12	1	5.06	30.21%	0.50%	0.15%	0.01%
110	CALEFFI	2016	12	1		28.96%	3.41%	0.99%	0.01%
110	CALEFFI	2015	12	1	5.27	28.82%	2.04%	0.59%	0.02%
111	FRENDY	2019	15	1		76.51%	0.03%	0.02%	0.00%
111	FRENDY	2018	15	1		72.64%	-30.50%	-22.15%	0.00%
111	FRENDY	2017	15	1		62.75%	-5.12%	-3.21%	0.01%
111	FRENDY	2016	15	1		61.60%	-3.60%	-2.22%	0.01%
111	FRENDY	2015	15	1		57.68%	0.26%	0.15%	0.01%
112	POLIGRAFICI PRINTING	2019	10	1	4.61	71.29%	6.72%	4.79%	1.53%
112	POLIGRAFICI PRINTING	2018	10	1	4.54	76.26%	8.82%	6.72%	2.32%
112	POLIGRAFICI PRINTING	2017	10	1	4.49	67.56%	12.16%	8.21%	2.64%
112	POLIGRAFICI PRINTING	2016	10	1	4.62	49.86%	6.06%	3.02%	2.24%
112	POLIGRAFICI PRINTING	2015	10	1	4.62	44.21%	7.68%	3.39%	2.30%

113	CULTI MILANO	2019	1	1	3.76	65.95%	3.83%	2.53%	0.35%
113	CULTI MILANO	2018	1	1	3.37	86.33%	-1.90%	-1.64%	0.66%
113	CULTI MILANO	2017	1	1	3.04	85.00%	4.61%	3.92%	0.45%
113	CULTI MILANO	2016	1	1		39.58%	-8.84%	-3.50%	0.88%
113	CULTI MILANO	2015	1	1		1.87%	87.34%	1.63%	1.24%
114	GIORGIO FEDON	2019	6	1	6.87	20.91%	1.82%	0.38%	0.09%
114	GIORGIO FEDON	2018	6	1		21.05%	-48.90%	-10.29%	0.15%
114	GIORGIO FEDON	2017	6	1	7.37	25.82%	-27.10%	-7.00%	0.25%
114	GIORGIO FEDON	2016	6	1	7.34	33.42%	8.31%	2.78%	0.35%
114	GIORGIO FEDON	2015	6	1	7.48	33.82%	7.96%	2.69%	0.57%
115	GAMBERO ROSSO	2019	10	2	4.61	34.61%	4.97%	1.72%	0.49%
115	GAMBERO ROSSO	2018	10	2	4.57	36.10%	7.94%	2.87%	0.80%
115	GAMBERO ROSSO	2017	10	2	4.60	32.39%	11.15%	3.61%	1.04%
115	GAMBERO ROSSO	2016	10	2	4.61	28.97%	7.15%	2.07%	0.92%
115	GAMBERO ROSSO	2015	10	2	4.62	28.18%	6.49%	1.83%	0.63%
116	VINCENZO ZUCCHI	2019	12	1	6.27	-12.61%		1.98%	0.27%
116	VINCENZO ZUCCHI	2018	12	1	6.27	-17.12%		4.25%	0.36%
116	VINCENZO ZUCCHI	2017	12	1	6.36	-22.18%		3.62%	0.27%
116	VINCENZO ZUCCHI	2016	12	1	6.29	-27.79%		4.91%	0.29%
116	VINCENZO ZUCCHI	2015	12	1	6.52	-42.18%		-20.80%	0.32%
117	ENERTRONICA	2019	15	1	4.82	0.29%	153.91%	0.45%	0.00%
117	ENERTRONICA	2018	15	1		-0.33%		-18.65%	0.09%
117	ENERTRONICA	2017	15	1	3.00	12.28%	-33.16%	-4.07%	0.07%
117	ENERTRONICA	2016	15	1	2.94	12.28%	22.48%	2.76%	0.08%
117	ENERTRONICA	2015	15	1		5.66%	33.52%	1.90%	0.11%
118	ILLA	2019	6	1	4.09	12.50%	-81.67%	-10.21%	0.33%
118	ILLA	2018	6	1		19.82%	-13.76%	-2.73%	0.30%
118	ILLA	2017	6	1		18.64%	2.10%	0.39%	0.24%
118	ILLA	2016	6	1		6.83%	19.27%	1.32%	0.20%
118	ILLA	2015	6	1		7.44%	15.64%	1.16%	0.19%
119	ITWAY	2019	3	1	3.78	21.14%	25.49%	5.39%	0.26%
119	ITWAY	2018	3	1	3.78	16.52%	8.34%	1.38%	0.25%
119	ITWAY	2017	3	1	3.81	17.49%	6.75%	1.18%	0.25%
119	ITWAY	2016	3	1	5.18	11.70%	-3.27%	-0.38%	0.08%
119	ITWAY	2015	3	1	5.40	11.51%	0.25%	0.03%	0.09%
120	TITANMET	2019	2	1		13.78%	-271.90%	-37.48%	0.00%
120	TITANMET	2018	2	1		36.25%	-33.86%	-12.28%	0.00%
120	TITANMET	2017	2	1		9.65%	161.83%	15.61%	0.00%
120	TITANMET	2016	2	1		4.24%	-981.82%	-41.63%	0.00%
120	TITANMET	2015	2	1		7.42%	-263.61%	-19.57%	0.00%
121	NATUZZI	2019	16	3	8.44	28.38%	-31.84%	-9.03%	0.10%
121	NATUZZI	2018	16	3	8.49	37.08%	24.09%	8.93%	0.06%
121	NATUZZI	2017	16	3	8.54	34.14%	-28.94%	-9.88%	0.59%
121	NATUZZI	2016	16	3	8.55	43.91%	-3.99%	-1.75%	0.49%
121	NATUZZI	2015	16	3	8.64	45.96%	-10.27%	-4.72%	0.67%
122	GVS	2019	6	1	7.75	31.97%	35.12%	11.23%	0.95%
122	GVS	2018	6	1	7.72	23.05%	24.94%	5.75%	0.97%
122	GVS	2017	6	1	7.76	20.29%	6.49%	1.32%	0.73%
122	GVS	2016	6	1	7.51	41.09%	17.87%	7.34%	1.16%
122	GVS	2015	6	1	7.49	41.92%	14.65%	6.14%	1.11%

