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The effect of innovation on employment: An empirical investigation on ‘complex’ and ‘discrete’ US manufacturing companies

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ABSTRACT

This study aims at enriching the empirical microeconomic literature regarding the relationship between innovation and employment.
The analysis is conducted in order to investigate how R&D Expenditures, used as an empirical proxy for the economic value of innovation efforts (Pandit, Wasley and Zach, 2011), affect the Total Number of Employees at the firm level.
A sample of 532 US manufacturing companies over a time period of five years, from 2013 to 2017, is analyzed and split into two different groups, according to the distinction made by Hall (2004) and Cohen et al. (2000): 'complex technology' companies and 'discrete technology' companies.
'Complex technology' sectors are the ones characterized by high patenting and high R&D expenditure.
Within the sample, 303 are the high-tech manufacturing companies that belong to 'complex technology' sectors (SIC between 34 and 39), and 229 are the manufacturing companies that belong to 'discrete technology' sectors (SIC between 19 and 33).
Therefore, four statistical models are built and a panel data regression is run for each model.
The final results show that an increase in R&D Expenditures has a positive and significant impact on the Total Number of Employees both for 'complex technology' companies and 'discrete technology' companies.
So this study is important because from one side it confirms the positive and significant relationship between innovation and employment in firms that belong to 'complex technology' sectors, as already showed by many scholars in the existing literature, and from the other side it demonstrates the positivity and the significance of this relationship also in firms that belong to 'discrete technology' sectors.

Key Words: R&D Expenditures, Total Number of Employees, US manufacturing companies, 'complex technology' sectors, 'discrete technology' sectors.

1. INTRODUCTION

During the last twenty years, lots of new technologies became available in the market, leading to important changes within business processes of many companies.
In particular, the diffusion of a new paradigm, based on information and communications technologies (ICTs) and automation, has caused some adjustments of the employment levels and structure in all the economy (Van Roy, Vértesy, Vivarelli, 2018).
For this reason, an increasing number of scholars decided to study the employment effects of innovation.

Innovation is often considered as the driver of employment growth but the debate on the potential adverse consequences of innovation on employment is still open.
In fact, as underlined by Van Roy, Vértesy and Vivarelli (2018), "*economic theory does not have a clear-cut answer about the employment effect of innovation so there is a strong need for empirical analyses able to test the final employment impact of technological change*".

From an empirical point of view, there is no common overall measure for innovation but R&D spending is often used as an empirical proxy for the economic value of innovation efforts (Pandit, Wasley and Zach, 2011).
So this study will investigate how R&D Expenditures affect the Total Number of Employees at the firm level.

However, data on R&D spending are not always available or they are limited because many companies have strict confidentiality policies (Kleinknecht, 1993).
For this reason, only firms incorporated in the United States of America will be analyzed because, under US accounting laws and regulations, annual R&D Expenditures' public disclosure by companies is required.

Furthermore, when talking about the relationship between innovation and employment, it is necessary to distinguish the likely labor-friendly impact of product innovation versus the possible labor-saving effect of process innovation.
Product innovation means introducing a good or a service that is new or significantly improved while process innovation is the implementation of new or significantly improved processes for the production or the delivery of products (OECD 2005).
Most empirical studies showed a clear and positive relationship between the introduction of new products and the growth of income and employment at the firm level; instead the empirical results on process innovations are ambiguous.
In this research, only product innovations will be considered because, as Van Roy, Dániel Vértesy and Marco Vivarelli (2018) explained in their paper, "*there is less debate about the positive employment effect of product innovations, that are generally understood to lead to the opening of new markets, or to an increased variety within the existing ones*".

In addition, according to the existing literature (see Francesco Bogliacino, Mariacristina Piva and Marco Vivarelli, 2012), product innovations are mainly and significantly connected with R&D Expenditures, especially in some sectors such as the high-tech manufacturing one.
In fact, firms included in the high-tech manufacturing and services sectors belong to dynamic and emerging sectors where a strong correlation between R&D and product innovation is even more likely than average (Francesco Bogliacino, Mariacristina Piva and Marco Vivarelli, 2012).

Many statistical researches demonstrated that product innovations have a positive impact on employment, but not so many studies have been conducted on US firms.
In addition, *in the previous literature, empirical analysis has very rarely been carried out according to sectoral belonging (Francesco Bogliacino, Mariacristina Piva and Marco Vivarelli, 2012)*.
So this thesis will be significant because both it takes into account US firms and it is mainly carried out according to the high-tech sector.

In particular, following what Coad and Rao (2011) have already done, for the empirical analysis concerning the high-tech manufacturing companies, four sectors of firms will be taken into account.
These four sectors are classified under the 'complex technology' class (SIC 35-36-37-38), because these sectors are characterized by high patenting and high R&D expenditure so there is a bigger possibility to get relatively accurate measures of firm-level innovation.
But, at the same time, the relationship between innovation and employment will be studied not only for 'complex technology' sectors but also for companies that belong to 'discrete technology' sectors (SIC 20-21-22-23-24-25-26-27-28-29-30-31-32).

The distinction between 'discrete technology' manufacturing companies (SIC between 19 and 33) and 'complex technology' manufacturing companies (SIC between 34 and 39) has been introduced by Hall (2004) and Cohen et al. (2000): they defined 'complex product' industries those industries where each product relies on many patents held by a number of other firms, while the 'discrete product' industries are those industries where each product relies on only a few patents.

The empirical analysis will test if firm-level innovative activity leads to employment creation not only for 'complex technology' sectors but also for 'discrete technology' sectors, always taking into account R&D Expenditures.
So this thesis will be challenging and very helpful because it will fill a gap in the literature since, as explained by Coad and Rao, *"it would have been interesting to include 'discrete technology' sectors in our study, but unfortunately we did not have a comparable number of observations for these sectors. This remains a challenge for future work"*.

In doing so, this study will address a **Research Question** *(Is the positive impact of R&D Expenditures on Employment limited solely to the US high-tech manufacturing firms, classified as 'complex technology' companies?)* that will be declined in **3 different hypotheses**: 1) US high-tech manufacturing companies are characterized by a positive and significant employment impact of R&D Expenditures; 2) US high-tech manufacturing firms, classified as ’complex technology’ companies, are characterized by a positive and significant employment impact of R&D Expenditures; 3) US manufacturing firms, classified as ’discrete technology’ companies, are characterized by a positive and significant employment impact of R&D Expenditures.

This thesis is structured in five different chapters, including the introduction.
Chapter 2 will go through a deep analysis of the available literature, examining what scholars have already found about the relationship between innovation and employment, and the last paragraph will be dedicated to the development of the research hypotheses.
Chapter 3, moving from the Literature Review to the Research Methodology, will provide a detailed description of the methodology through which the research has been conducted, underlying how the relationship between innovation and employment has been addressed. First of all the construction of the sample data and the criteria adopted will be illustrated, then the variables employed in the empirical analysis will be deeply described and finally the statistical methodology used to reach the conclusions will be presented.
Chapter 4 will describe the process used for the construction of the four models and it will also provide the statistical results with the relative demonstration of the three hypotheses.
Chapter 5 will focus on the conclusions with a specific section regarding the implications and the limitations of the study and with another section concerning some suggestions for future researches.

2. LITERATURE REVIEW

The idea to analyze the relationship between innovation and employment came from the evolving technologies that are radically changing the way organizations work nowadays.
The empirical literature confirmed the strong positive relationship between innovation and long term economic growth but the classical debate on the potential adverse consequences of innovation on employment is still open.
This debate, since the beginning, is characterized by the competition between two opposing views: from one side, the fear of technological unemployment as a direct consequence of labour-saving innovations (Mariacristina Piva and Marco Vivarelli, 2017), remembering what happened during the first Industrial Revolution in England where workers decided to destroy machines under the lead of Ned Ludd in the industrial areas; from the other side, there are indirect economic forces (income and price) that could counterbalance the reduction of employment, due to process innovation incorporated in the new machineries (Francesco Bogliacino, Mariacristina Piva and Marco Vivarelli, 2012).

The widespread diffusion of new technologies, especially new information and communications technologies (ICTs) and automation, that a lot of companies are implementing with the aim to enhance productivity, reduce errors and improve the quality of outputs, is leading to significant adjustments within businesses and work environments (Van Roy, Vértesy, Vivarelli, 2018).
For example, automation, especially robotics and artificial intelligence, is replacing office workers but, at the same time, is requiring companies to hire more programmers and other skilled digital employees who must work side by side with machines.

So, to investigate the relationship between innovation and employment, Chapter 2 will go through a deep analysis of the available literature, examining what scholars have already found about these two topics, before moving to the research hypotheses and the description of the related variables taken into account.

2.1 Innovation

2.1.1 Definition of Innovation

During the last years, customers' needs and lifestyles are progressively changing, competitive pressure is increasing and innovation is becoming more complex. *Innovation has become the mainstay of every organization* (du Plessis, 2007) and, as explained by A. Baregheh, J. Rowley and S. Sambrook (2009), *organizations need to innovate in order to capitalize on opportunities offered by technology and changing marketplaces, structures and dynamics.*

Innovation has been defined by scholars in many different ways throughout the years. Joseph Schumpeter (1883-1950) was one of the first theorists who focused his attention on the role of innovation in economic and social change.
He defined innovation as "new combinations" of existing resources and he talked about new products, new methods of production, new sources of supply, the exploitation of new markets, and new ways to organize business as some examples of innovation.
After Schumpeter (1934), as early as 1965, one of the first definitions of innovation came from Victor A. Thompson who defined innovation as *"the generation, acceptance and implementation of new ideas, processes, products and services"*.
However, innovation is defined as *"the introduction of new things, ideas or ways of doing something"* (Oxford Learner's Dictionaries).

As mentioned above, Joseph Schumpeter talked about new products, new methods of production, new sources of supply, the exploitation of new markets, and new ways to organize business as some examples of innovation.

New products and new methods of production, defined “product innovation” and “process innovation” respectively, are the most relevant ones in economics.
The distinction between product and process innovations has been introduced by Joseph Schumpeter in his *Theory of Economic Development (1934).*
In his *Theory of Economic Development,* product innovation is defined as ‘the introduction of a new good - that is one with which consumers are not yet familiar - or a new quality of a good’, while process innovation is defined as ‘the introduction of a new method of production, that is one not yet tested by experience in the branch of manufacture concerned ... and can also exist in a new way of handling a commodity commercially’.

In addition, product innovation has been recognized as ‘a primary means of organizational renewal’ (Dougherty, 1992) and as ‘an engine of renewal’ (Bowen et al., 1994).
According to Floyd and Lane (2000), *‘a theory of strategic renewal must recognize that maintaining adaptiveness requires both exploiting existing competences and exploring new ones’.*
So to survive, prosper and remain competitive in dynamic environments, organizations need to continuously innovate in order to renew the value of their asset endowment.

Finally, it is important to underline that innovations are not all the same; there are, in fact, different typologies of innovation that a firm could conduct. These typologies of innovation vary with the size, the industry and the country of incorporation of the related firm and depend on their innovative characteristics or on the degree of innovativeness, contingent upon the firm’s capabilities and competencies (Garcia and Calantone, 2001).

2.1.2 How to measure Innovation

Since, in the available literature, the understanding and definitions of innovation are not the same from one another, it is not easy to identify innovation from an empirical point of view and, in fact, there is no common overall measure for innovation.

The amount of money spent on research and experimental development (R&D Expenditures) has been recognized as the most important input into innovation and newly created or improved products or process innovations as the output of the innovation process (Klomp and Van Leeuwen, 2001).
So R&D spending is often used as an indicator of a company's willingness to invest (Adams et al., 2006), as a good indicator of the firm's technological position (Hall, 2004) and so as an empirical proxy for the economic value of innovation efforts (Pandit, Wasley and Zach, 2011).
In addition, as underlined by Romijn and Albaladejo (2002), R&D indicators are good in representing organizational innovativeness but they don't provide insights into the specific innovativeness of a company (Godin, 2002) so R&D Expenditures are an indirect measure of innovation.

According to The Frascati Manual of the Organisation for Economic Cooperation and Development (OECD, 2015, p.28):

"R&D comprise creative and systematic work undertaken in order to increase the stock of knowledge – including knowledge of humankind, culture and society – and to devise new applications of available knowledge".

In order to be an R&D activity, an activity must satisfy five core criteria: novelty, creativity, uncertainty, systematicity and transferability and/or reproducibility (OECD, 2015). R&D is a term that covers three different types of activities: Basic Research, Applied Research and Experimental Development (OECD, 2015, p.29).

1. Basic Research means experimental or theoretical work addressed primarily to the acquisition of new knowledge of the related phenomena and facts without any future application or use.

2. Applied Research is original investigation through a specific, practical aim or objective, addressed to the acquisition of new knowledge.

3. Experimental Development is systematic work that both uses knowledge coming from basic research and practical experience and produces additional knowledge to produce new products or processes or to improve existing ones.

However, data on R&D spending are not always available or they are limited because many companies have strict confidentiality policies to secure their competitive advantage (Kleinknecht, 1993) and so they are not willing to provide sensitive answers about their innovation processes (Hansen, 1985; Chesnais, 1992).
For this reason, scholars sometimes use also the number of patents or citations based on patent data as another common measure for innovation, due to the large amount of information available on them and due to the fact that patents reflect the continuous developments within technology.
But there are some limits of using patent data as an innovation indicator (Kleinknecht et al., 2002) because 1) patents protect inventions and not innovations, 2) not all innovations are patented, and 3) different propensities of patenting behavior are dependent on a company's strategy and sectors (Arundel and Kabla, 1998).

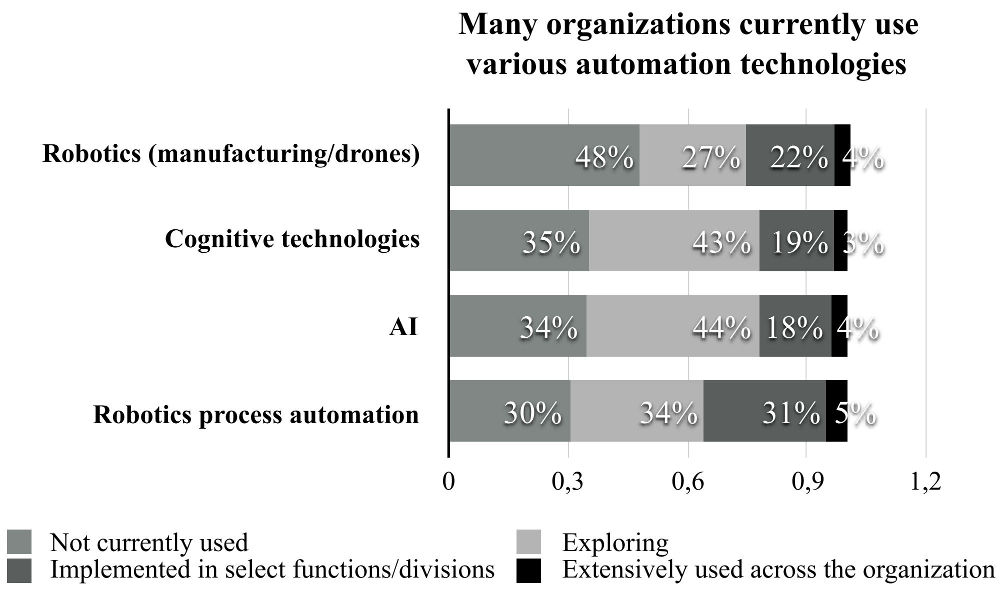
So, for these limitations, in this study, R&D Expenditures will be used as the indicator of innovation and only companies incorporated in the United States of America will be analyzed.
The decision to restrict the empirical sample to the American firms is due to the large availability of Research and Development Expenditures' data and the country specifics, and also because the world top leader in R&D investment is the United States, followed by China, Japan, Germany, Republic of Korea, France, India, United

Kingdom, Russian Federation and Brazil (UNESCO Institute for Statistics, June 2019).