Appendix 2: Data for Regression on Risk of Bankruptcy

ID	NAME	YEAR	SECTOR ID	REGION ID	LN EMPLOYEES	SOLVENCY RATIO	Z SCORE	RESULT	SOFTWARE/TOT.ASSETS
1	MONCLER	2019	9	1	8.43	50.92%	7.39	2	1.07%
1	MONCLER	2018	9	1	8.33	65.75%	8.66	2	0.94%
1	MONCLER	2017	9	1	8.16	66.92%	17.91	2	0.93%
1	MONCLER	2016	9	1	8.08	61.09%	9.83	2	0.95%
1	MONCLER	2015	9	1	7.72	54.03%	6.00	2	0.92%
2	RECORDATI	2019	1	1	8.37	42.68%	4.95	2	5.70%
2	RECORDATI	2018	1	1	8.33	44.54%	5.16	2	7.87%
2	RECORDATI	2017	1	1	8.34	49.95%	7.32	2	8.76%
2	RECORDATI	2016	1	1	8.32	57.92%	8.50	2	0.23%
2	RECORDATI	2015	1	1	8.28	59.23%	11.36	2	0.27%
3	DIASORIN	2019	1	1	7.57	79.79%	73.43	2	2.80%
3	DIASORIN	2018	1	1	7.59	77.79%	10.03	2	3.21%
3	DIASORIN	2017	1	1	7.55	78.45%	20.87	2	3.01%
3	DIASORIN	2016	1	1	7.52	76.37%	15.01	2	3.24%
3	DIASORIN	2015	1	1	7.41	82.94%	52.75	2	3.85%
4	AMPLIFON	2019	5	1		24.41%	2.75	1	1.79%
4	AMPLIFON	2018	5	1	9.25	26.88%	2.14	1	1.74%
4	AMPLIFON	2017	5	1	9.00	40.15%	3.67	2	2.20%
4	AMPLIFON	2016	5	1	8.88	39.66%	3.10	2	2.18%
4	AMPLIFON	2015	5	1	8.75	38.86%	3.19	2	1.78%
5	INWIT	2019	2	1	4.80	60.22%	4.14	2	2.50%
5	INWIT	2018	2	1	4.76	80.12%	5.22	2	3.22%
5	INWIT	2017	2	1	4.57	84.09%	62.55	2	3.06%
5	INWIT	2016	2	1	4.48	83.66%	6.14	2	1.99%
5	INWIT	2015	2	1	4.25	83.61%	20.33	2	0.73%
6	BREMBO	2019	10	1	9.29	50.61%	3.86	2	0.36%
6	BREMBO	2018	10	1	9.27	48.55%	3.27	2	0.31%
6	BREMBO	2017	10	1	9.19	46.29%	4.19	2	0.20%
6	BREMBO	2016	10	1	9.11	44.91%	5.03	2	0.15%
6	BREMBO	2015	10	1	8.97	43.39%	4.86	2	0.16%
7	FERRAGAMO	2019	9	2	8.32	42.59%	3.23	2	0.11%
7	FERRAGAMO	2018	9	2	8.35	65.73%	5.60	2	0.22%
7	FERRAGAMO	2017	9	2	8.34	63.29%	6.77	2	0.24%
7	FERRAGAMO	2016	9	2	8.32	60.46%	8.50	2	0.12%
7	FERRAGAMO	2015	9	2	8.30	54.17%	6.38	2	0.14%
8	ENAV	2019	10	2	8.34	54.76%	3.11	2	1.18%
8	ENAV	2018	10	2	8.32	55.61%	2.53	1	0.77%
8	ENAV	2017	10	2	8.34	55.90%	3.03	2	0.74%
8	ENAV	2016	10	2	8.35	55.82%	1.98	1	0.60%
8	ENAV	2015	10	2					
9	REPLY	2019	7	1	8.98	44.89%	4.23	2	0.41%
9	REPLY	2018	7	1	8.86	45.22%	3.24	2	0.35%
9	REPLY	2017	7	1	8.77	46.15%	3.32	2	0.37%
9	REPLY	2016	7	1	8.70	43.80%	3.41	2	0.49%
9	REPLY	2015	7	1	8.57	42.25%	4.26	2	0.53%
10	IMA	2019	5	1	8.69	21.94%	2.00	1	8.44%
10	IMA	2018	5	1	8.63	25.36%	2.59	1	6.21%
10	IMA	2017	5	1	8.63	25.91%	3.06	2	4.14%
10	IMA	2016	5	1	8.57	19.63%	2.79	1	4.75%
10	IMA	2015	5	1	8.47	14.96%	2.57	1	5.96%
11	TECHNOGYM	2019	11	1	7.66	40.73%	6.27	2	2.62%
11	TECHNOGYM	2018	11	1	7.67	34.60%	4.97	2	2.49%
11	TECHNOGYM	2017	11	1	7.57	26.90%	5.06	2	3.06%
11	TECHNOGYM	2016	11	1	7.53	19.15%			1.90%
11	TECHNOGYM	2015	11	1	7.54	12.33%			1.96%
12	CUCINELLI	2019	9	2	7.54	30.03%	2.92	1	1.02%
12	CUCINELLI	2018	9	2	7.46	57.97%	7.26	2	1.89%
12	CUCINELLI	2017	9	2	7.38	58.48%	9.29	2	1.42%
12	CUCINELLI	2016	9	2	7.27	52.54%	7.35	2	1.29%
12	CUCINELLI	2015	9	2	7.22	47.87%	4.76	2	0.75%
13	RAI WAY	2019	7	2	6.42	53.65%	9.32	2	1.58%
13	RAI WAY	2018	7	2	6.42	61.51%	7.64	2	0.93%
13	RAI WAY	2017	7	2	6.40	52.39%	7.69	2	0.63%
13	RAI WAY	2016	7	2	6.43	44.02%	4.19	2	0.29%
13	RAI WAY	2015	7	2	6.46	41.17%	5.05	2	0.19%
14	FALCK	2019	12	1	6.15	33.97%	1.36	0	0.32%
14	FALCK	2018	12	1	5.97	34.53%	1.03	0	0.07%
14	FALCK	2017	12	1	5.85	31.27%	0.94	0	0.08%
14	FALCK	2016	12	1	5.77	31.88%	0.63	0	0.07%
14	FALCK	2015	12	1	5.70	36.23%	0.68	0	0.04%
15	MARR	2019	13	1	6.71	30.66%	3.27	2	0.22%
15	MARR	2018	13	1	6.74	31.58%	3.53	2	0.21%
15	MARR	2017	13	1	6.70	30.76%	3.68	2	0.18%
15	MARR	2016	13	1	6.74	30.48%	3.38	2	0.12%
15	MARR	2015	13	1	6.69	31.66%	3.90	2	0.09%

16	CEMENTIR	2019	6	2	8.02	52.14%	1.66	0	0.22%
16	CEMENTIR	2018	6	2	8.03	52.92%	1.45	0	0.19%
16	CEMENTIR	2017	6	2	8.01	43.09%	1.69	0	0.18%
16	CEMENTIR	2016	6	2	8.21	43.54%	1.02	0	0.11%
16	CEMENTIR	2015	6	2	8.02	61.16%	1.65	0	0.11%
17	DATALOGIC	2019	5	1	8.03	50.23%	3.07	2	1.01%
17	DATALOGIC	2018	5	1	8.06	45.27%	3.05	2	0.90%
17	DATALOGIC	2017	5	1	7.98	42.19%	4.21	2	0.46%
17	DATALOGIC	2016	5	1	7.90	45.28%	3.41	2	0.37%
17	DATALOGIC	2015	5	1	7.85	43.28%	3.19	2	0.37%
18	ASCOPIAVE	2019	12	1	6.18	67.28%	3.70	2	0.31%
18	ASCOPIAVE	2018	12	1	6.52	52.97%	2.25	1	0.16%
18	ASCOPIAVE	2017	12	1	6.51	56.89%	2.65	1	0.78%
18	ASCOPIAVE	2016	12	1	6.43	60.58%	2.71	1	0.44%
18	ASCOPIAVE	2015	12	1	6.42	53.70%			0.03%
19	IGD	2019	3	1	5.18	46.48%	0.56	0	0.00%
19	IGD	2018	3	1	5.19	50.86%	0.38	0	0.00%
19	IGD	2017	3	1	5.17	48.97%	0.66	0	0.00%
19	IGD	2016	3	1	5.14	47.76%	0.48	0	0.00%
19	IGD	2015	3	1	5.11	47.47%	0.54	0	0.00%
20	FILA	2019	1	1	9.22	31.05%	1.78	0	0.00%
20	FILA	2018	1	1	9.17	29.24%	1.62	0	0.00%
20	FILA	2017	1	1	9.04	35.44%	2.65	1	0.01%
20	FILA	2016	1	1	8.96	35.12%	2.10	1	0.01%
20	FILA	2015	1	1	8.71	55.07%	2.87	1	0.02%
21	RCS	2019	8	1	7.38	26.94%	1.53	0	0.10%
21	RCS	2018	8	1	8.10	28.85%	2.04	1	0.11%
21	RCS	2017	8	1	8.13	18.00%	1.24	0	0.19%
21	RCS	2016	8	1	8.18	9.72%	0.69	0	0.29%
21	RCS	2015	8	1	8.30	7.69%	-0.18	0	0.23%
22	AEROPORTO MARCONI	2019	10	1	6.31	66.24%	3.96	2	0.65%
22	AEROPORTO MARCONI	2018	10	1	6.27	66.61%	3.07	2	0.62%
22	AEROPORTO MARCONI	2017	10	1	6.16	66.08%	4.81	2	0.42%
22	AEROPORTO MARCONI	2016	10	1	6.08	63.88%	3.88	2	0.34%
22	AEROPORTO MARCONI	2015	10	1	6.05	61.58%			0.26%
23	CEMBRE	2019	5	1	6.18	78.90%	10.35	2	0.77%
23	CEMBRE	2018	5	1	6.61	78.46%	5.11	2	0.59%
23	CEMBRE	2017	5	1	6.16	83.86%	17.76	2	0.50%
23	CEMBRE	2016	5	1		84.10%	9.73	2	0.34%
23	CEMBRE	2015	5	1	6.44	84.22%	8.56	2	0.44%
24	OVS	2019	9	1	8.62	27.78%	0.45	0	0.00%
24	OVS	2018	9	1	8.77	44.35%	0.98	0	0.00%
24	OVS	2017	9	1	8.76	42.28%	1.71	0	0.00%
24	OVS	2016	9	1	8.80	45.02%	1.62	0	0.00%
24	OVS	2015	9	1	8.78	43.38%	1.70	0	0.00%
25	AVIO	2019	10	2	6.80	29.89%	0.92	0	0.16%
25	AVIO	2018	10	2	6.70	35.58%	1.07	0	0.06%
25	AVIO	2017	10	2		33.49%	0.98	0	0.06%
25	AVIO	2016	10	2		38.05%	1.15	0	0.09%
25	AVIO	2015	10	2		41.44%			0.08%
26	BASICNET	2019	9	1	6.70	41.52%	2.63	1	1.27%
26	BASICNET	2018	9	1	6.39	47.95%	2.80	1	1.49%
26	BASICNET	2017	9	1	6.34	44.19%	2.25	1	1.86%
26	BASICNET	2016	9	1	6.30	44.51%	2.17	1	2.14%
26	BASICNET	2015	9	1	6.23	45.09%	3.67	2	2.20%
27	RENO DE MEDICI	2019	8	1	7.47	39.86%	2.48	1	0.81%
27	RENO DE MEDICI	2018	8	1	7.46	38.61%	2.03	1	0.66%
27	RENO DE MEDICI	2017	8	1	7.30	41.13%	2.21	1	0.13%
27	RENO DE MEDICI	2016	8	1	7.34	38.53%	1.69	0	0.16%
27	RENO DE MEDICI	2015	8	1	7.06	41.35%	1.92	1	0.23%
28	DIGITAL BROS	2019	11	1	5.39	51.35%	6.47	2	1.25%
28	DIGITAL BROS	2018	11	1	5.27	52.95%	2.32	1	1.41%
28	DIGITAL BROS	2017	11	1	5.18	67.44%	3.33	2	2.32%
28	DIGITAL BROS	2016	11	1		58.78%	5.34	2	1.66%
28	DIGITAL BROS	2015	11	1		44.45%	3.00	2	4.17%
29	LA DORIA	2019	4	3	6.68	37.90%	2.00	1	0.10%
29	LA DORIA	2018	4	3	6.63	37.86%	1.97	1	0.16%
29	LA DORIA	2017	4	3	6.61	39.52%	2.93	1	0.22%
29	LA DORIA	2016	4	3	6.46	37.77%	2.35	1	0.24%
29	LA DORIA	2015	4	3	6.63	34.18%	2.77	1	0.18%
30	CALTAGIRONE ED.	2019	8	2	6.42	75.85%	0.81	0	0.00%
30	CALTAGIRONE ED.	2018	8	2	6.46	76.32%	0.59	0	0.00%
30	CALTAGIRONE ED.	2017	8	2	6.51	77.22%	2.65	1	0.00%
30	CALTAGIRONE ED.	2016	8	2	6.61	75.18%	0.79	0	0.00%
30	CALTAGIRONE ED.	2015	8	2	6.69	75.70%	1.15	0	0.00%