2.2 Employment

2.2.1 How technology is changing the work landscape

The market for technologies is growing at 20% per year and will reach US $5 billion by 2024 (Global Human Capital Trends Survey, Deloitte 2019).
Regarding how technology is changing work and organizations, Cascio and Montealegre (2016) considered five technologies that are transforming the manner in which businesses create and capture value: cloud and mobile computing, big data and machine learning, sensors and intelligent manufacturing, advanced robotics and drones, and clean-energy technologies.
These technologies are allowing people to perform tasks in a faster and better way but, at the same time, they are profoundly changing how work is done within and across organizations (Cascio and Montealegre, 2016).
As shown in the following picture, 31% of respondents are doing a growing use of automation.



Source: Deloitte Global Human Capital Trends survey, 2019

Robotic Process Automation (RPA) - software for the automatization of manual tasks - is the most used; another 26% of respondents use robotics mostly, 22% use AI and 22% use cognitive technologies.

As underlined by Cascio and Montealegre (2016), *the advent of machine learning, in which computers teach themselves tasks and rules by analyzing large sets of data (The Economist 2015a) will surely lead to large-scale worker dislocation as areas such as speech recognition, pattern recognition, and image classification eliminate wide swaths of white-collar workers (The Economist 2015b).*

Even if, over the next years, some kinds of jobs performed by humans will disappear and others will be substituted by robots or digital agents, *however, history suggests it is a temporary, although painful, shock* (Cascio and Montealegre, 2016).
Obviously, because of this new work landscape, fear and uncertainty are growing but, at the same time, many new machines are showing to not be able to tolerate high levels of ambiguity and to have some problems when they need to address more complex and broader questions.
Only 6% of the respondents to the Deloitte survey showed that their organizations were "very ready" to address the impact of the new technologies, demonstrating how human workers will continue to be central to problem solving and how humans will continue to represent a strong comparative advantage over machines.

"*As organizations adopt these technologies, by removing routine work, they're finding that virtually every job must change, and that the jobs of the future are more digital, more multidisciplinary, more machine-powered and more data-and information-driven than in the past. They also require more human skills in problem-solving, communication, interpretation and design, enabling the role and contribution of people in work to rise in importance and value"* (Global Human Capital Trends Survey, Deloitte 2019).

So the challenge for businesses will be to recode work instead of redesign jobs, where recoding work means *integrating machines and humans in the flow of work and creating meaningful roles for people* (Global Human Capital Trends Survey, Deloitte 2019).
From one side, companies need to welcome and adapt themselves to these new technologies in a more flexible way and have to learn how to use them in the most strategic way possible; from the other side, humans have to try to overcome this situation, working side by side with machines and adjusting their skills.
In fact, in the Deloitte survey, 86% of respondents underlined the necessity to reinvent their ability to learn, in order to face with the accelerated use of artificial intelligence (AI), cognitive technologies and robotics, and 84% of respondents underlined the necessity to rethink their workforce experience in order to enhance productivity.

Because of all these transformations, the nature of the work and the job itself are changing so the new landscape is leading to the creation of a new category of roles that are called "superjobs": they are new kinds of jobs that, requiring new skills and putting aspects of traditional jobs together with integrated roles, are able to increase the productivity and the efficiency.
Superjobs are more than the so-called "hybrid jobs".
Hybrid jobs put together technical skills, including technology operations and data analysis and interpretation, and soft skills related to communication, service and collaboration[1]. While superjobs not only put together technical skills with soft skills but also put aspects of traditional jobs together with integrated roles, *using technology to both augment and broaden the scope of the work performed and involving a more complex set of domain, technical, and human skills* (Global Human Capital Trends Survey, Deloitte 2019).

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[1] Matt Sigelman, "By the numbers: The job market for data science and analytics" Burning Glass Technologies, February 10, 2017.

2.2.2 The qualitative effects of innovation on employment

From an empirical perspective, there is a particular branch of labor economics literature that is composed by studies which are mainly focused on the qualitative employment effects of innovation[2], rather than on the quantitative ones.
The literature regarding the qualitative consequences of innovation and so the literature regarding the impact of innovation over skills and tasks started in the '90s and nowadays is very vast, featuring that technological change is not skill-neutral[3].
At the beginning, this debate, as Van Roy, Vértesy and Vivarelli (2018) wrote in their paper, was focused on the so called "Skill-Biased Technological Change" (SBTC) and was based on the fact that *"technological unemployment" was far more likely for the low skilled and less educated workers,* thus increasing wage inequality (see Acemoglu and Autor, 2011; Berman et al., 1994; Bogliacino and Lucchese, 2016; Machin and Van Reenen, 1998; Piva et al., 2005).
For example in US, according to Acemoglu and Autor (2011), demand for middle-skilled people has decreased as a consequence of the fault of the demand for routine tasks, while demand for both high-skilled and low-skilled (paid accordingly) ones has risen. This trend has been called 'job polarisation'.

Then this debate has shifted and now it is focused on the difference between routine-based and non-routine-based tasks, with routine-based tasks that risk to be cancelled (see Autor and Dorn, 2009; Cirillo, 2017a; Frey and Osborne, 2017; Goos and Manning, 2007; Michaels et al., 2014).
For example, *"Frey and Osborne (2017) – using a Gaussian process classifier applied to data from the US Department of Labor – predict that 47% of the occupational categories, mostly middle and low-skilled professions, are at high risk of being automated, due to the routine-nature of their tasks, including a wide range of*

[2] Daniela Freddi, "The employment effects of digitalisation - a literature review" Paper

[3] Bernhard Dachs (2018). "The impact of new technologies on the labour market and the social economy" Paper

service/white-collar/cognitive tasks such as accountancy, logistics, legal works, translation and technical writing" (Barbieri, Mussida, Piva and Vivarelli, 2019).

In my study, I will not take into account the qualitative effects of innovation but I can affirm that the empirical research will enrich the existing literature, providing more insights about the relationship between innovation and employment and bringing some light on this evolutionary landscape.

2.3 Innovation and Employment

2.3.1 Background

Among Europe 2020 Strategy's targets, that the European Union (EU) has defined as five objectives to be reached by 2020, the first two are represented by employment and innovation (European Commission 2013, 2015).
This strategy aims at: (1) increasing employment by raising the employment rate of population to at least 75% and (2) promoting innovation by increasing research and innovation expenditures to at least 3% of the GDP.
So, since increasing R&D is one of the five main targets of European economic policy, studying the possible impact of this policy on employment is relevant.

As underlined by Van Roy, Vértesy and Vivarelli (2018), *economic theory does not have a clear-cut answer about the employment effect of innovation so there is a strong need for empirical analyses able to test the final employment impact of technological change*.

The existing literature, studying the relationship between innovation and employment, suggests that this relationship is much more complicated than one can think initially (Smolny, 1998).
If technological change creates or destroys jobs is a question that lots of scholars have already posed in their researches during all these years and that recently is acquiring

increasing importance because of the diffusion of a "new technological paradigm" (Dosi, 1982 and 1988), based on information and communications technologies (ICTs) and automation.

This question has been addressed since the beginning of the classical economics of Karl Marx:

"*Suppose that the making of the new machinery affords employment to a greater number of mechanics, can that be called compensation to the carpet makers, thrown on the streets?"* (Marx (1867): 479)[4].

Many scholars considered innovation as the driver of employment growth, especially in the long run (Freeman et al. 1982; Van Reenen 1997; Edquist et al. 2001; Pianta 2005; Vivarelli 2014) but, at the same time, the results coming from diverse empirical studies are contradictory between them.

In fact, as said by Jisun Lim and Keun Lee (2018), *the relationship between innovation and employment has not been clearly identified and the overall employment effect of innovation cannot be predetermined* especially because, from an economic perspective, two are the employment effects of innovation that contrast each other (Harrison et al., 2008; Vivarelli, 2014): the displacement effect and the compensation effect.

The former means that labor-saving process innovations displace workers by capital and so has a negative influence on jobs, creating technological unemployment; the latter means that innovation increases demand for workers in the production process, affirming that there are indirect economic effects (through decreasing prices and increasing incomes, both triggered by technological change itself) that can compensate or over-compensate for the direct job-destructive effect of process innovations (Laura Barbieri, Mariacristina Piva, Marco Vivarelli, 2016).

[4] Das Kapital (1867), Volume I, Chapter 15, Section 6.

So the studies concerning the relationship between innovation and employment are largely increasing in the empirical literature *given that economic theory does not ascribe an exact net effect of innovation* (Jisun Lim, Keun Lee, 2018).
As explained by d'Artis and Boriss (2017), from an empirical point of view, the employment effects of innovation depend on the firm's sector of activity, formal and informal institutions, the time frame of analysis, specifics of the existing production technology, the radical or incremental dimension of innovation, consumer preferences, the fierceness of competition in intermediate input and labour markets, and the structure of workforce skills (Bogliacino and Vivarelli, 2012; Bogliacino et al., 2012; Vivarelli, 2007; Lachenmaier and Rottmann, 2007).
So the quantitive effects of innovation on employment, usually measured in terms of number of jobs or number of hours worked, can be analyzed at the firm level, industry level or macroeconomic level (Pianta, 2005) and it can also differ in short and long run perspectives[5].

Daniela Freddi in her paper, called "The employment effects of digitalisation - a literature review", showed how a great amount of studies conducted at the firm level (for reviews see Petit, 1995; Chennells and Van Reenen, 1999; Spiezia and Vivarelli, 2002) demonstrates a positive relationship between innovation and employment, *as firms that introduce product, process, organisational innovations tend to be more competitive, more productive, expand their markets and therefore they grow faster, with positive implications on the number of jobs*.
But these studies show only what happens to the sample of firms analyzed and do say nothing about the whole economy.

In order to overcome these limitations, some studies began to be conducted at the industry level so considering both the direct effects at the firm level and the indirect effects at the industry level.
These studies, conducted at the industry level, represent the *"most satisfactory level of analysis, as it is able, on the one hand, to differentiate between the variety of*

[5] 5 Daniela Freddi - "The employment effects of digitalisation - a literature review"

technological regimes and strategies and, on the other hand, to bring in the demand dynamics of specific sectors, taking into account country differences in economic structures" (Pianta, 2005, p. 579).

2.3.2 The distinction between product innovation and process innovation

When talking about the relationship between innovation and employment, the first distinction that has to be made is the one between product innovation and process innovation, even if this distinction is not always straightforward.
In fact, *as an innovation may have features of being both a product and a process innovation, the overall effect of innovation on employment becomes too complex to be resolved by theoretical work alone, and needs to be investigated empirically (Coad and Rao, 2011).*

As already explained, product innovation means introducing a good or a service that is new or significantly improved while process innovation is the implementation of new or significantly improved processes for the production or the delivery of products (OECD 2005). Product and process innovations are both considered by the OECD as technological innovations.

The employment effect of innovation depends on the nature of innovation (product or process innovation) (Pianta, 2004) and so the consequences on employment are different if considering product or process innovations.
Most empirical studies showed a clear and positive relationship between the introduction of new products and the growth of income and employment at the firm level; instead process innovations are more likely to lead to the same amount of output but with less capital and/or labour so improving productivity but with an higher rate of unemployment.
However, some studies stated the opposite, demonstrating how the empirical results on process innovations are ambiguous. For example, van Reenen (1997) and Entorf and Pohlmeier (1990) found a small and not significant impact of process innovations

on employment; Greenan and Guellec (2000) or Lachenmaier and Rottmann (2011) found a significant positive effect, while Blechinger and Pfeiffer (1999) and also Evangelista and Savona (2003) studies resulted in a labour displacement by process innovations, especially in larger firms.
To summarize, therefore, it is important to consider that *product innovations generally have a positive impact on employment, whilst the role of process innovations is more ambiguous* (Hall et al. 2008).

In this research, I will consider only product innovations because, as Van Roy, Dániel Vértesy and Marco Vivarelli (2018) explained in their paper, *there is less debate about the positive employment effect of product innovations, that are generally understood to lead to the opening of new markets, or to an increased variety within the existing ones.*
In fact, *"the employment impacts of innovation generally are more positive in economies in which new-product generation and investment in new economic activities are higher, and in which the demand-increasing effects of price reductions are greater" (Pianta, 2000, p. 582)*.

In addition, product innovations, according to recent empirical studies (see Francesco Bogliacino, Mariacristina Piva and Marco Vivarelli, 2011), are mainly and significantly connected with R&D, as also Cincera (2005) confirmed, showing that R&D Expenditures are addressed to product innovations in 77% of cases.
While other innovative expenditures, such as those for new machinery and equipment, turn out to be mainly related to process innovations, especially in the traditional manufacturing sectors (see Conte and Vivarelli (2005), Parisi et al. (2006)).

2.3.3 Differences between sectors

According to Schumpeter, one reason why innovations can be disruptive for the whole economy is that innovations don't occur across the economic system but they are likely to concentrate themselves in key sectors, leading to structural adjustments between sectors[6].

So the relationship between innovation and employment creation is also influenced by the sector of the firm. In fact, between sectors there are significant technological differences that also lead to different employment performances.

As resulted from a study conducted by the European Commission in 2016 and analyzing employment by technology intensity of the sector between 2008 and 2013, the fastest growing sector was the market knowledge-intensive services, followed by high-tech knowledge intensive services sector, that includes also information and communication technology (ICT) services.

In addition, this study showed a significant gap between manufacturing and services industries in employment growth, with high-tech manufacturing performing best.

These are the reasons why, as we will see in the next paragraph of this chapter, some empirical researches, studying the relationship between innovation and employment, have been conducted on high-tech manufacturing firms, and some of these studies on US firms since US is the country that invests more in R&D (Unesco Institute for Statistics, 2019).

Finally it is important to underline how both the organization of innovation and its economic and social effects change also according to the specific nature of the technology in question[7].

In fact, as explained by Harrison et al. (2008, 2014), since innovations have different purposes and can have different employment effects, the distinction between the innovation type leads to a better understanding of the employment effect of innovation.

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[6] Daniela Freddi - "The employment effects of digitalisation - a literature review"

[7] Jan Fagerberg (2006). "Innovation: A Guide to the Literature" - The Oxford Handbook of Innovation

Recently, the World Economic Forum (WEF 2016) had conducted a survey about the technological drivers of future change in the economy, in which respondents showed that the main drivers of future change in the economy are all related to information and communications technologies (ICTs) except for advanced materials and health applications of biotechnology. These main drivers are: 1) mobile internet and cloud technology, 2) advances in computing power and big data, 3) new energy supplies and technologies, 4) the internet of things, 5) crowdsourcing, the sharing economy and peer-to-peer platforms, 6) advanced robotics and autonomous transport, 7) artificial intelligence and machine learning, 8) advanced manufacturing and 3D printing[8].

[8] "The Future of Jobs" Report 2018, World Economic Forum - http://www3.weforum.org/docs/WEF_Future_of_Jobs_2018.pdf

2.4 Research Purpose

This study aims at enriching the empirical microeconomic literature regarding the relationship between innovation and employment.
As already said, I will focus only on the quantitative employment effects of innovation and I will consider only product innovations.
I will mainly concentrate the empirical analysis on a sample of US High-Tech Manufacturing firms for diverse reasons:

1) US because it is the country with the highest R&D Expenditures and the highest R&D Intensity, as a percentage of domestic GDP; in addition, the decision to restrict the empirical sample to the American firms is due to the large availability of Research and Development Expenditures' data and the country specifics.

2) High-Tech sector because it is one of the fastest growing sectors and so it is critical for innovation, productivity and growth; in addition, High-Tech is one of the sectors where R&D is closely connected with product innovations and so R&D and employment are complements.

3) Manufacturing firms because manufacturing is the industry covered by many last studies, conducted also on US firms, so, in this way, I am able to provide an update examination of the topic, comparing the conclusions and seeing if something has changed.

The existing literature found that product innovations have a positive impact on employment, but not so many studies have been conducted on US firms.
In addition, *in the previous literature, empirical analysis has very rarely been carried out according to sectoral belonging (Francesco Bogliacino, Mariacristina Piva and Marco Vivarelli, 2012)*.
So my thesis will be significant because both it takes into account US firms and it is mainly carried out according to sectoral belonging, the High-Tech one.

Having a look at the previous studies, Marco Vivarelli (1995), using Italian and US data over the period 1960-1988, found that the US economy turned out to be more product-oriented and so characterized by a positive relationship between technology and employment.
Also Simonetti, Taylor and Vivarelli (2000), using a database covering American, Italian, French and Japanese firms over the period 1965-1993, found that product innovation significantly reveals its labor intensive potentiality only in US, considered as the technological leader country in that period.

While considering the sector, the labor-friendly impact is generally limited only to the high-tech sectors, characterized by a higher R&D Intensity, by the prevalence of product innovation (Vincent Van Roy, Dániel Vértesy and Marco Vivarelli, 2018) and by an increasing demand for innovative products (see also Harrison et al. (2008)), while more traditional manufacturing sectors are characterized by process innovations and a stagnating demand.
In fact, firms included in the high-tech manufacturing and services sectors belong to dynamic and emerging sectors where a strong correlation between R&D and product innovation is even more likely than average (Francesco Bogliacino, Mariacristina Piva and Marco Vivarelli, 2012).
So the first hypothesis of this research paper would be:

H1: US High-Tech Manufacturing companies are characterized by a positive and significant employment impact of R&D Expenditures

There is a big gap in the existing literature since the last study about US high-tech manufacturing industries has been conducted in 2011 by Coad and Rao over the period 1963-2002.
Following what Coad and Rao (2011) have already done, for the empirical analysis concerning high-tech manufacturing companies, I will take into account four sectors

of firms, classified under the ‘complex products’ class, because these sectors are characterized by high patenting and high R&D expenditure so there is a bigger possibility to get relatively accurate measures of firm-level innovation.

So my dataset will include four high-tech manufacturing industries that can be classified as ‘complex technology’ sectors (SIC 35 (industrial and commercial machinery and computer equipment), SIC 36 (electronic and other electrical equipment and components, except computer equipment), and SIC 38 (measuring, analyzing and controlling instruments; photographic, medical and optical goods; watches and clocks)) as well as a ‘complex technology’ sector that is, technologically speaking, more mature (SIC 37 (transportation equipment))

One of the main differences is that Coad and Rao (2007) conducted their empirical analysis generating a firm and year specific ‘innovativeness’ index by extracting the common variance in a firm’s patenting and R&D expenditure histories, demonstrating that firm-level innovative activity leads to employment creation; while, in this research, as already said, only R&D Expenditures will be used as the indicator of innovation within firms.

Therefore it will be interesting to test if firm-level innovative activity leads to employment creation by taking into account R&D Expenditures instead of the ‘innovativeness’ index.

So the second hypothesis of this research paper would be:

H2: US High-Tech Manufacturing firms, classified as ’complex technology’ companies, are characterized by a positive and significant employment impact of R&D Expenditures

The ‘complex products’ classification has been introduced by Hall (2004) and Cohen et al. (2000). They defined ‘complex product’ industries those industries where each product relies on many patents held by a number of other firms, while the ‘discrete

product' industries are those industries where each product relies on only a few patents.
As per Cohen et al. (2000), Contigiani, Hsu and Barankay (2018) focused on manufacturing sectors, using forward-citation-weighted patent counts, and categorized each SIC as either discrete (SIC between 19 and 33) or complex (SIC between 34 and 39).
Established in the United States in 1937, the Standard Industrial Classification (SIC) is a system for classifying industries by a four-digit code, used by government agencies to classify industry areas[9].

The distinction between 'discrete technology' manufacturing companies (SIC between 19 and 33) and 'complex technology' manufacturing companies (SIC between 34 and 39) will be very helpful to fill a gap in the literature because, as explained by Coad and Rao, *"It would have been interesting to include 'discrete technology' sectors in our study, but unfortunately we did not have a comparable number of observations for these sectors. This remains a challenge for future work"*.
Therefore it will be interesting to test if firm-level innovative activity leads to employment creation not only for 'complex technology' sectors but also for 'discrete technology' sectors, always taking into account R&D Expenditures.
So the third hypothesis of this research paper would be:

H3: US Manufacturing firms, classified as 'discrete technology' companies, are characterized by a positive and significant employment impact of R&D Expenditures

For this reason, my dataset will also include industries that can be classified as 'discrete technology' sectors (SIC 20 (food and kindred products), SIC 21 (tobacco

[9] Standard Industrial Classification - Wikipedia. https://en.wikipedia.org/wiki/Standard_Industrial_Classification

products), SIC 22 (textile mill products), SIC 23 (apparel and other finished products made from fabrics and similar materials), SIC 24 (lumber and wood products, except furniture), SIC 25 (furniture and fixtures), SIC 26 (paper and allied products), SIC 27 (printing, publishing and allied industries), SIC 28 (chemicals and allied products), SIC 29 (petroleum refining and related industries), SIC 30 (rubber and miscellaneous plastics products), SIC 31 (leather and leather products), SIC 32 (stone, clay, glass and concrete products)).

So **my Research Question would be: Is the positive impact of R&D Expenditures on employment limited solely to the US High-Tech Manufacturing firms, classified as 'complex technology' companies?**

3. RESEARCH METHODOLOGY

Moving from the Literature Review to the Research Methodology, this chapter will provide a detailed description of the methodology through which the research has been conducted, underlying how the relationship between innovation and employment has been addressed.

First of all, there will be an illustration of the process followed to construct the sample of companies, with an explanation of the criteria and methods adopted to deeply analyze the collected dataset.
Afterwards, the characteristics of the sample will be described thanks to the use of some specific graphs.
Consequently, in order to understand the form that the regression will have, the dependent and independent variables will be illustrated, together with the control variables taken into account, also according to those scholars who, in the existing literature, decided to use the same variables.
Finally, the development of the research models and the expected results will be addressed.

3.1 Sample and Dataset Construction

The sample of companies, together with their financial data, has been drawn from Orbis database, a database owned by a Moody’s Analytics Company, called Bureau Van Dijk.
Orbis is the world’s most powerful comparable data resource on private companies, with information regarding more than 365 million companies all over the world.
It can be used for the research, analysis and comparison between organizations and also to improve decision making processes[10].
Provided by Luiss Guido Carli University, this database has been extremely useful to collect the necessary data, with the aim to accomplish the goal of the empirical

[10] https://www.bvdinfo.com/en-gb/our-products/data/international/orbis

analysis that is, as already said, exploring the effect of innovation propensity of firms on employment.

To construct the dataset, 7 subsequent steps have been followed, as described below and also showed in Table 1:

1. all companies with an active status have been selected with the aim to not consider in the analysis those firms that do not operate anymore or with an unknown situation; the final result led to 269,041,360 available active companies from all over the world

2. all companies incorporated only in the United States of America have been selected, because of the large availability of Research and Development Expenditures' data and the country specifics. In fact, in many European countries like France, Germany and Italy, which are characterized by a civil law system, data related to annual R&D expenditures are not easily accessible because public disclosure is not required by the national accounting laws and regulations (Hall and Oriani, 2006). While, under US accounting laws and regulations, annual R&D expenditures' public disclosure by companies is required. The final result led to 61,317,617 active companies in the United States of America

3. all companies that are publicly listed have been selected so excluding private companies which lack the necessary data for the empirical analysis. The final result led to 17,399 publicly listed and active companies in the United States of America

4. only corporations have been selected with the aim to analyze a sample of business organizations. The final result led to 16,510 publicly listed and active corporations in the United States of America

5. High-Tech manufacturing industries that can be classified as 'complex technology' sectors (SIC between 34 and 39), and manufacturing industries that can be classified as 'discrete technology' sectors (SIC between 19 and

33) have been selected. As already said, this distinction will be very helpful not only to answer **the research question (Is the positive impact of R&D Expenditures on employment limited solely to the US high-tech manufacturing firms, classified as 'complex technology' companies?)** but also to fill a gap in the literature because *"It would have been interesting to include 'discrete technology' sectors in our study, but unfortunately we did not have a comparable number of observations for these sectors. This remains a challenge for future work" (Coad and Rao)*. The final result led to 2,485 companies

6. since R&D Expenditures will be used as the innovation indicator within firms, only companies having R&D expenditures' data availability for the period 2012-2017 have been selected, reducing the sample to 846 companies

7. since the total number of employees will represent the dependent variable in the empirical analysis, only companies having number of employees' data availability for the period 2012-2017 have been selected, bringing the sample to 532 final companies, as shown in the following table:

Companies' Sample Construction			
Search Step		**Step Result**	**Search Result**
Status:	Active Companies	269,016,853	269,016,853
World Region/Country/Region in Country:	United States of America	61,566,000	61,317,617
Listed/Unlisted Companies:	Publicly Listed Companies	95,173	17,399
Accounting Template:	Corporate	371,566,938	16,510
US SIC Code:	SIC between 19 and 33; SIC between 34 and 39	18,170,166	2,485
R&D Expenditure:	All companies with a known value: period 2012-2017	29,604	846
Number of Employees:	All companies with a known value: period 2012-2017	4,268,618	532
TOTAL			**532**

Table 1: Sample Construction Procedure

(Source: Personal Representation)

For all these companies, the financial data necessary to describe the characteristics of the sample and to build the models have been collected:

- US SIC Code
- Bureau Van Dijk Sectors' Classification
- Research and Development Expenditures for the period 2012-2017
- Total Number of Employees for the period 2012-2017
- Total Assets for the period 2013-2017
- EBIT (Earnings before interest and taxes) for the period 2013-2017

First of all, the 532 final US manufacturing companies of the sample belong to 12 different sectors, according to the Bureau Van Dijk Sectors' Classification.
The distribution of these companies by sector is showed in Figure 1:

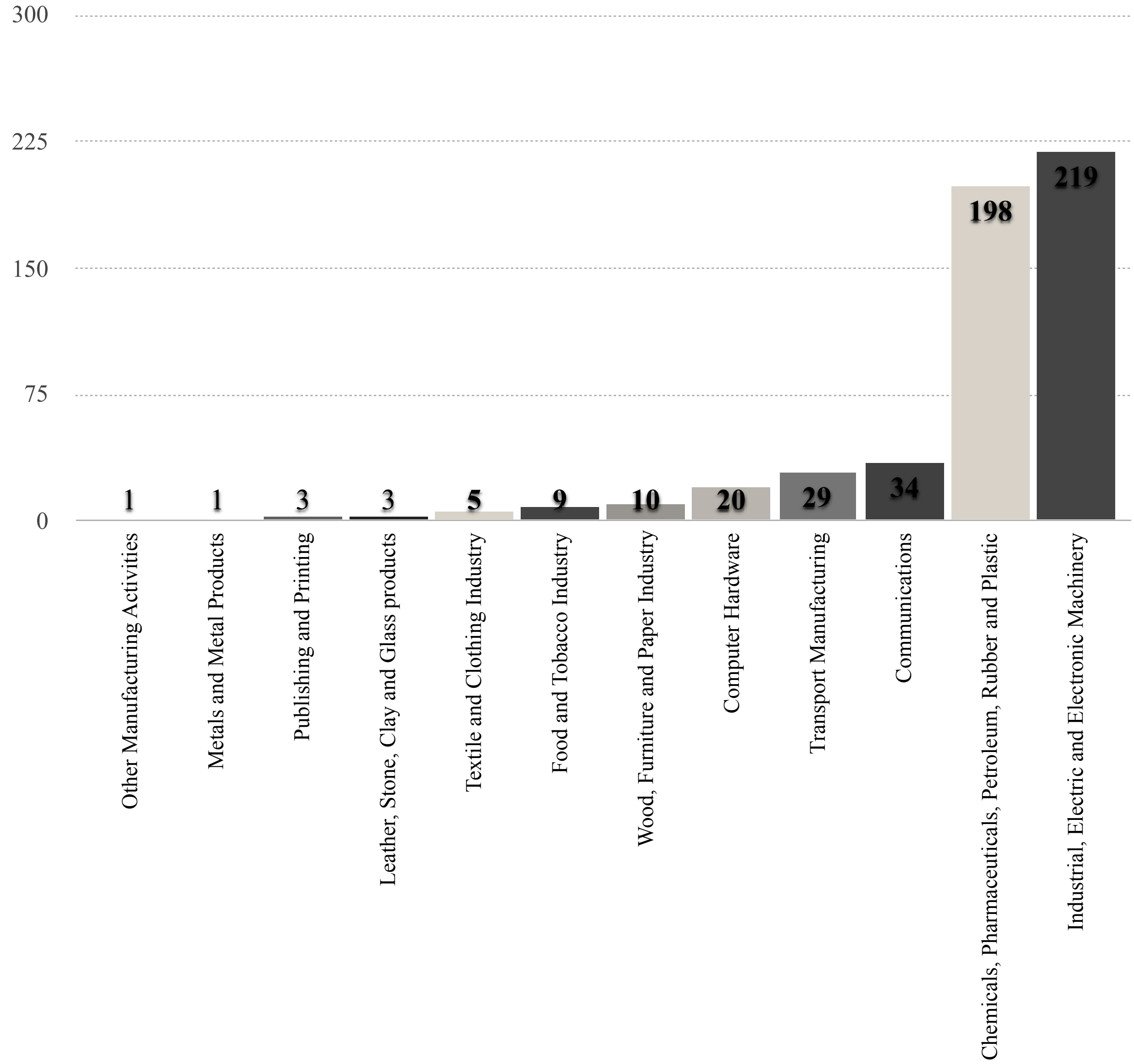

Figure 1: Firms' distribution based on Bureau Van Dijk Sectors' Classification

(Source: Personal Representation)