31	PHARMANUTRA	2019	1	2	3.99	57.58%	11.59	2	2.75%
31	PHARMANUTRA	2018	1	2	3.87	58.94%	8.61	2	3.27%
31	PHARMANUTRA	2017	1	2	3.74	57.17%	7.29	2	3.29%
31	PHARMANUTRA	2016	1	2	3.56	35.06%			5.91%
31	PHARMANUTRA	2015	1	2		26.73%			7.81%
32	AEFFE	2019	9	1	7.20	40.44%	1.48	0	0.23%
32	AEFFE	2018	9	1	7.15	48.89%	2.02	1	0.35%
32	AEFFE	2017	9	1	7.18	46.19%	2.10	1	0.35%
32	AEFFE	2016	9	1	7.17	44.90%	1.19	0	0.38%
32	AEFFE	2015	9	1	7.15	39.63%	1.20	0	0.55%
33	MASSIMO ZANETTI	2019	4	1	8.18	36.01%	1.66	0	0.41%
33	MASSIMO ZANETTI	2018	4	1	8.12	39.37%	1.94	1	0.26%
33	MASSIMO ZANETTI	2017	4	1	8.10	37.67%	2.08	1	0.15%
33	MASSIMO ZANETTI	2016	4	1	8.09	39.81%	2.04	1	0.22%
33	MASSIMO ZANETTI	2015	4	1	8.01	44.91%	2.55	1	0.24%
34	IMMSI	2019	10	1	8.79	17.75%	0.80	0	0.01%
34	IMMSI	2018	10	1	8.83	17.97%	0.68	0	0.00%
34	IMMSI	2017	10	1	8.85	18.16%	0.76	0	0.00%
34	IMMSI	2016	10	1	8.86	18.13%	0.53	0	0.00%
34	IMMSI	2015	10	1	8.91	19.86%	0.60	0	0.00%
35	CARRARO	2019	10	1		13.54%	1.53	0	0.03%
35	CARRARO	2018	10	1	8.09	14.77%	1.71	0	0.03%
35	CARRARO	2017	10	1	8.06	15.10%	1.76	0	0.02%
35	CARRARO	2016	10	1	8.00	9.61%	1.34	0	0.00%
35	CARRARO	2015	10	1	8.09	5.35%	1.19	0	0.00%
36	SOMEC	2019	13	1	6.54	20.66%	2.04	1	0.00%
36	SOMEC	2018	13	1	6.22	23.71%	2.19	1	0.04%
36	SOMEC	2017	13	1	5.57	11.13%	0.68		0.23%
36	SOMEC	2016	13	1					
36	SOMEC	2015	13	1					
37	PRIMA INDUSTRIE	2019	5	1	7.48	33.67%	1.57	0	0.20%
37	PRIMA INDUSTRIE	2018	5	1	7.53	31.26%	1.64	0	0.19%
37	PRIMA INDUSTRIE	2017	5	1	7.48	29.01%	1.92	1	0.16%
37	PRIMA INDUSTRIE	2016	5	1		29.82%	1.58	0	0.19%
37	PRIMA INDUSTRIE	2015	5	1	7.40	30.07%	1.52	0	0.18%
38	ROSETTI MARINO	2019	3	1	7.14	48.87%	1.92	1	0.11%
38	ROSETTI MARINO	2018	3	1		47.77%	1.85	1	0.05%
38	ROSETTI MARINO	2017	3	1	6.94	49.50%	26.18	2	0.12%
38	ROSETTI MARINO	2016	3	1	6.97	49.30%	6.80	2	0.07%
38	ROSETTI MARINO	2015	3	1	6.70	53.68%	2.74	1	0.08%
39	B&C SPEAKERS	2019	2	2	5.23	52.60%	7.54	2	0.75%
39	B&C SPEAKERS	2018	2	2	5.16	49.99%	5.89	2	1.00%
39	B&C SPEAKERS	2017	2	2	5.09	41.38%	5.50	2	1.95%
39	B&C SPEAKERS	2016	2	2		69.70%	11.96	2	1.11%
39	B&C SPEAKERS	2015	2	2	4.74	64.84%	10.53	2	0.98%
40	SABAF	2019	5	1	6.94	49.10%	1.76	0	0.32%
40	SABAF	2018	5	1	6.68	52.21%	2.10	1	0.28%
40	SABAF	2017	5	1	6.63	62.29%	4.35	2	0.33%
40	SABAF	2016	5	1	6.63	62.74%	2.45	1	0.26%
40	SABAF	2015	5	1	6.62	64.47%	2.51	1	0.29%
41	EMAK	2019	5	1	6.04	40.29%	1.80	1	0.22%
41	EMAK	2018	5	1	6.07	40.22%	2.10	1	0.22%
41	EMAK	2017	5	1	6.11	37.96%	2.02	1	0.21%
41	EMAK	2016	5	1	6.11	44.73%	2.21	1	0.26%
41	EMAK	2015	5	1	6.10	39.89%	1.95	1	0.11%
42	RATTI	2019	9	1	6.72	42.61%	3.29	2	1.07%
42	RATTI	2018	9	1	6.67	40.48%	2.52	1	0.78%
42	RATTI	2017	9	1	6.59	41.56%	2.41	1	0.68%
42	RATTI	2016	9	1	6.53	40.81%	2.06	1	0.59%
42	RATTI	2015	9	1	6.51	42.24%	2.33	1	0.65%
43	CAREL	2019	5	1	7.43	40.88%	2.40	1	0.93%
43	CAREL	2018	5	1	7.36	37.29%	2.13	1	0.78%
43	CAREL	2017	5	1	7.22	51.43%			0.87%
43	CAREL	2016	5	1					
43	CAREL	2015	5	1					
44	BASTOGI	2019	3	1	5.71	17.25%	0.61	0	0.06%
44	BASTOGI	2018	3	1	5.60	18.97%	1.05	0	0.09%
44	BASTOGI	2017	3	1	5.56	10.52%	0.48	0	0.07%
44	BASTOGI	2016	3	1	5.58	9.31%	0.03	0	0.08%
44	BASTOGI	2015	3	1	5.69	11.75%	0.25	0	0.09%
45	VALSOIA	2019	4	1	4.80	72.74%	4.36	2	2.28%
45	VALSOIA	2018	4	1	4.84	72.03%	3.55	2	2.61%
45	VALSOIA	2017	4	1	4.81	72.34%	6.42	2	3.31%
45	VALSOIA	2016	4	1	4.78	72.98%	6.00	2	0.61%
45	VALSOIA	2015	4	1	4.73	64.78%	6.73	2	0.72%