So the 12 different sectors, according to the Bureau Van Dijk Sectors' Classification, are listed below together with the respective percentage of the belonging firms:

- Other Manufacturing Activities: 0,19% of firms
- Metals and Metal Products: 0,19% of firms
- Publishing and Printing: 0,56% of firms
- Leather, Stone, Clay and Glass Products: 0,56% of firms

- Textile and Clothing Industry: 0,94% of firms
- Food and Tobacco Industry: 1,69% of firms
- Wood, Furniture and Paper Industry: 1,88% of firms
- Computer Hardware: 3,76% of firms
- Transport Manufacturing: 5,45% of firms
- Communications: 6,39% of firms
- Chemicals, Pharmaceuticals, Petroleum, Rubber and Plastic: 37,22% of firms
- Industrial, Electric and Electronic Machinery: 41,17% of firms

Afterwards, the 532 final US manufacturing companies of the sample are characterized by a different US SIC Code.
Distinguishing them between 'discrete technology' manufacturing companies (SIC between 19 and 33) and 'complex technology' manufacturing companies (SIC between 34 and 39), the distribution of the sample by SIC Code is showed in Figure 2 and Figure 3:

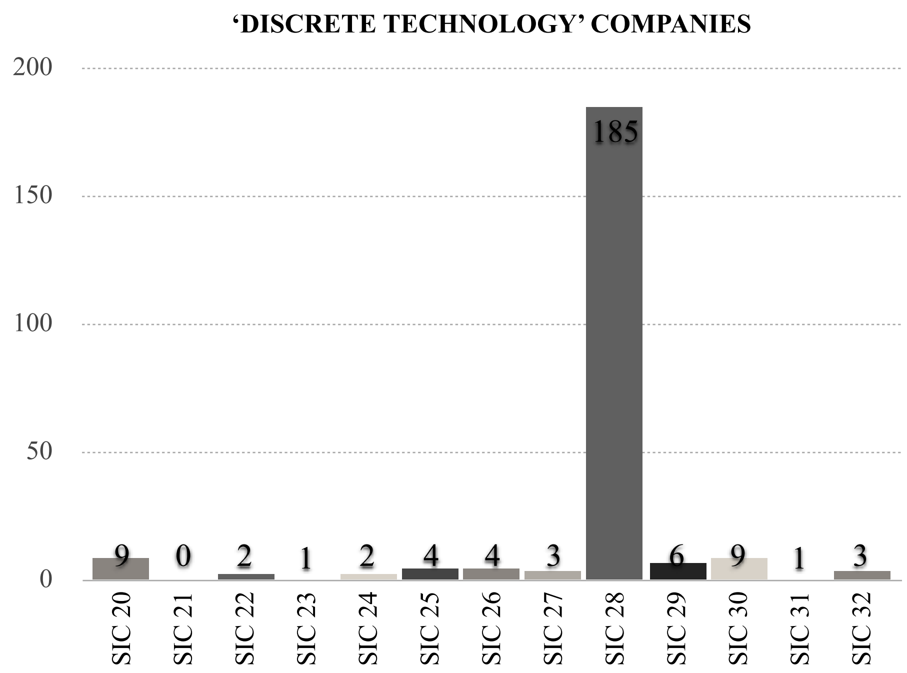

Figure 2: Firms' distribution based on US SIC Codes' Classification

(Source: Personal Representation)

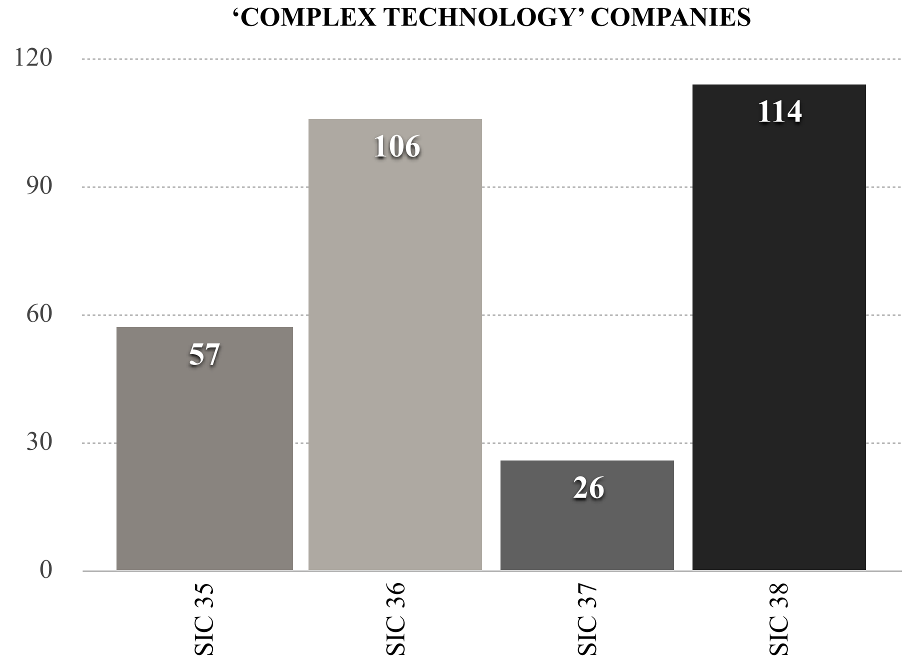

Figure 3: Firms' distribution based on US SIC Codes' Classification

(Source: Personal Representation)

As shown in Figure 2, the companies of the sample that belong to 'discrete technology' sectors are 229 of 532 and the 13 different 'discrete technology' codes, according to the US SIC Classification, are listed below together with the respective percentage of the belonging firms:

- SIC 20 - food and kindred products: 3,93% of firms
- SIC 21 - tobacco products: 0% of firms
- SIC 22 - textile mill products: 0,87% of firms
- SIC 23 - apparel and other finished products made from fabrics and similar materials: 0,44% of firms
- SIC 24 - lumber and wood products, except furniture: 0,87% of firms
- SIC 25 - furniture and fixtures: 1,75% of firms
- SIC 26 - paper and allied products: 1,75% of firms
- SIC 27 - printing, publishing and allied industries: 1,31% of firms
- SIC 28 - chemicals and allied products: 80,79% of firms
- SIC 29 - petroleum refining and related industries: 2,62% of firms

- SIC 30 - rubber and miscellaneous plastics products: 3,93% of firms
- SIC 31 - leather and leather products: 0,44% of firms
- SIC 32 - stone, clay, glass and concrete products: 1,31% of firms

While, as shown in Figure 3, the companies of the sample that belong to 'complex technology' sectors are 303 of 532 and the 4 different 'complex technology' codes, according to the US SIC Classification, are listed below together with the respective percentage of the belonging firms:

- SIC 35 - industrial and commercial machinery and computer equipment: 18,81% of firms
- SIC 36 - electronic and other electrical equipment and components, except computer equipment: 34,98% of firms
- SIC 37 - transportation equipment: 8,58% of firms
- SIC 38 - measuring, analyzing and controlling instruments; photographic, medical and optical goods; watches and clocks: 37,62% of firms

In addition, in order to provide a better understanding of the size of the sample companies, the following picture will provide information regarding the average number of total assets at the firm level, for the period 2013-2017.
As shown in Figure 4, 52% of companies has, on average, a total assets value between USD 1.000 and USD 500.000; 46% of companies has, on average, a total assets value between USD 500.001 and USD 50.000.000, and only 3% of companies has, on average, a total assets value higher than USD 50.000.000[11].

[11] All values are expressed in Thousands

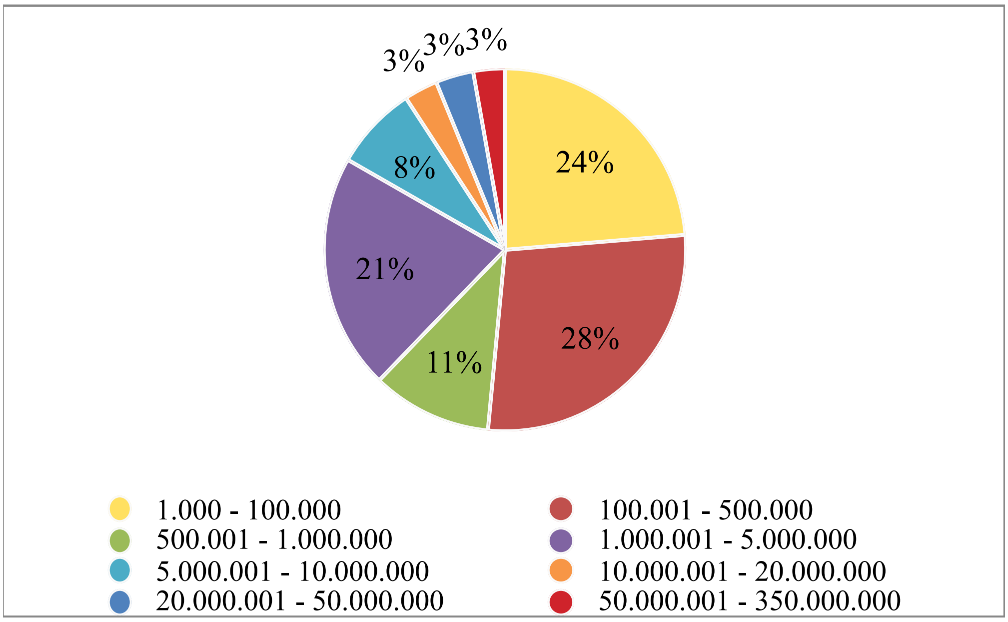

Figure 4: Distribution of Average Total Assets' Value (in $ Thousands)

(Source: Personal Representation)

3.2 Variables and Measures

3.2.1 Independent Variable

In this study, in order to investigate the effect of innovation on employment, R&D Expenditures will be considered as the independent variable for the empirical analysis. In fact, as already said in the Literature Review, R&D spending is often used as an indicator of a company's willingness to invest (Adams et al., 2006), as a good indicator of the firm's technological position (Hall, 2004) and so as an empirical proxy for the economic value of innovation efforts (Pandit, Wasley and Zach, 2011).

The average Research and Development Expenditures at the firm level, for the period 2013-2017, is provided in Figure 5:

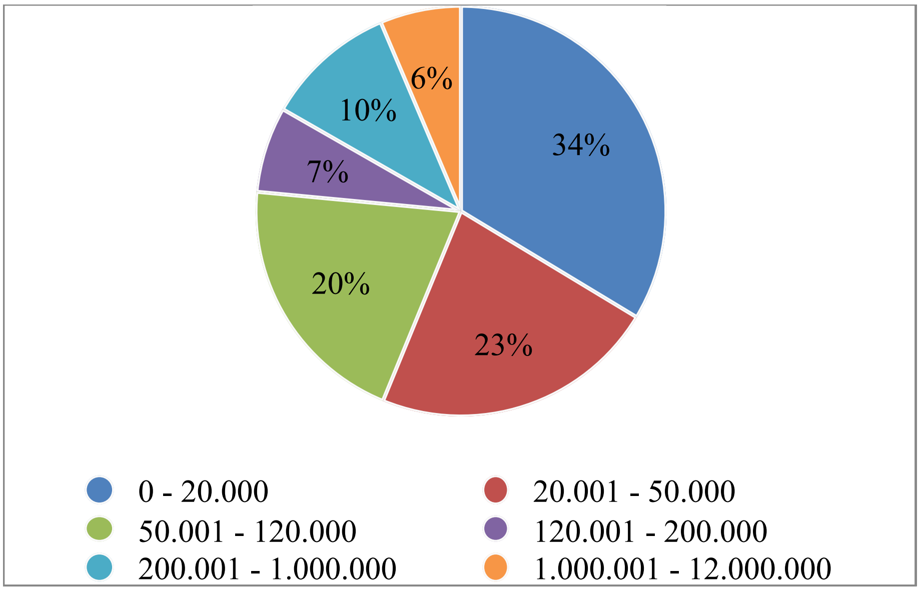

Figure 5: Distribution of Average R&D Expenditures (in $ Thousands)

(Source: Personal Representation)

As shown in Figure 5, 57% of companies has, on average, R&D Expenditures lower than USD 50.001; 27% of companies has, on average, R&D Expenditures between USD 50.001 and USD 200.000; 10% of companies has, on average, R&D Expenditures higher than USD 200.000 but lower than USD 1.000.001, and only 6% of companies has, on average, R&D Expenditures higher than USD 1.000.000[12].

While, splitting the 532 sample companies into 'complex technology' sectors (SIC between 34 and 39) and 'discrete technology' sectors (SIC between 19 and 33), Figure 6 and Figure 7 will represent the average Research and Development Expenditures at the firm level, for the period 2013-2017:

[12] All values are expressed in Thousands

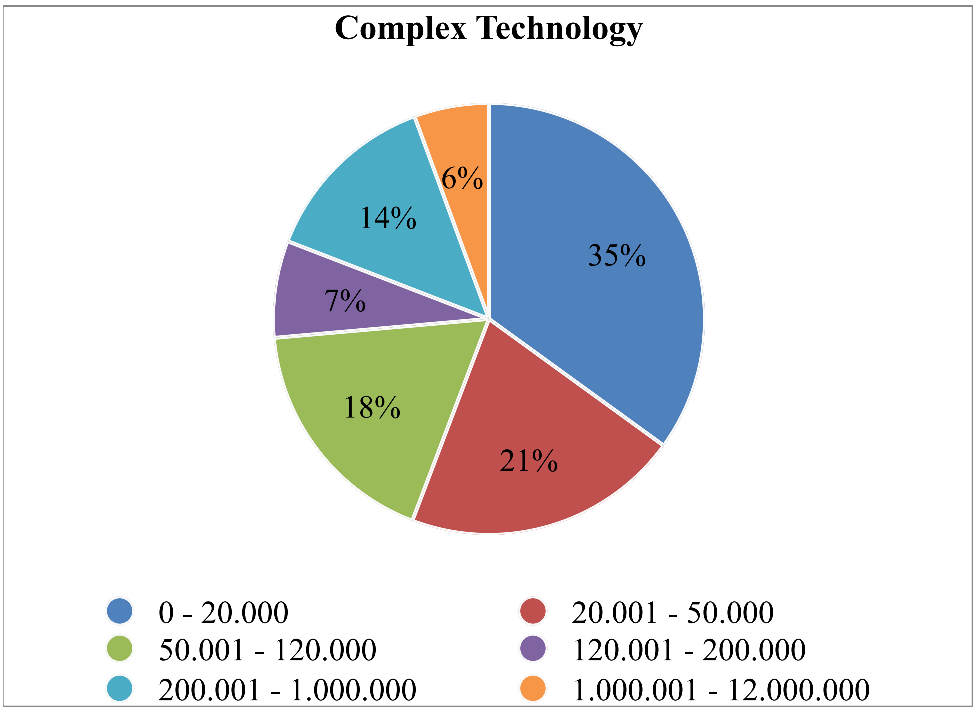

Figure 6: Distribution of Average R&D Expenditures (in $ Thousands)

(Source: Personal Representation)

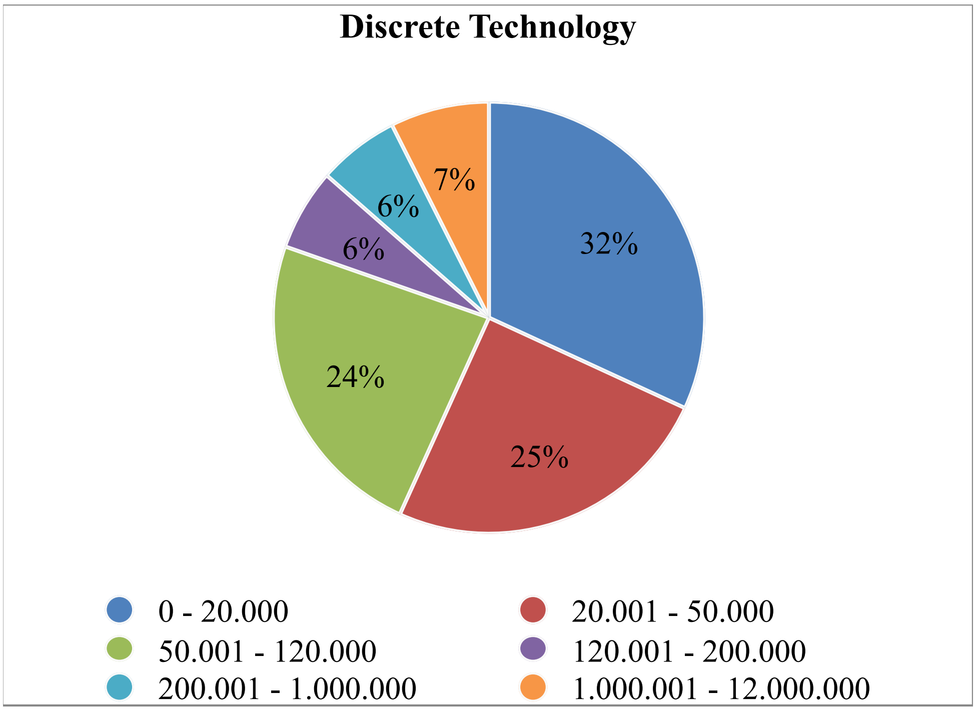

Figure 7: Distribution of Average R&D Expenditures (in $ Thousands)

(Source: Personal Representation)

As shown in Figure 6, 39% of companies that belong to ‘complex technology’ sectors, so 118 of 303 companies, has, on average, R&D Expenditures between USD 50.001 and USD 1.000.000[13]; 6% of companies, so 18 of 303 companies, has, on average, R&D Expenditures higher than USD 1.000.000 but lower than USD 12.000.001.

While, as shown in Figure 7, 36% of companies that belong to ‘discrete technology’ sectors, so 82 of 229 companies, has, on average, R&D Expenditures between USD 50.001 and USD 1.000.000[14]; 7% of companies, so 16 of 229 companies, has, on average, R&D Expenditures higher than USD 1.000.000 but lower than USD 12.000.001.

In addition, in order to provide deeper information about the independent variable, the following picture will show which are the sectors, according to the Bureau Van Dijk Classification, that, on average, invested more in Research and Development, during the period 2013-2017.

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[13] All values are expressed in Thousands

[14] All values are expressed in Thousands

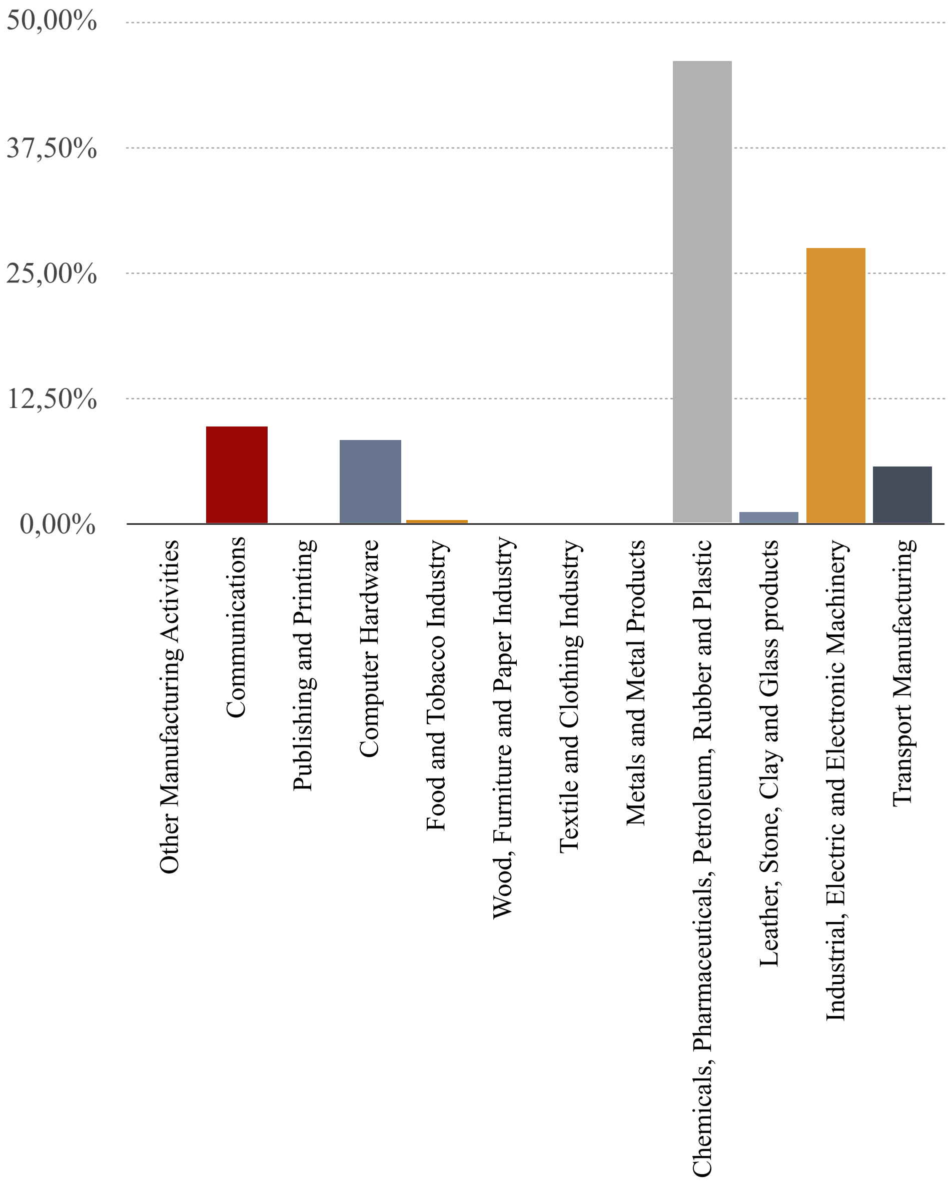

Figure 8: Distribution of Average R&D Expenditures by Sector (%)

(Source: Personal Representation)

As shown in Figure 8, the sector with the highest value of Average R&D Expenditures is ‘Chemicals, Pharmaceuticals, Petroleum, Rubber and Plastic’ (approximately 46,15% with USD 73.694.291[15]), followed by ‘Industrial, Electric and Electronic Machinery’ (approximately 27,57% with USD 44.021.211), ‘Communications’ (approximately 9,87% with USD 15.767.404) and ‘Computer Hardware’ (approximately 8,33% with USD 13.297.610).

[15] All values are expressed in Thousands

This confirms the results obtained by the survey conducted by the World Economic Forum (WEF 2016) about the technological drivers of future change in the economy, in which respondents showed that the main drivers of future change in the economy are all related to information and communications technologies (ICTs) except for advanced materials and health applications of biotechnology.

Furthermore, descriptive statistic of Research and Development Expenditures, related to ‘complex technology’ sectors, is provided in Table 2:

Variable	**Obs**	**Mean**	**Std.Dev.**	**Min**	**Max**
R&D Expenditures	1515	265.098	1.016.935	0	13.035.000

Table 2: R&D Expenditures Descriptive Statistic for ‘complex technology’ (in $ Thousands)

(Source: Personal Representation)

While, descriptive statistic of Research and Development Expenditures, related to ‘discrete technology’ sectors, is provided in Table 3:

Variable	**Obs**	**Mean**	**Std.Dev.**	**Min**	**Max**
R&D Expenditures	1145	337.335	1.150.446	0	10.594.000

Table 3: R&D Expenditures Descriptive Statistic for ‘discrete technology’ (in $ Thousands)

(Source: Personal Representation)

3.2.2 Dependent Variable

In this study, the relationship between R&D Expenditures and Total Number of Employees is investigated.

Therefore, the Total Number of Employees at the firm level, for the period 2013-2017, is used as the dependent variable for the empirical analysis.

The average Total Number of Employees at the firm level, for the period 2013-2017, is provided in Figure 9:

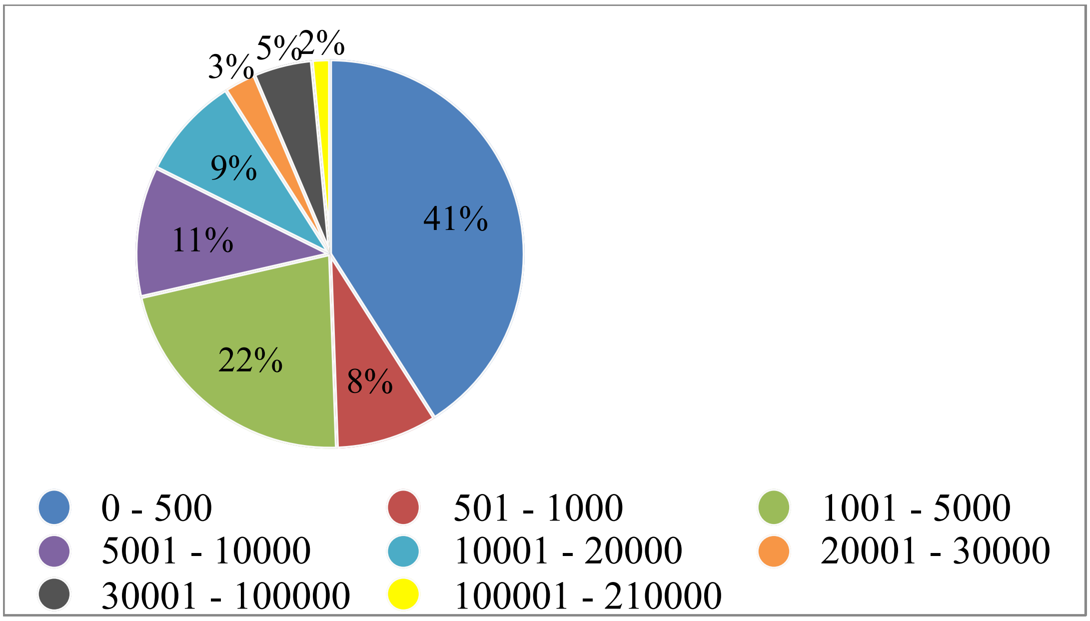

Figure 9: Distribution of Average Total Number of Employees

(Source: Personal Representation)

Figure 9 highlights that 71% of the sample companies, on average, for the period 2013-2017, employed less than 5001 employees, while the remaining 29% employed, on average, a total number of employees between 5001 and 210000, with only 2% of companies that employed more than 100000 employees.

In addition, being this study conducted on a period of 5 years, from 2013 to 2017, the compound annual growth rate (CAGR) of Total Number of Employees for each firm of the sample, is provided. The results are shown in Figure 10, where a distinction is made between companies that show a negative CAGR and those that show a positive CAGR.

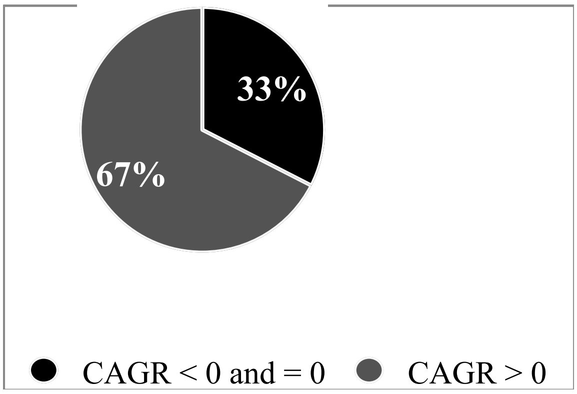

Figure 10: Total Number of Employees' Compound Annual Growth Rate (2013-2017)

(Source: Personal Representation)

From Figure 10, it is possible to underline that most of the sample companies (67% so approximately 356 companies) show a positive CAGR (CAGR > 0).

In addition, in order to provide deeper information about the dependent variable, the following picture will show which are the sectors, according to the Bureau Van Dijk Classification, that, on average, employed more employees, during the period 2013-2017.