46	GAS PLUS	2019	1	1	5.08	39.08%	0.37	0	0.02%
46	GAS PLUS	2018	1	1	5.07	40.68%	0.33	0	0.01%
46	GAS PLUS	2017	1	1	5.20	40.54%	0.40	0	0.01%
46	GAS PLUS	2016	1	1	5.26	40.30%	0.57	0	0.01%
46	GAS PLUS	2015	1	1	5.23	41.06%	0.57	0	0.02%
47	LANDI RENZO	2019	1	1	6.35	30.44%	1.61	0	0.18%
47	LANDI RENZO	2018	1	1	6.22	30.07%	1.80	0	0.15%
47	LANDI RENZO	2017	1	1	6.64	29.21%	2.01	1	0.21%
47	LANDI RENZO	2016	1	1	6.66	21.24%	0.59	0	0.23%
47	LANDI RENZO	2015	1	1	6.74	27.64%	0.48	0	0.33%
48	MASI AGRICOLA	2019	4	1	4.93	75.95%	2.10	1	0.07%
48	MASI AGRICOLA	2018	4	1	4.88	80.95%	2.81	1	0.12%
48	MASI AGRICOLA	2017	4	1	4.90	79.11%	3.42	2	0.13%
48	MASI AGRICOLA	2016	4	1		79.14%	4.65	2	0.17%
48	MASI AGRICOLA	2015	4	1		77.07%			0.17%
49	GEFRAN	2019	5	1	6.72	47.57%	2.11	1	0.20%
49	GEFRAN	2018	5	1	6.65	53.08%	2.40	1	0.19%
49	GEFRAN	2017	5	1	6.59	49.75%	2.84	1	0.17%
49	GEFRAN	2016	5	1		47.88%	1.69	0	0.20%
49	GEFRAN	2015	5	1	6.72	42.18%	0.99	0	0.24%
50	PIQUADRO	2019	6	1	7.01	29.74%	1.61	0	0.89%
50	PIQUADRO	2018	6	1	7.06	47.19%	2.56	1	1.14%
50	PIQUADRO	2017	6	1	6.69	40.59%	3.23	2	1.81%
50	PIQUADRO	2016	6	1	6.63	42.28%	2.96	1	2.11%
50	PIQUADRO	2015	6	1	6.53	51.68%	3.32	2	0.50%
51	RISANAMENTO	2019	3	1	3.37	20.07%	1.28	0	0.01%
51	RISANAMENTO	2018	3	1	3.40	14.96%	0.76	0	0.00%
51	RISANAMENTO	2017	3	1	3.40	17.15%			0.00%
51	RISANAMENTO	2016	3	1	3.47	18.93%	0.25	0	0.00%
51	RISANAMENTO	2015	3	1	3.56	23.71%	0.29	0	0.00%
52	LEONE FILM	2019	7	2	3.78	25.22%	0.89	0	0.00%
52	LEONE FILM	2018	7	2	3.69	28.26%	1.43	0	0.01%
52	LEONE FILM	2017	7	2	3.37	26.34%	1.29	0	0.01%
52	LEONE FILM	2016	7	2	3.04	30.71%	0.86	0	0.02%
52	LEONE FILM	2015	7	2	2.89	37.11%	1.06	0	0.04%
53	ENERVIT	2019	1	1	5.45	41.72%	2.36	1	0.99%
53	ENERVIT	2018	1	1	5.31	54.02%	3.33	2	1.05%
53	ENERVIT	2017	1	1	5.29	50.61%	3.50	2	1.21%
53	ENERVIT	2016	1	1	5.30	51.45%	3.16	2	1.41%
53	ENERVIT	2015	1	1		53.41%	3.09	2	1.57%
54	FOPE	2019	11	1	4.03	52.46%	3.77	2	3.03%
54	FOPE	2018	11	1	3.26	49.53%	3.24	2	1.50%
54	FOPE	2017	11	1	3.14	49.34%	4.07	2	1.82%
54	FOPE	2016	11	1		45.95%	2.53	1	2.45%
54	FOPE	2015	11	1		35.39%			2.72%
55	BEGHELLI	2019	5	1	7.08	39.29%	0.98	0	0.11%
55	BEGHELLI	2018	5	1	7.27	35.85%	0.98	0	0.12%
55	BEGHELLI	2017	5	1	7.25	35.88%	1.45	0	0.10%
55	BEGHELLI	2016	5	1	7.23	34.80%	1.24	0	0.11%
55	BEGHELLI	2015	5	1	7.27	32.94%	1.24	0	0.11%
56	COVER 50	2019	9	1	4.08	77.93%	5.74	2	0.23%
56	COVER 51	2018	9	1	4.01	75.90%	5.56	2	0.27%
56	COVER 52	2017	9	1	3.93	76.32%	5.87	2	0.39%
56	COVER 53	2016	9	1		75.51%	4.18	2	0.37%
56	COVER 54	2015	9	1		76.29%			0.06%
57	TESMEC	2019	5	1	5.89	15.56%	0.98	0	0.06%
57	TESMEC	2018	5	1	5.84	15.74%	0.97	0	0.08%
57	TESMEC	2017	5	1	5.80	19.23%	1.08	0	0.12%
57	TESMEC	2016	5	1	5.75	21.31%	0.83	0	0.19%
57	TESMEC	2015	5	1	6.34	22.82%	1.37	0	0.24%
58	PIERREL	2019	1	3	4.52	41.32%	2.56	1	0.14%
58	PIERREL	2018	1	3	4.51	32.81%	2.12	1	0.14%
58	PIERREL	2017	1	3	4.44	8.60%	1.08	0	0.19%
58	PIERREL	2016	1	3	4.47	-24.83%			0.15%
58	PIERREL	2015	1	3	4.52	1.66%	-0.16	0	0.03%
59	B&T GROUP	2019	5	1	6.39	33.44%	1.39	0	0.05%
59	B&T GROUP	2018	5	1	6.36	37.54%	1.76	0	0.05%
59	B&T GROUP	2017	5	1	6.35	34.01%	1.90	1	0.04%
59	B&T GROUP	2016	5	1	6.30	30.65%	1.72	0	0.03%
59	B&T GROUP	2015	5	1	6.32	23.01%			0.03%
60	PLC	2019	3	1	6.03	37.75%	1.28	0	0.03%
60	PLC	2018	3	1	5.30	36.17%	1.74	0	0.01%
60	PLC	2017	3	1	4.84	40.35%	1.58	0	0.00%
60	PLC	2016	3	1	1.10	-77.95%			0.08%
60	PLC	2015	3	1	1.95	-17.99%			0.05%