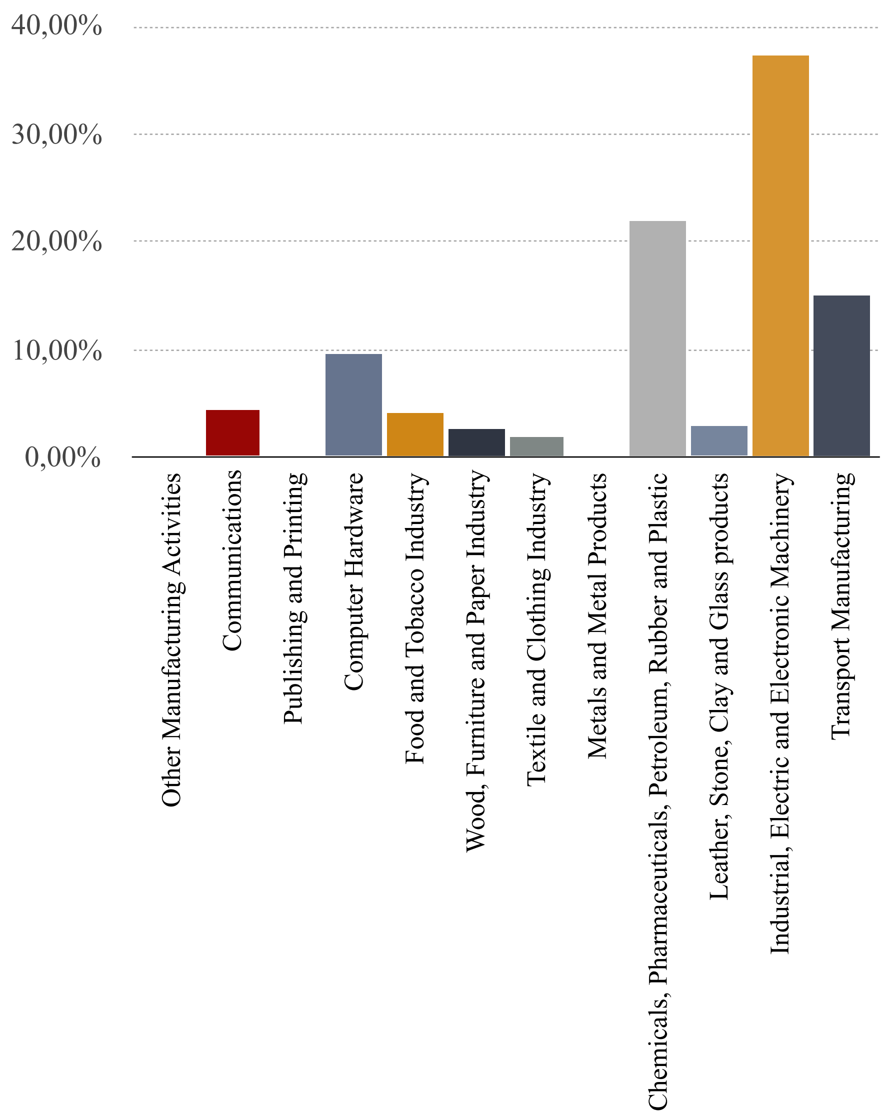

Figure 11: Distribution of Average Total Number of Employees by Sector (%)

(Source: Personal Representation)

As shown in Figure 11, the sector with the highest value of Average Total Number of Employees is 'Industrial, Electric and Electronic Machinery' (approximately 37,25% with 1662592 Employees (Average)), followed by 'Chemicals, Pharmaceuticals, Petroleum, Rubber and Plastic' (approximately 21,86% with 975556 Employees (Average)), 'Transport Manufacturing' (approximately 14,96% with 667602 Employees (Average)) and 'Computer Hardware' (approximately 9,58% with 427452 Employees (Average)).

So, looking at both Figure 8 and Figure 11, it is possible to underline how the sectors that, on average, invested more in R&D, like 'Chemicals, Pharmaceuticals, Petroleum, Rubber and Plastic' and 'Industrial, Electric and Electronic Machinery', are also the ones that, on average, employed more employees during the period 2013-2107.

While, splitting the 532 sample companies into 'complex technology' sectors (SIC between 34 and 39) and 'discrete technology' sectors (SIC between 19 and 33), Figure 12 and Figure 13 will represent the average Total Number of Employees at the firm level, for the period 2013-2017:

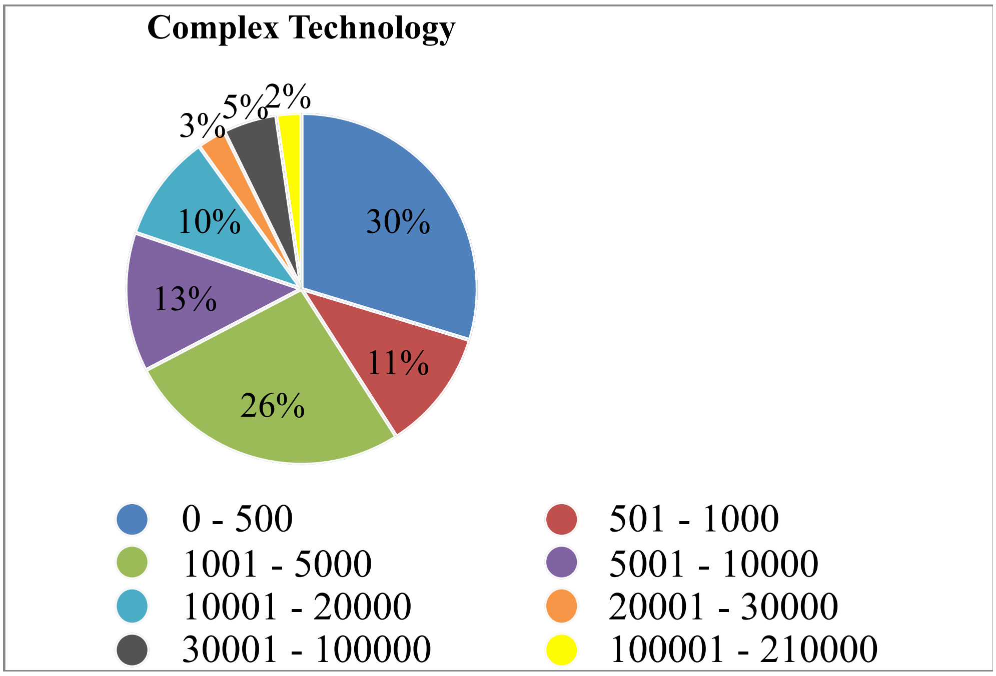

Figure 12: Distribution of Average Total Number of Employees

(Source: Personal Representation)

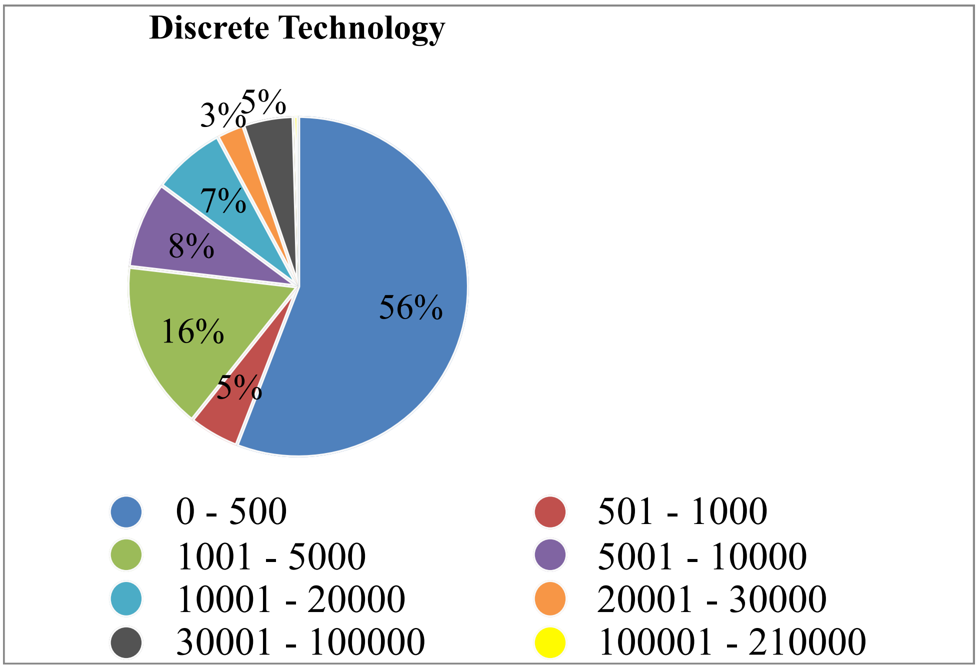

Figure 13: Distribution of Average Total Number of Employees

(Source: Personal Representation)

Figure 12 highlights that 67% of the sample companies, that belong to ‘complex technology’ sectors, so 203 of 303 companies employed, on average, for the period 2013-2017, less than 5001 employees, while the remaining 33% of the sample companies, so 100 companies, employed, on average, a total number of employees between 5001 and 210000, with only 2% of companies that employed more than 100000 employees.

While, as shown in Figure 13, 77% of companies, that belong to ‘discrete technology’ sectors, so 176 of 229 companies employed, on average, for the period 2013-2017, less than 5001 employees, while the remaining 23% of the sample companies, so 53 companies, employed, on average, a total number of employees between 5001 and 210000 with only 1 company that employed more than 100000 employees.

In addition, always splitting the 532 sample companies into ‘complex technology' sectors (SIC between 34 and 39) and ‘discrete technology’ sectors (SIC between 19 and 33) and being this study conducted on a period of 5 years, from 2013 to 2017, the compound annual growth rate (CAGR) of Total Number of Employees for each firm of the sample, is provided.

The results are shown in the following pictures, where a distinction is made between companies that show a negative CAGR and those that show a positive CAGR.

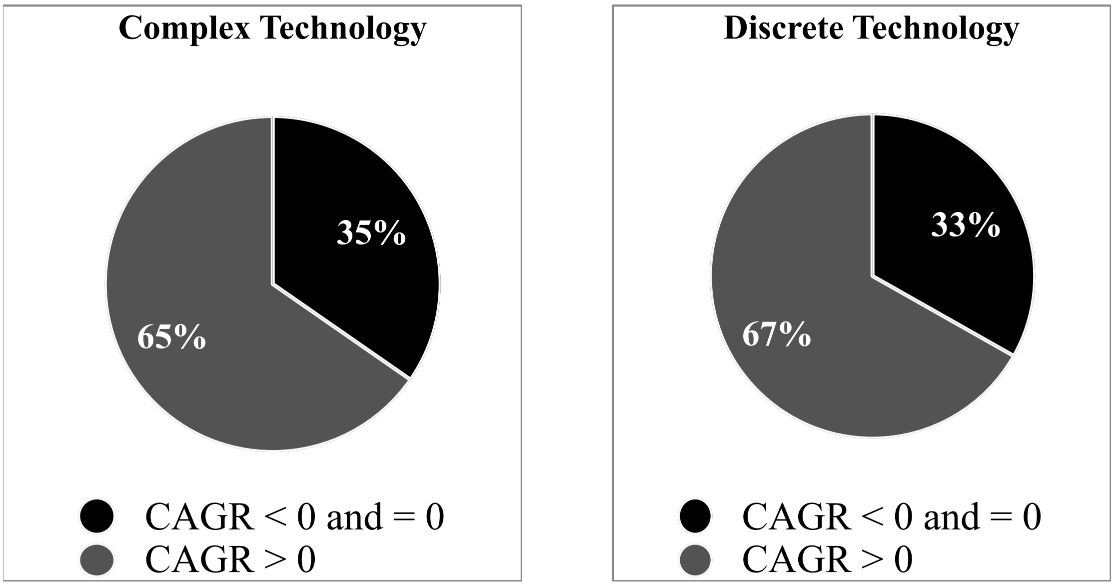

Figure 14: Total Number of Employees Compound Annual Growth Rate (2013-2017)

(Source: Personal Representation)

From Figure 14, it is possible to underline that most of the sample companies that belong to ‘complex technology’ sectors (65% so approximately 197 companies) show a positive CAGR (CAGR > 0) and also most of the sample companies that belong to ‘discrete technology’ sectors (67% so approximately 153 companies) show a positive CAGR (CAGR > 0).

Furthermore, descriptive statistic of Total Number of Employees, related to ‘complex technology’ sectors, is provided in Table 4:

Variable	**Obs**	**Mean**	**Std.Dev.**	**Min**	**Max**
Total Number of Employees	1515	9.137	24.014	5	317.500

Table 4: Total Number of Employees Descriptive Statistic for ‘complex technology’

(Source: Personal Representation)

While, descriptive statistic of Total Number of Employees, related to ‘discrete technology’ sectors, is provided in Table 5:

Variable	Obs	Mean	Std.Dev.	Min	Max
Total Number of Employees	1145	6.545	17.459	2	134.000

Table 5: Total Number of Employees Descriptive Statistic for ‘discrete technology’

(Source: Personal Representation)

3.2.3 Control Variables

In the empirical analysis, in order to study the effect of R&D Expenditures on Total Number of Employees, several variables will be inserted as control variables for the correct building of the model.
According to some scholars, who conducted researches on the same topic, the set of covariates, that influence the dependent variable, will include:

- Operating Profit
- Size of the Firm
- Lagged Employees

As explained by d’Artis and Boriss (2017) and by Hall et al. (2008, 2010), one of the control variables mostly used in previous studies regarding the employment effect of innovation, is represented by the Operating Profit, that is the profit from business operations before deduction of interest and taxes; so EBIT data have been drawn from Orbis database and will be inserted in the model during the empirical analysis.

The descriptive statistic of EBIT, related to ‘complex technology’ sectors, is provided in Table 6:

Variable	Obs	Mean	Std.Dev.	Min	Max
EBIT	1515	593.567	3.669.249	-1.632.086	71.230.000

Table 6: EBIT Descriptive Statistic for ‘complex technology’

(Source: Personal Representation)

While, the descriptive statistic of EBIT, related to ‘discrete technology’ sectors, is provided in Table 7:

Variable	Obs	Mean	Std.Dev.	Min	Max
EBIT	1145	669.428	3.008.332	-7.672.000	40.301.000

Table 7: EBIT Descriptive Statistic for ‘discrete technology’

(Source: Personal Representation)

Afterwards, regarding the size of the firm, the existing academic literature generally recognizes that the efficiency of companies can increase with their size. In fact, larger companies can count on more and better resources. For example, bigger companies can invest more in the training of their employees and can employ managers with more years of experience. In addition, a bigger company can invest its resources in the improvement of processes and so in the improvement of its operations, that results in increasing its revenues and decreasing its costs.
In this study, the natural logarithm of total assets, as a measure of firm’s size, is adopted and financial data about total assets are provided by Orbis database.

The descriptive statistic of LN of Total Assets, related to 'complex technology' sectors, is provided in Table 8:

Variable	Obs	Mean	Std.Dev.	Min	Max
LNTA	1515	13.396	2.097	7.037	19.743

Table 8: LN Total Assets Descriptive Statistic for 'complex technology'

(Source: Personal Representation)

While, the descriptive statistic of LN of Total Assets, related to 'discrete technology' sectors, is provided in Table 9:

Variable	Obs	Mean	Std.Dev.	Min	Max
LNTA	1145	12.980	2.493	5.896	19.672

Table 9: LN Total Assets Descriptive Statistic for 'discrete technology'

(Source: Personal Representation)

The third control variable is lagged employees because *"when estimating regression models for longitudinal panel data, many researchers include a lagged value of the dependent variable as a predictor. It's easy to understand why. In most situations, one of the best predictors of what happens at time t is what happened at time t-1"*[16].

The descriptive statistic of Lagged Employees, related to 'complex technology' sectors, is provided in Table 10:

Variable	Obs	Mean	Std.Dev.	Min	Max
Lagged Employees	1515	9.110	25.305	6	331.800

Table 10: Lagged Employees Descriptive Statistic for 'complex technology'

(Source: Personal Representation)

[16] 'Don't Put Lagged Dependent Variables in Mixed Models' Article - JUNE 2015 BY PAUL ALLISON; https://statisticalhorizons.com/lagged-dependent-variables

While, the descriptive statistic of Lagged Employees, related to ‘discrete technology’ sectors, is provided in Table 11:

Variable	Obs	Mean	Std.Dev.	Min	Max
Lagged Employees	1145	6.463	17.410	2	128.100

Table 11: Lagged Employees Descriptive Statistic for ‘discrete technology’

(Source: Personal Representation)

3.3 Research Models Building Process

In order to test the hypotheses underlined in Chapter 2, four different models are built, all based on a panel data regression.

Panel data analysis is a statistical method, widely used to study the same sample units in different periods of time. In addition, a panel data regression is more accurate than a multi-variate linear regression because the former provides more information and so it allows the results to be more efficient.

If each individual *i* (persons, firms, cities, …) is observed in all time periods *t*, this is called balanced panel; while, when there are missing data across individuals and time periods, the panel data regression is considered as unbalanced.

In this study, 532 companies will be observed during a time period of 5 years, from 2013 to 2017, and the panel data regression will be balanced since no units have some missing data.

Another distinction is between long panel data regressions and short panel data regressions. In this empirical analysis, there will be many individuals and few time periods so the panel data regression will be considered as short.

According to the objective of the analysis and the role of the explanatory variables (dummy variables), when both individual effects and time effects are taken into account, a fixed effects model or a random effects model could be considered.

In the random effects model, the individual-specific effect is a random variable that is uncorrelated with the explanatory variables within the models; while, in the fixed effects model, the individual-specific effect is a random variable that is allowed to be correlated with the explanatory variables within the models.

In order to conduct the panel data regression and to statistically analyze the relationship between innovation and employment, the data collected from Orbis database are uploaded on Gretl, an open-source statistical package mainly used for econometrics. The name is an acronym for Gnu Regression, Econometrics and Time-series Library[17].

Gretl allows to analyze the inserted data and to graphically represent them, providing results on the statistical analysis of the variables and on the feasibility and correctness of the models built.

After building panel data regression models, Gretl shows the respective outputs, providing some important information like the coefficients, the standard errors, the t-values, the p-values of each coefficient and also the 95% confidence interval of the standard errors.

To assess if a coefficient is statistically significant or not and so to decide if accepting or rejecting the null hypothesis, the p-values are analyzed with a standard threshold at $\alpha = 0.05$. For p-values equal or lower than $\alpha = 0.05$, the null hypothesis is rejected, in favor of the alternative hypothesis, implying that there is a linear relationship between the dependent and independent variables and that this relationship is significant.

Four models are built, two related to 'complex technology' companies and two related to 'discrete technology' companies.

The first model is aimed at testing the statistical relationship between the control variables and the dependent variable, the Total Number of Employees, using data coming from the 303 companies that belong to 'complex technology' sectors.

The second model is aimed at testing the statistical relationship between Research and Development Expenditures at time t and Total Number of Employees at time t, using

[17] https://en.wikipedia.org/wiki/Gretl

data coming from the 303 companies that belong to ‘complex technology’ sectors.
The third model is aimed at testing the statistical relationship between the control variables and the dependent variable, the Total Number of Employees, using data coming from the 229 companies that belong to ‘discrete technology’ sectors.
The fourth model is aimed at testing the statistical relationship between Research and Development Expenditures at time t and Total Number of Employees at time t, using data coming from the 229 companies that belong to ‘discrete technology’ sectors.

In order to conduct a correct panel data regression analysis, aggregate time-effects are considered so years’ dummy variables are included in the models.
Consequently, it is checked if the predictors follow the assumptions of non-multicollinearity, non-heteroskedasticity and normality, with the aim to verify the appropriateness of the model.

Multicollinearity is useful to analyze if the explanatory variables are not correlated with each other. To do so, the graph matrix is inserted and described for each model, in order to visually check that no big issues of multicollinearity exist.

In order to check for heteroskedasticity, the plot of residuals versus fitted values is inserted and commented for each model. On the x-axis there are the predicted values and on the y-axis there are the residuals. If the plot shows a particular pattern, it means that an issue of heteroskedasticity exists.

To complete the analysis of the statistical models, the normality of residuals is checked as well. To do so, the histogram of residuals and the normal probability plot are both used. In the latter, the z-scores are plotted against the standardized residuals. The observed points should be distributed closely to the line that begins in the axis’ origin and has a 45 degrees inclination, meaning that the residuals are normally distributed.

The illustrated procedure is followed in order to test the truthfulness of the hypotheses and to verify the following sentences:

1. R&D Expenditures in US high-tech manufacturing companies have a positive and significant impact on Total Number of Employees;

2. R&D Expenditures in US ‘complex technology’ companies have a positive and significant impact on Total Number of Employees;

3. R&D Expenditures in US ‘discrete technology’ companies have a positive and significant impact on Total Number of Employees.

4. MODEL BUILDING AND RESULTS

The fourth and last chapter will be based on the construction of the statistical models with the aim to test the positivity and the significance of the relationship between R&D Expenditures and Total Number of Employees, both for ‘complex technology’ and ‘discrete technology companies, and to demonstrate the hypotheses underlined in Chapter 2.

As already said in the last paragraph of Chapter 3, four statistical models are built and for each model a panel data regression is run on Gretl software, considering a time period of 5 years (2013-2017).
Model 1 is aimed at testing the statistical relationship between the control variables and the dependent variable, the Total Number of Employees at time t, using data coming from the 303 companies that belong to ‘complex technology’ sectors.
In Model 2, Research and Development Expenditures’ data at time t are added to the control variables with the aim to test the statistical relationship between the dependent and independent variables at time t, using data coming from the 303 companies that belong to ‘complex technology’ sectors.
Model 3 is aimed at testing the statistical relationship between the control variables and the dependent variable, the Total Number of Employees at time t, using data coming from the 229 companies that belong to ‘discrete technology’ sectors.
In model 4, Research and Development Expenditures’ data at time t are added to the control variables with the aim to test the statistical relationship between the dependent and independent variables at time t, using data coming from the 229 companies that belong to ‘discrete technology’ sectors.

4.1 Model 1

In Model 1, the statistical relationship between the control variables and the dependent variable, the Total Number of Employees, is tested for a time period of five

years (2013-2017), using data coming from the 303 companies that belong to ‘complex technology’ sectors.
The variables of the sample of 303 US ‘complex technology’ companies employed in Model 1 are the following and the respective descriptive statistics are showed in Table 12:

- Total Number of Employees is the dependent variable which assumes values between 5 and 317.500;

- LN of Total Assets (LNTA) is a control variable which assumes values between 7.037 and 19.743;

- Operating Profit (EBIT) is a control variable which assumes values between -1.632.086 and 71.230.000;

- Lagged Employees is a control variable which assumes values between 6 and 331.800;

Variable	**Obs**	**Mean**	**Std.Dev.**	**Min**	**Max**
Total Number of Employees	1515	9.137	24.014	5	317.500
EBIT	1515	593.567	3.669.249	-1.632.086	71.230.000
LNTA	1515	13.396	2.097	7.037	19.743
Lagged Employees	1515	9.110	25.305	6	331.800

Table 12: Descriptive Statistics of variables of Model 1

(Source: Personal Representation)

So, a panel data regression will be run in order to test if the p-values of the variables confirm or not that the relationship between the control and the dependent variables is significant. In addition, in the statistical analysis, the time effect is considered, including years’ dummy variables.

As already explained, a fixed effects model or a random effects model could be considered.

In the random effects model, the individual-specific effect is a random variable that is uncorrelated with the explanatory variables within the models; while, in the fixed effects model, the individual-specific effect is a random variable that is allowed to be correlated with the explanatory variables within the models.
In order to choose between a fixed effects model or a random effects model, for the correctness of the panel data regression, both are shown in the next two figures and a comparison between them is made with the aim to select and analyze only the most significant one.

The following is the equation of the regression with fixed effects:

$$\textbf{\textit{Total Number of Employees (t)}} = \beta 0 + \beta 1 * \textbf{\textit{EBIT (t)}} + \beta 2 * \textbf{\textit{LN(TA (t))}} + \beta 3 * \textbf{\textit{Lagged Employees (t)}} + \beta 4 * \textbf{\textit{Iyears}} + \varepsilon$$

The output of the Panel Data Regression using fixed effects is shown in Table 13:

Total Number of Employees	Coef.	St.Err.	t-value	p-value	Sig
const	-8344,89	7541,86	-1,106	0,2687	
EBIT	0,00102184	0,000297467	3,435	0,0006	***
LNTOTALASSETS	756,958	568,736	1,331	0,1835	
LAGGEDEMPLOYEES	0,772100	0,0248123	31,12	2,20e-156	***
dt_2	-224,930	502,845	-0,4473	0,6547	
dt_3	-125,982	507,217	-0,2484	0,8039	
dt_4	-983,302	510,423	-1,926	0,0543	*
dt_5	-158,149	527,731	-0,2997	0,7645	

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Table 13: Panel Data Regression Results of Model 1

(Source: Gretl statistical software)

While, the output of the Panel Data Regression using random effects is shown in Table 14:

Total Number of Employees	Coef.	St.Err.	t-value	p-value	Sig
const	-5920,27	1214,30	-4,875	1,09e-06	***
EBIT	0,000354133	4,78921e-05	7,394	1,42e-13	***
LNTOTALASSETS	533,991	90,2316	5,918	3,26e-09	***
LAGGEDEMPLOYEES	0,870297	0,00773300	112,5	0,0000	***
dt_2	-206,181	498,676	-0,4135	0,6793	
dt_3	-54,2694	498,768	-0,1088	0,9134	
dt_4	-951,209	498,834	-1,907	0,0565	*
dt_5	39,7171	499,350	0,07954	0,9366	

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Table 14: Panel Data Regression Results of Model 1

(Source: Gretl statistical software)

Thanks to the results obtained, it is possible to test the significance of the coefficients and to check how the control variables affect the dependent one.
In addition, after running Model 1, it will be easier to understand how the additional variable in the next model, the independent variable (R&D Expenditures), affect the dependent one (the Total Number of Employees), together with the control variables.

Looking at the significance of the single variables both in Table 13 and Table 14, when the p-values are considered, the control variables and the years' dummy variables are analyzed:

- In the fixed effects model (Table 13), the coefficients of all the control variables are positive but LN of Total Assets is not significant ($\alpha > 0.05$). Also the years' dummy variables are not all significant; only Year 2014 reaches statistical little significance ($\alpha < 0.1$). Year 2017 is by default omitted by the software Gretl, in order to avoid *'The Dummy Variable Trap'*.

- In the random effects model (Table 14), the coefficients of all the control variables are positive and all the control variables are highly significant (**α** < 0.05). This is in line with the literature since the expectations were to find all positive and significant relationships among every single control variable and the Total Number of Employees. While the years' dummy variables are not all significant but this does not affect the validity of the study; only Year 2014 reaches statistical little significance (**α** < 0.1). Year 2017 is by default omitted by the software Gretl, in order to avoid *'The Dummy Variable Trap'*.

Comparing the two models, it is possible to underline how the results in Table 14 are more statistically significant than the ones in Table 13 so I will analyze only the random effects model.

Regarding the results in Table 14, the following figure represents the residuals against the fitted values with the aim to check for potential issues of heteroskedasticity:

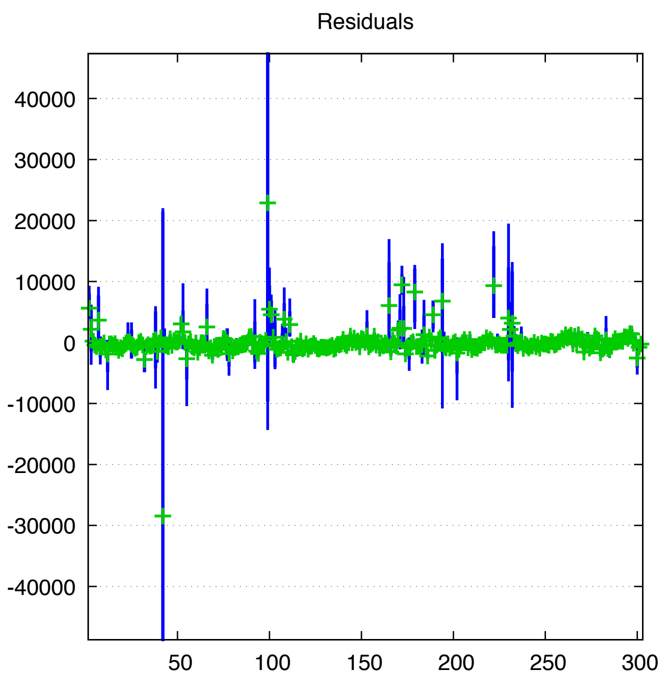

Figure 15: Residuals versus Fitted Plot of Model 1

(Source: Gretl statistical software)

The output of the regression in Figure 15 shows that a minor issue of heteroskedasticity can exist, since the variance seems to increase with the predicted values.