61	VIANINI	2019	6	2		36.03%	0.26	0	0.00%
61	VIANINI	2018	6	2	1.79	38.18%	0.52	0	0.00%
61	VIANINI	2017	6	2	1.95	37.44%	0.83	0	0.01%
61	VIANINI	2016	6	2	3.43	33.42%	0.68	0	0.02%
61	VIANINI	2015	6	2	3.33	91.41%	2.73	1	0.04%
62	GIBUS	2019	9	1	5.22	51.92%	3.90	2	3.69%
62	GIBUS	2018	9	1	5.19	39.05%			4.95%
62	GIBUS	2017	9	1	5.06	41.95%			2.39%
62	GIBUS	2016	9	1					
62	GIBUS	2015	9	1					
63	TPS	2019	10	1	6.17	54.55%	3.56	2	1.24%
63	TPS	2018	10	1	6.05	61.13%	2.88	1	1.36%
63	TPS	2017	10	1	5.42	45.94%	4.14	2	1.73%
63	TPS	2016	10	1	4.90	35.95%	3.46		2.47%
63	TPS	2015	10	1	4.67	22.74%	2.39		2.34%
64	PRISMI	2019	13	1	4.98	6.74%	0.13	0	0.06%
64	PRISMI	2018	13	1		12.71%	0.78	0	0.00%
64	PRISMI	2017	13	1	4.76	7.07%	0.54	0	0.01%
64	PRISMI	2016	13	1		6.06%	0.41	0	0.03%
64	PRISMI	2015	13	1		6.88%	-0.64	0	0.19%
65	TREVI	2019	3	1	8.68	-21.11%	-0.62	0	0.01%
65	TREVI	2018	3	1	8.76	-13.19%	-0.37	0	0.01%
65	TREVI	2017	3	1		-0.09%	-0.11	0	0.01%
65	TREVI	2016	3	1	8.89	28.21%	0.86	0	0.01%
65	TREVI	2015	3	1	8.97	29.92%	1.15	0	0.01%
66	POLIGRAFICI EDITORIALE	2019	8	1	6.71	18.49%	0.78	0	0.19%
66	POLIGRAFICI EDITORIALE	2018	8	1	6.73	22.94%	0.89	0	0.26%
66	POLIGRAFICI EDITORIALE	2017	8	1	6.72	21.32%	0.73	0	0.34%
66	POLIGRAFICI EDITORIALE	2016	8	1	6.73	21.89%	0.58	0	0.34%
66	POLIGRAFICI EDITORIALE	2015	8	1	6.77	20.59%	0.61	0	0.43%
67	EUKEDOS	2019	5	2	6.93	20.09%	0.52	0	0.00%
67	EUKEDOS	2018	5	2	6.92	48.44%	1.32	0	0.00%
67	EUKEDOS	2017	5	2	6.89	46.12%	1.24	0	0.00%
67	EUKEDOS	2016	5	2	6.89	48.09%	1.24	0	0.00%
67	EUKEDOS	2015	5	2	6.77	40.09%	1.00	0	0.00%
68	CSP	2019	9	1		45.72%	1.39	0	0.21%
68	CSP	2018	9	1	6.61	48.92%	1.19	0	0.03%
68	CSP	2017	9	1	6.66	51.71%	1.72	0	0.30%
68	CSP	2016	9	1	6.71	51.75%	1.87	1	0.23%
68	CSP	2015	9	1	6.74	53.68%	1.81	1	0.27%
69	FRENDY	2019	12	1		76.51%	1.78	0	0.00%
69	FRENDY	2018	12	1		72.64%	0.20	0	0.00%
69	FRENDY	2017	12	1		62.75%	1.38	0	0.01%
69	FRENDY	2016	12	1		61.60%	0.85	0	0.01%
69	FRENDY	2015	12	1		57.68%	1.00	0	0.01%
70	GIORGIO FEDON	2019	5	1	6.87	20.91%	1.78	0	0.09%
70	GIORGIO FEDON	2018	5	1		21.05%	1.36	0	0.15%
70	GIORGIO FEDON	2017	5	1	7.37	25.82%	1.75	0	0.25%
70	GIORGIO FEDON	2016	5	1	7.34	33.42%	2.18	1	0.35%
70	GIORGIO FEDON	2015	5	1	7.48	33.82%	2.50	1	0.57%
71	TITANMET	2019	2	1		13.78%	-21.67	0	0.00%
71	TITANMET	2018	2	1		36.25%	-15.90	0	0.00%
71	TITANMET	2017	2	1		9.65%	-8.50	0	0.00%
71	TITANMET	2016	2	1		4.24%	-7.63	0	0.00%
71	TITANMET	2015	2	1		7.42%	-5.42	0	0.00%

Appendix 3: Ohlson O Score

"Trailblazing"

NAME	YEAR	CLASS	O SCORE	PROB DEF
DIASORIN	2019	5	-18.04	0.00%
DIASORIN	2018	5	-7.58	0.05%
DIASORIN	2017	5	-10.38	0.00%
DIASORIN	2016	5	-9.37	0.01%
DIASORIN	2015	5		
AMPLIFON	2019	5	-3.65	2.53%
AMPLIFON	2018	5	-2.95	4.99%
AMPLIFON	2017	5	-4.54	1.06%
AMPLIFON	2016	5	-4.54	1.06%
AMPLIFON	2015	5		
INWIT	2019	5	-6.26	0.19%
INWIT	2018	5	-6.98	0.09%
INWIT	2017	5	-17.21	0.00%
INWIT	2016	5	-7.74	0.04%
INWIT	2015	5		
IMA	2019	5	-3.36	3.37%
IMA	2018	5	-3.18	4.00%
IMA	2017	5	-3.32	3.48%
IMA	2016	5	-3.27	3.66%
IMA	2015	5		
CUCINELLI	2019	5	-3.63	2.59%
CUCINELLI	2018	5	-5.36	0.47%
CUCINELLI	2017	5	-6.66	0.13%
CUCINELLI	2016	5	-6.21	0.20%
CUCINELLI	2015	5		
BASICNET	2019	5	-3.99	1.82%
BASICNET	2018	5	-4.75	0.86%
BASICNET	2017	5	-3.92	1.95%
BASICNET	2016	5	-3.51	2.90%
BASICNET	2015	5		
DIGITAL BROS	2019	5	-7.40	0.1%
DIGITAL BROS	2018	5	-3.04	4.6%
DIGITAL BROS	2017	5	-4.29	1.4%
DIGITAL BROS	2016	5	-5.55	0.4%
DIGITAL BROS	2015	5		
FOPE	2019	5	-5.18	0.56%
FOPE	2018	5	-4.12	1.60%
FOPE	2017	5	-4.92	0.72%
FOPE	2016	5	-3.29	3.61%
FOPE	2015	5		

"Minimalist"

NAME	YEAR	CLASS	O SCORE	PROB DEF
OVS	2019	1	-2.53	7.35%
OVS	2018	1	-2.97	4.89%
OVS	2017	1	-3.77	2.25%
OVS	2016	1	-4.32	1.31%
OVS	2015	1		
CARRARO	2019	1	-1.89	13.16%
CARRARO	2018	1	-1.64	16.21%
CARRARO	2017	1	-4.75	0.86%
CARRARO	2016	1	-1.40	19.71%
CARRARO	2015	1		
GAS PLUS	2019	1	-3.30	3.55%
GAS PLUS	2018	1	-1.62	16.48%
GAS PLUS	2017	1	-3.56	2.77%
GAS PLUS	2016	1	-0.48	38.30%
GAS PLUS	2015	1		
RISANAMENTO	2019	1	-4.57	1.02%
RISANAMENTO	2018	1	-2.55	7.24%
RISANAMENTO	2017	1	-2.44	8.05%
RISANAMENTO	2016	1	-1.65	16.08%
RISANAMENTO	2015	1		
LEONE FILM	2019	1	-1.73	15.10%
LEONE FILM	2018	1	-2.62	6.76%
LEONE FILM	2017	1	-2.71	6.24%
LEONE FILM	2016	1	-2.47	7.82%
LEONE FILM	2015	1		
TREVI	2019	1	-0.11	47.35%
TREVI	2018	1	-0.20	45.08%
TREVI	2017	1	0.79	68.71%
TREVI	2016	1	-2.38	8.46%
TREVI	2015	1		
EUKEDOS	2019	1	-1.41	19.67%
EUKEDOS	2018	1	-4.41	1.20%
EUKEDOS	2017	1	-2.14	10.52%
EUKEDOS	2016	1	-3.76	2.28%
EUKEDOS	2015	1		
FRENDY	2019	1	-4.38	1.24%
FRENDY	2018	1	-2.33	8.85%
FRENDY	2017	1	-3.99	1.82%
FRENDY	2016	1	-2.28	9.25%
FRENDY	2015	1		
TITANMET	2019	1	3.82	97.84%
TITANMET	2018	1	3.08	95.60%
TITANMET	2017	1	-0.90	28.90%
TITANMET	2016	1	5.58	99.63%
TITANMET	2015	1		

Appendix 4: ROE, ROA & Soft. Ass. / Tot. Ass. per Year

-> YEAR = 2015

Variable	Obs	Mean	Std. Dev.	Min	Max
ROE	112	-.0113504	.5488224	-4.0092	.87342
ROA	116	.0116036	.0937127	-.51411	.17991
SOFTWARETO~S	116	.0080603	.018866	0	.1549529

-> YEAR = 2016

Variable	Obs	Mean	Std. Dev.	Min	Max
ROE	114	-.0284375	.9593034	-9.81818	.67394
ROA	117	.0277509	.0802002	-.41629	.21375
SOFTWARETO~S	117	.0077448	.0166782	0	.1412689

-> YEAR = 2017

Variable	Obs	Mean	Std. Dev.	Min	Max
ROE	119	.0850776	.2545133	-1.38334	1.61828
ROA	121	.0367684	.0652319	-.35889	.18093
SOFTWARETO~S	121	.0096162	.0216848	0	.1748373

-> YEAR = 2018

Variable	Obs	Mean	Std. Dev.	Min	Max
ROE	119	.0886017	.1779308	-1.03769	.47007
ROA	122	.0366826	.0735132	-.25171	.22184
SOFTWARETO~S	122	.0097832	.0213774	0	.1755603

-> YEAR = 2019

Variable	Obs	Mean	Std. Dev.	Min	Max
ROE	120	.0574231	.3664875	-2.71895	1.53906
ROA	122	.0306712	.0802203	-.37477	.3799
SOFTWARETO~S	122	.00868	.0186122	0	.1563916

Appendix 5: Best and Worst Sectors in Digital Maturity[20]

-> SECTORID = 14

Variable	Obs	Mean	Std. Dev.	Min	Max
ROE	30	.173346	.2007968	-.36956	.65161
ROA	30	.056169	.0550911	-.09283	.15383
SOFTWARETO~S	30	.0146119	.0105399	.0010334	.0417165

-> SECTORID = 4

Variable	Obs	Mean	Std. Dev.	Min	Max
ROE	40	.011692	.1386177	-.34181	.39153
ROA	45	-.0123484	.0808869	-.35889	.15799
SOFTWARETO~S	45	.000849	.0016367	0	.0075087

[20] Within the computation are considered just the sectors with at least 30 observations. Sector ID 14 is Travel, Personal & Leaisure, while Sector 4 is Construction and Property Services.

Summary

This thesis had the aim to get insights about the impact of digitalization on performance and risk of bankruptcy of Italian listed companies.

The summary will be divided into three chapters, with the purpose of highlighting the most important steps and findings obtained through this work.

The first chapter pertains to the field of digitalization, with the aim of understanding the main features of this phenomenon and how this event can shape companies' business models, the impact on Small and Medium-sized Enterprises (SMEs), how to succeed in becoming a digital champion and an overview of the capability of Italy to deal with this process. This chapter is then concluded with an overview on how digitalization can be concretely measured.

The second chapter analyses performance and risk of bankruptcy, starting with a contextualization of this first term. Secondly, some models for performance measurement are presented in order to give a wider perspective and then are presented the most commonly used indicators of the literature. The part of risk bankruptcy begins instead with an overview of what bankruptcy really is, after which is described its evolution starting from 2008 crisis. To conclude the chapter are presented some of the principal models to estimate risk of bankruptcy.

The third chapter embeds the empirical analysis. Firstly, the research questions are clearly stated, after which is described the process of data mining, from the selection of the sample and the sources to the selection of the necessary variables to use during the regression analysis. In the following step some descriptive statistics with the purpose of providing some insights and hints about what is expected to obtain through the regression analysis are proposed. Concluded this part, is chosen the most effective model to represents our data, after which, the results of the

regressions are showed and discussed. In conclusion of the chapter, are synthesized the limits of the analysis and some suggestions to widen the scope of this thesis.

CHAPTER I – DIGITALIZATION

Digitalization is described as the process of employing digital technologies and information to transform business operations (Kulkarni et al., 2017). The modernity of this phenomenon, accompanied by a rapid technological change, increased complexity and changing customer preferences and legal requirements led many companies to strongly adapt some aspects of their business models or to radically change them (El-Darwiche et al., 2012). Notwithstanding the innovative character of this process, it could also be perceived as a concrete opportunity by the most prepared firms. Many information and data are now possible to be gathered with lower efforts and for those capable of understanding the right data to focus on this can be an incredible value added (Gray & Rumpe, 2015).

According to Press (2015), even if digitalization is an extremely recent process, has its first milestone in 1679, with the intuition of the philosopher and mathematician Gottfried Wilhelm Leibniz, developing in that year the binary number system, still actually adopted as the basis for computer technology. Notwithstanding this ancestor, the actual process began in the 1950s and became widely popular during 1990s. The advent of the World Wide Web allowed then the spreading of this phenomenon and a research conducted by El-Darwiche et al. (2012) showed that the number of personal computers, mobile phone users and internet users grew exponentially from 1990 to 2010. Though these results are outstanding, a study of McKinsey Global Institute estimated that the US economy, widely recognized as one of the most advanced, only uses 18% of its digital potential, with the possibility of adding up to $2.2 trillion to its annual GDP by 2025.

To give an understanding of the relevance of this phenomenon to guarantee the success of a firm, is presented the Nokia case. This company, after becoming the leader of the sector for a decade, has been wiped away from its dominant role by competitors more conscious about the desires of the customers, deriving from their needs connected to digitalization, as a faster internet access, a wide range of apps to download or an adequate ecosystem that Nokia's Symbian OS was never able to build (Joshi & Panigrahi, 2020).

Reached a first overview of the relevance of digitalization process, is important to present two technologies representing its foundation, as machine learning and big data analytics. The first consists in a mix of computational methods using experience to improve performance or to make accurate predictions, where experience refers to previous information available to the learner, which use to take form of electronic data collected and made available for the analysis (Mohri et al., 2018).

The second concept refers to big data, that is described by Sagiroglu & Sinanc (2013) as a term used for huge data sets having large, varying and complex structure with the difficulties of storing, analyzing and visualizing for further processes or results. The abovementioned term refers so to the ability of obtaining information from these huge amount of data.

After evidencing some important technologies at the base of digitalization, is important to understand how this process shapes companies' businesses. In this perspective has been demonstrated that this revolution shows a concrete necessity of renewing actual business models and Boardman et al. (2017) provide a roadmap to guide the digital transformation of the latter in five steps.

Later, is proposed further evidence from the literature aimed at stating that SMEs and large corporations have obviously different possibilities of adapting to digitalization. In this field, Härting et al. (2017) state that the crucial evidence consists in the fact that large corporations are more experienced and have a bigger capital base to deal with advanced digitalization, while small sized companies are often more flexible and faster when it is the moment to implement new technologies and to change processes. On the other hand, small firms use to have a lower capital base and generally less experts capable to run this revolution.

A study published by Boston Consulting Group (2019), with the purpose of going in detail into the phenomenon of digitalization, proposes the DAI index to evaluate the digital maturity of companies. With this device, has been possible to divide the panel analyzed between digital champions and laggards, in order to study the best practices that allow companies to scale up positions in terms of digitalization. In the research the authors suggest also useful tips to become digital champions as: creating a digital talent agenda, strive for a world-class tech function and create a data centric organization.

While this study included companies from Asia, Europe and US (resulting that the less digitalized were the European), the next step has been to approach the perspective that will be taken during the empirical analysis and for this reason is prepared an overview of the level of digitalization of Italy. This has been done through the Network Readiness Index (NRI), an indicator measuring the degree to which economies across the world leverage Information and Communication Technologies (ICT) for enhanced competitiveness, firstly proposed by the World Economic Forum in collaboration with INSEAD in 2002.

From the 2019 NRI for Italy (showed in figure 3), is evidenced a lower capability of Italy to deal and adapt to digitalization compared to the other developed and high-income countries.

In conclusion of the chapter are proposed some methodologies used in the literature to measure digitalization. The predominant methodology, especially when the panel of interest is composed by SMEs, is to send a survey to the firms under observation and is often the only way possible, given the difficulty in gathering the data, when referring about non-listed companies. Notwithstanding this way, other ways have been proposed by the literature, as the Biesiot indicator (Domnicheva et al., 2018) or the methodology based on the software assets of the firm proposed by Banga (2019).

CHAPTER II – PERFORMANCE AND RISK OF BANKRUPTCY

The first necessary step in this field of study is a contextualization of the concept and in support of this need, Ramanujam & Venkatram (1986) described a model to circumscribe performance domain. In their perspective the inner domain is that of financial performance, seen as a final synthesis of the overall health of companies, surrounded by business performance, whose peculiarity is to enlarge the perspective even to the operational one and this typology includes nonfinancial indicators such as market share, product quality or marketing effectiveness. The larger field is instead that of organizational effectiveness, that due to its particularly conceptual classification is afflicted by strong debates in the literature: however, a summary of the most important models is provided by Cameron (2015).

After a contextualization, is proposed an overview of the most successful models for performance measurement in the literature, in a chronological order:

- Sink & Tuttle (1989) give an introduction and an interesting overview of the argument suggesting that performance is a complicated interrelation between seven criteria, namely effectiveness, efficiency, quality, productivity, quality of work life, innovation and profitability or budget ability.
- Keagan et al. (1989) proposed the performance measurement matrix, dividing the framework in four different dimensions (cost, non-cost, internal and external) where in each combination box are described some features linked to performance to look at.
- Cross & Lynch (1992) proposed the Performance Pyramid, with this precise shape starting from the idea that companies operate at different levels, each of them with different focus. This model evidences the continuous interrelation between levels and shows differences between measures of external effectiveness as quality or customer satisfaction and measure of internal effectiveness as cycle time and productivity.
- Kaplan & Norton (1992) presented the Balanced Scorecard, with the purpose of not making necessary a choice between financial and operational measures, giving however a fast and comprehensive view of the business. This framework rotates around four perspectives, each of them reflecting an important dimension of the

company's business, namely customer perspective, internal business perspective, innovation and learning perspective and financial perspective.

- Bredrup & Moseng (1993) described the TOPP model, embedding the first two dimensions proposed by Sink & Tuttle (1989) and adding adaptability. According to them, this model is the basis to develop two other sets of methodologies to measure productivity, namely a self-audit based on a questionnaire answered by the companies and an external audit performed by experts analyzing the companies.
- Neely et al. (2001) prepared the Performance Prism, consisting in five interrelated facets each of them answering to a different question aimed at understanding different needs of the company, namely stakeholder satisfaction, strategies, process, capabilities and stakeholder contribution.
- Tangen (2005) developed the Triple-P model in order to reduce the confusion in terminology, by explaining the basic meaning of frequently used terms into the field of productivity and performance management.

After the analysis of these models, have been presented the following as the most adopted indicators in the literature:

- ROE is, together with ROA, proposed by the majority of practitioners as the preferred performance parameter and indicates the capability of the company to repay its shareholders, used to verify concretely the rate of return of the capital conferred as equity.
- ROA obtains in the literature the same high level of relevance of ROE, with the majority of papers interested in measuring performance embedding it. It represents the rate of return on total assets instead of on equity, with the possibility of accounting for different leverage choices that does not increase the denominator in ROE computation.
- Gan et al. (2017) propose the asset turnover, helpful to state the effectiveness of the company, investigating whether the net operating assets were effective at generating sales and the price to book ratio dividing the market capitalization for the book value of the firm. This indicator, differently from the others already

quoted, embeds a term that refers to the perspective of the market rather than effective results as net income or sales, with all its strength and weaknesses.

- Hartono & Santhanam (2003), in addition to the usual ROA use the return on sales, describing what percentage of sales become operating profit and the operating income to employee, suitable to identify management's ability to employ its workforce effectively to create profits for the company.
- Lakhal et al. (2006), in addition to ROA, use the ROI that explains how much EBIT is obtained exploiting the operating assets and the growth rate of sales, which aims at identifying the percentual increase (or decrease) of sales compared to the previous year.
- Fu et al. (2016) use as performance measure the EBITDA margin, investigating the EBITDA, seen as a raw measure to understand what is left after the repayment of all the operating costs, which is expressed in percentage of sales.
- Abdi et al. (2020) use to measure performance the Tobin's q, that in the case of the average q of the firm is calculated as total market value of the firm divided total asset value of the firm.
- Neely (2002) describes even some liquidity ratios, that are not used singularly to measure the performance of a company, but are important complementary parameters to take in consideration. Between those quoted, the most relevant are the current ratio, purposeful to detect the capability of the company to face current liabilities through current assets and the quick ratio (or acid test), that investigates whether company's most liquid assets (so current assets not comprehensive of inventories) are able to cover short term obligations.

Completed the part referring to performance, is provided a definition of bankruptcy, that, according to Oxford dictionary, is a term that can be referred both to a person or to an organization declared by the law as unable to pay its debts. To have an overview of the spread of this phenomenon, figure 9 depicts the evolution of the level of bankruptcies between 2007 and 2015. The graph shows a pretty similar path for all the countries analyzed with an increase in failures in 2008 and 2009, quickly reverted back to normality in the following years, except Italy that from 2008 onwards has always seen the number of failures constantly increasing.

As final part of the chapter, are proposed three of the principal models for predicting the risk of bankruptcy:

- The Altman Z Score is probably the most known parameter used to make predictions about risk of bankruptcy. The first version of the model was provided by Altman in 1968 and was oriented to evaluate the riskiness that a listed company would have been bankrupt in a 2-year horizon based on five specific indicators. The concrete study was performed analyzing a panel of 66 manufacturing companies and the results in terms of z score obtained through the specific formula were clustered in three categories. Firms achieving a score higher than 2.99 were inserted in the "safe zone", suggesting a practically inexistent probability to fail in the next two years, companies with a score between 1.81 and 2.99 (both included) were inserted in the "grey area", with no possibility of providing a sound and accurate prediction and finally those with a score lower than 1.81 were in the "distress zone", with a consistent probability of getting bankrupt. After this first model, in 1993 Altman provided two adjusted formulas to cope the need to predict the risk of bankruptcy of private companies or non-manufacturing companies, with different score ranges to fall in each of the three zones.
- The Ohlson O Score is a parameter that, similarly to its predecessor Altman Z Score, owes its name to the researcher that constructed the model. Ohlson (1980) prepared its framework over a larger panel of firms (105 bankrupted and 2058 non-bankrupted) between 1970 and 1976, for companies classified near the industrial perimeter (excluding so, as Altman did, financial institutions). The model obtained uses nine indicators to derive the "o score", but the most relevant peculiarity is the possibility to convert the result obtained in a probability of default (in a year time horizon).
- Zmijevski formula derives from a further study on this topic done in 1984. The author, in this case, took as reference the sample of all firms listed on the American and New York Stock Exchanges between 1972 and 1978, also in this case making

exception for those pertaining to the financial sector, with a final population range swinging between 2082 and 2241 companies. In this case the final model considers just three parameters and the result obtained can be converted in a probability of default through a probit model with cutoff score 0.5 between bankrupt and nonbankrupt firms.

CHAPTER III – EMPIRICAL ANALYSIS

This chapter has the aim to bring a worthy contribution to the previous literature, investigating exactly the impact of digitalization on performance and risk of bankruptcy of Italian listed companies.

To achieve the abovementioned goal, some research questions should be stated. The choice of how to calculate the performance of a company is influenced by the previously quoted overview of the most important indictors used in the literature and especially by the research conducted by Chaghadari & Chaleshtori (2011). From the general analysis, emerged that there is an undoubted predominance of two indicators in this field, namely ROE and ROA. This evidence is due especially to their complementarity, given that, taken alone, the drawbacks of each of the two would be consistent. In this perspective, the final decision fell on performing a first regression with the ROE as dependent variable representing performance and a further one substantially equal, but with ROA instead of ROE. This choice should be intended as a robustness check, to improve the reliability of the analysis. In the light of the above discussion, the following hypothesis have been proposed:

Hypothesis 1: *Companies with a greater level of digitalization obtain a higher ROE.*

Hypothesis 2: *Companies with a greater level of digitalization obtain a higher ROA.*

While these two hypothesis pertain to the field of the impact of digitalization on performance, the last one will be oriented to identify how this phenomenon affects the risk of bankruptcy. In this case, the selection of the dependent variable was linked to one of the three models proposed in the literature. From the study of their peculiarities, Altman Z Score and Ohlson O Score seemed the most appropriate, believing the model proposed by Zmijevski (1984) less suitable for this purpose, due to the low number of variables considered in its construction. The final decision fell on an adaptation of the model proposed by Altman, although also the one of Ohlson is used to make some final considerations.

In this perspective, the last hypothesis states:

Hypothesis 3: *Companies with a greater level of digitalization have a lower risk of getting bankrupt.*

After the exhibition of the research questions, the necessary data were collected, principally from Bureau Van Dijk Orbis. For those referred to the independent variable connected to digitalization however this has not been possible, making necessary a research in the annual reports of each company for the five-year time horizon adopted (2015-2019). This procedure, connected with the elimination of the organization operating in banking, insurance and business services to avoid biased results, led to a consistent decrease in the sample size, from an initial number of more than 350 Italian listed companies, to 122 for performance analysis. Further reduction has been necessary for the part concerning the risk of bankruptcy, leading the sample to 71 firms to comply as much as possible with the constraints applied by Altman.

The following is a resume of the variables adopted in the regressions:

- **Dependent variables**: For the first two regressions have been adopted respectively ROE and ROA, similarly to what suggested by Chaghadari &

Chaleshtori (2011). For the part on risk of bankruptcy has been used the variable "result", with values of 0, 1 or 2 if the observation fell respectively in the "distress zone", "grey zone" or "safe zone" based on the Altman Z Score.

- **Independent variable**: The independent variable considered at the numerator the software assets of the firms, considered a reliable indicator of digitalization by Banga (2019) and has been scaled by the total assets of the firm to have a value relative to the size of the company.
- **Control variables**: The five control variables used were: year, natural logarithm of employees (representing the size), solvency ratio (interesting proxy for the structure of the company, similar to the debt to equity ratio), "sector ID" (representing the specific sector in which the company operates) and "region ID" (representing the three macro-areas in which Italy is divided, namely north, center and south).

Before passing to the regression analysis, are provided some descriptive statistics with the purpose to illustrate the path that should then be certified through the regression analysis.

The first analysis consisted in a categorization per year of the ROE, ROA and software assets over total assets ratio. Figure 10 demonstrates that the level of digital maturity is highly connected with the results achieved, because indeed in 2015-2016, where digitalization ratio is lower, ROE and ROA are still very low on average, while in 2017-2018 when this ratio consistently increased, the same upward trend has been followed by performance parameters.

For the next analysis, the level of digital maturity of companies has been clustered according to the five ranges suggested by Egloffstein & Ifenthaler (2020), namely Minimalist, Conservative, Pragmatist, Advanced and Trailblazing (ordered from the lowest level to the highest level). This division allowed to analyze the database in terms of digital maturity and the results were absolutely in line with what expected. From figure 11 can be derived how a higher digital maturity can influence the performance of the companies and the toughest results emerge from those firms pertaining to “Minimalist”, where the average ROE and ROA is even negative. Although the growth from category to category is pretty evident, the highest impact is obtained, both in terms of ROE and ROA, passing from the category to which pertains those firms with the lowest digital maturity, to “Conservative”, suggesting that reaching at least a small level of digitalization can avoid the strong risks deriving from barely not consider this process.

A similar result is achieved performing a similar reasoning with the “z score”. Figure 12 shows that the average score obtained by companies pertaining to “Minimalist” is 0.31, meaning that these firms have a high risk of being bankrupt. Passing to “Conservative”, the average score passes already to 2.50, suggesting not to make predictions on the effective risk of bankruptcy, reaching an average “safe zone” from “Pragmatist” onwards, with a concrete upward trend from class to class.

Concluded the descriptive statistics, is chosen the model to perform the regressions. In the light of the strengths and weaknesses of the models presented, to study the panel dataset previously presented, is used a random effects model, more suitable than a fixed effects model for the purpose.

Table 1 presents the results of the first regression. The value of 1.323 (significant at 0.1), justifies the belief that an increase in digitalization (measured in the case as software assets over total assets) produces a consistent increase in ROE, confirming the first hypothesis. A further interesting feature to be noticed refers to the year. Being in the market on the years following 2015, seems to have a positive effect and to be an added value in terms of ROE (significant at 0.1 for 2016-2017 and at 0.01 for 2018-2019). Although this characteristic increase year by year, the effective impact of this phenomenon is not outstanding in absolute value.

Table 2 presents the results of the second regression. The value of 0.310 (significant at 0.1), depicts a positive relation between digitalization (measured as software assets over total assets) and ROA, confirming the second hypothesis. Similarly to the first regression, even in this case operating in the market in the year following 2015 seems to guarantee a small value added. Although in this case the effect seems to be even lower than the one for ROE, the results obtained are significant at 0.001.

Table 3 presents the results of the third regression. In this case the dependent variable is “result” derived from the Altman Z Score and the value of 7.63 verifies also the hypothesis that an increase in digitalization (measured as before as software assets over total assets) leads to a lower risk of bankruptcy. In this case, differently from the previous two regressions, the year of operation seems not have an impact (or at least it is not significant even at 0.1, except for 2017). In addition to this last regression, is provided a further study based on the Ohlson O Score to transform the evidence proposed in a probability of default. This trial is done for the companies that between 2016 and 2019 pertained continuously to the categories of “Minimalist” and “Trailblazing”, respectively that with lower and higher digital maturity and for which all the data were available for these 4 years (given that Ohlson O Score needs a high number of variables to embed in the calculation). From the panel of 17 companies (8 pertaining to “Trailblazing” and 9 to “Minimalist”) the average probability of default estimated were 1.51% for the category with the highest digital maturity and 20.60% for that with the lowest, suggesting that digitalization has a strong impact also on risk of bankruptcy.

Although the analysis produced satisfying results in all the fields investigated, it has some limits. This research uses in fact a certain indicator representing digitalization, that, although carefully studied, can not comprehend all the features embedded in the digitalization process, given also the many facets of this phenomenon. A further issue could pertain to the extraction of the data referred to the software assets of the firm, taken from the annual reports of the companies under observation. Notwithstanding the high attention is however possible a different policy adopted by each entity, slightly altering the analysis. Other problems could pertain to the variable used in the regression analysis, that although carefully controlled, are not for sure the most appropriate or the selection of the panel of companies. In this perspective, for the regression considering the risk of bankruptcy, the firms have been selected in the way more compliant with what done by Altman, but due to the impossibility of finding a panel composed by totally manufacturing firms, are just eliminated those too far from the definition, as service companies or those of public administration. A final concern, due also to this last action performed to comply as much as possible to Altman's study, refers to the sample size. Indeed, notwithstanding the final samples, respectively of 122 and 71 firms for the regressions on performance and risk of bankruptcy, are composed by a consistent number of firms, they are much less than the more of 350 Italian listed companies.

In conclusion, this work presents some suggestions for future research connected with this thesis, prompting as interesting follow up the analysis of a panel of Italian SMEs (as proposed by Alford (2020) and Joensuu-Salo (2018) respectively for Austrians and Finnish SMEs), a research conducted over companies of different countries (with the due attention to differences in terms of accounting standards, regulations and general comparability), a study interested in evaluating the effect on each sector (for which is necessary a bigger panel of data) or a similar project conducted with different variables (as the online turnover in percentage of total turnover representing digitalization).