In addition, also a minor issue of non-normality is shown in Figure 16:

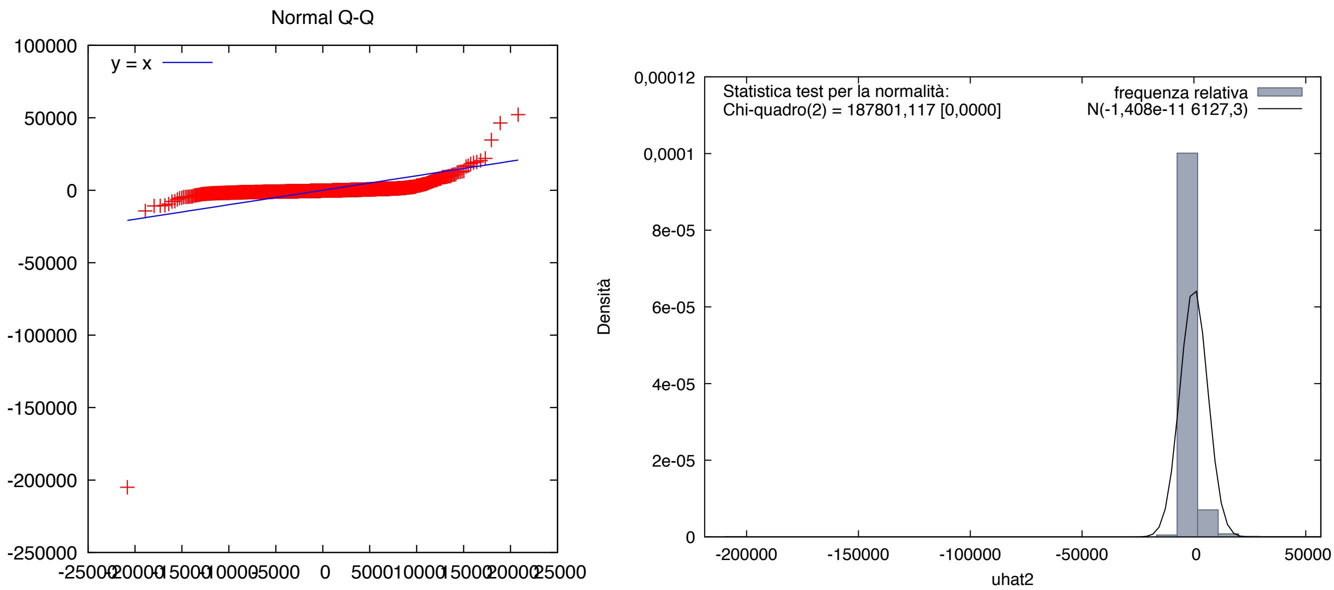

Figure 16: Normal Distribution of Model 1

(Source: Gretl statistical software)

Furthermore, the overall significance of the random effects model indicates that the control variables are jointly significant in their relationship with the Total Number of Employees.

4.2 Model 2

In Model 2, the statistical relationship between R&D Expenditures and Total Number of Employees is tested for the five years period considered (2013-2017), using data coming from the 303 companies that belong to ‘complex technology’ sectors.

In this way, it is possible to demonstrate the validity of the first and the second hypotheses underlined in Chapter 2.

The variables of the sample of the 303 US ‘complex technology’ companies employed in Model 2 are the following and the respective descriptive statistics are showed in Table 15:

- Total Number of Employees is the dependent variable which assumes values between 5 and 317.500;

- LN of Total Assets (LNTA) is a control variable which assumes values between 7.037 and 19.743;

- Operating Profit (EBIT) is a control variable which assumes values between -1.632.086 and 71.230.000;

- Lagged Employees is a control variable which assumes values between 6 and 331.800;

- R&D Expenditures is the independent variable which assumes values between 0 and 13.035.000;

Variable	**Obs**	**Mean**	**Std.Dev.**	**Min**	**Max**
Total Number of Employees	1515	9.137	24.014	5	317.500
EBIT	1515	593.567	3.669.249	-1.632.086	71.230.000
LNTA	1515	13.396	2.097	7.037	19.743
Lagged Employees	1515	9.110	25.305	6	331.800
R&D Expenditures	1515	265.098	1.016.935	0	13.035.000

Table 15: Descriptive Statistics of variables of Model 2

(Source: Personal Representation)

So, a panel data regression will be run in order to test if the p-values of the variables confirm or not that the relationship between the dependent and the independent variables is significant. In addition, in the statistical analysis, the time effect is considered, including years’ dummy variables.

As already explained, a fixed effects model or a random effects model could be considered.

In order to choose between a fixed effects model or a random effects model, for the correctness of the panel data regression, both are shown in the next two figures and a comparison between them is made with the aim to select and analyze only the most significant one.

The following is the equation of the regression with fixed effects:

$$\textit{Total Number of Employees (t)} = \beta 0 + \beta 1 * \textit{EBIT (t)} + \beta 2 * \textit{LN(TA (t))} + \beta 3 * \textit{Lagged Employees (t)} + \beta 4 * \textit{R\&D Expenditures (t)} + \beta 5 * \textit{Iyears} + \varepsilon$$

The output of the Panel Data Regression using fixed effects is shown in Table 16:

Total Number of Employees	Coef.	St.Err.	t-value	p-value	Sig
const	-7948,21	7533,38	-1,055	0,2916	
EBIT	0,000666134	0,000341537	1,950	0,0514	*
LNTOTALASSETS	710,810	568,341	1,251	0,2113	
LAGGEDEMPLOYEES	0,761665	0,0252654	30,15	4,26e-149	***
RDExpenditures	0,00213967	0,00101397	2,110	0,0350	**
dt_2	-237,851	502,161	-0,4737	0,6358	
dt_3	-144,897	506,569	-0,2860	0,7749	
dt_4	-1062,78	511,081	-2,079	0,0378	**
dt_5	-244,281	528,552	-0,4622	0,6440	

**** p<0.01, ** p<0.05, * p<0.1*

Table 16: Panel Data Regression Results of Model 2

(Source: Gretl statistical software)

While, the output of the Panel Data Regression using random effects is shown in Table 17:

Total Number of Employees	Coef.	St.Err.	t-value	p-value	Sig
const	-5410,34	1228,86	-4,403	1,07e-05	***
EBIT	0,000252644	6,24760e-05	4,044	5,26e-05	***
LNTOTALASSETS	492,207	91,5804	5,375	7,68e-08	***
LAGGEDEMPLOYEES	0,865210	0,00797819	108,4	0,0000	***
RDExpenditures	0,000618332	0,000245054	2,523	0,0116	**
dt_2	-207,280	497,788	-0,4164	0,6771	
dt_3	-55,6124	497,879	-0,1117	0,9111	
dt_4	-968,509	497,992	-1,945	0,0518	*
dt_5	21,9347	498,511	0,04400	0,9649	

**** p<0.01, ** p<0.05, * p<0.1*

Table 17: Panel Data Regression Results of Model 2

(Source: Gretl statistical software)

Thanks to the results obtained, it is possible to test the significance of the coefficients and to check the positive and significant relationship between the dependent and the independent variables.

Looking at the significance of the single variables both in Table 16 and Table 17, when the p-values are considered, the control variables, the years' dummy variables and the added variable, R&D Expenditures, are analyzed:

- In the fixed effects model (Table 16), the coefficients of all the control variables are positive but LN of Total Assets is not significant (α > 0.05), as already verified in Model 1, and EBIT reaches statistical little significance (α < 0.1). Also the years' dummy variables are not all significant; only Year 2014 reaches statistical significance (α < 0.05). Year 2017 is by default omitted by the software Gretl, in order to avoid *'The Dummy Variable Trap'.* In addition, the newly added variable, R&D Expenditures, is positive and significant (α < 0.05).

- In the random effects model (Table 17), the coefficients of all the control variables are positive and all the control variables are highly significant ($\alpha < 0.05$), as already verified in Model 1. This is in line with the literature since the expectations were to find all positive and significant relationships among every single control variable and the Total Number of Employees. While the years' dummy variables are not all significant but this does not affect the validity of the study; only Year 2014 reaches statistical little significance ($\alpha < 0.1$). Year 2017 is by default omitted by the software Gretl, in order to avoid *'The Dummy Variable Trap'*. In addition, the newly added variable, R&D Expenditures, is positive and significant ($\alpha < 0.05$).

Comparing the two models, it is possible to underline how the results in Table 17 are more statistically significant than the ones in Table 16 so I will analyze only the random effects model, as in Model 1.

Regarding the results in Table 17, the following figure represents the residuals against the fitted values with the aim to check for potential issues of heteroskedasticity:

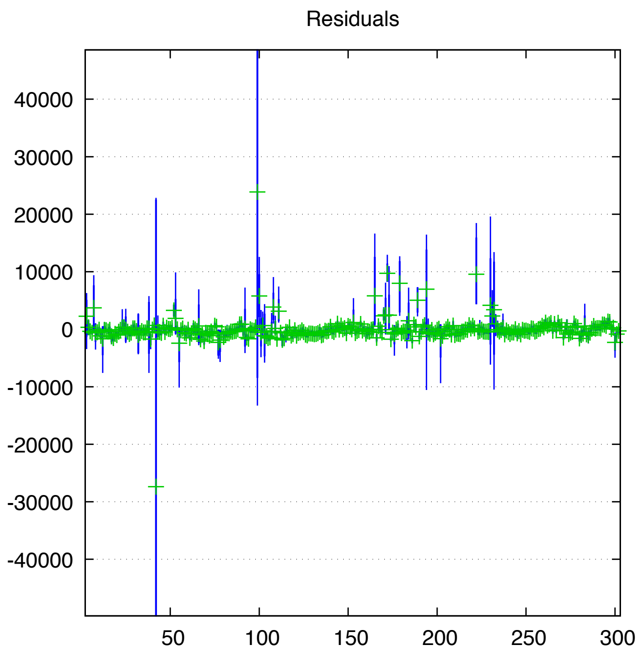

Figure 17: Residuals versus Fitted Plot of Model 2

(Source: Gretl statistical software)

The output of the regression in Figure 17 shows that a minor issue of heteroskedasticity can exist, since the variance seems to increase with the predicted values.

In addition, also a minor issue of non-normality is shown in Figure 18:

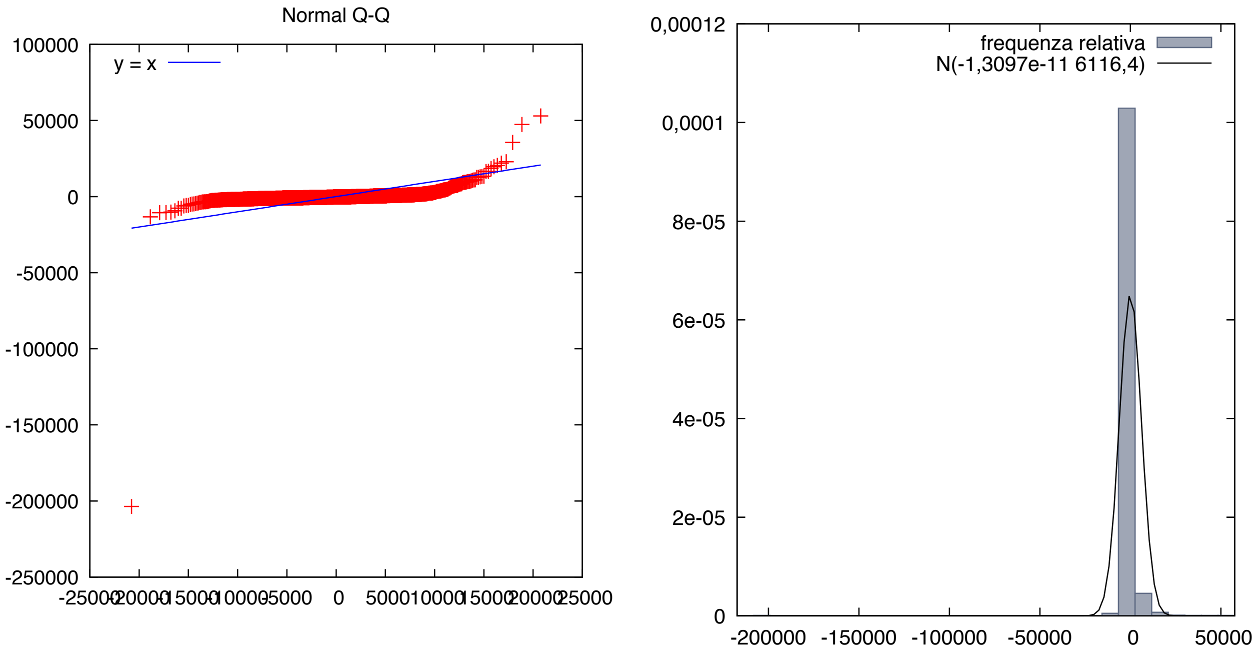

Figure 18: Normal Distribution of Model 2

(Source: Gretl statistical software)

Furthermore, the overall significance of the random effects model indicates that the control variables are jointly significant in their relationship with the Total Number of Employees and also R&D Expenditures affect the Total Number of Employees in a positive and significant way, so demonstrating that US high-tech manufacturing firms, and in particular US high-tech manufacturing firms classified as ’complex technology’ companies, are characterized by a positive and significant employment impact of R&D Expenditures (Hypotheses 1 and 2).

Looking at the coefficients’ estimates in Model 2, it can be stated that, on average, and holding the other coefficients constant:

- When EBIT increases by 1 unit, the change in the Total Number of Employees is equal to an increase of 0 % units;

- When LN of Total Assets increases by 1 unit, the change in the Total Number of Employees is equal to an increase of 4.92 % units;

- When Lagged Employees increases by 1 unit, the change in the Total Number of Employees is equal to 0.09 % units;

- When R&D Expenditures increase by 1 unit, the change in the Total Number of Employees is so little (0 % units);

So it is possible to conclude that there is a statistical significant and positive relationship between R&D Expenditures and Total Number of Employees.

4.3 Model 3

In Model 3, the statistical relationship between the control variables and the dependent variable, the Total Number of Employees, is tested for a time period of five years (2013-2017), using data coming from the 229 companies that belong to 'discrete technology' sectors.

The variables of the sample of 229 US 'discrete technology' companies employed in Model 3 are the following and the respective descriptive statistics are showed in Table 18:

- Total Number of Employees is the dependent variable which assumes values between 2 and 134.000;

- LN of Total Assets (LNTA) is a control variable which assumes values between 5.896 and 19.672;

- Operating Profit (EBIT) is a control variable which assumes values between -7.672.000 and 40.301.000;

- Lagged Employees is a control variable which assumes values between 2 and 128.100;

Variable	Obs	Mean	Std.Dev.	Min	Max
Total Number of Employees	1145	6.545	17.459	2	134.000
EBIT	1145	669.428	3.008.332	-7.672.000	40.301.000
LNTA	1145	12.980	2.493	5.896	19.672
Lagged Employees	1145	6.463	17.410	2	128.100

Table 18: Descriptive Statistics of variables of Model 3

(Source: Personal Representation)

So, a panel data regression will be run in order to test if the p-values of the variables confirm or not that the relationship between the control and the dependent variables is significant. In addition, in the statistical analysis, the time effect is considered, including years' dummy variables.

As already explained, a fixed effects model or a random effects model could be considered.
In order to choose between a fixed effects model or a random effects model, for the correctness of the panel data regression, both are shown in the next two figures and a comparison between them is made with the aim to select and analyze only the most significant one.

The following is the equation of the regression with fixed effects:

$$\textit{Total Number of Employees (t)} = \beta 0 + \beta 1 * \textit{EBIT (t)} + \beta 2 * \textit{LN(TA (t))} + \beta 3 * \textit{Lagged Employees (t)} + \beta 4 * \textit{Iyears} + \varepsilon$$

The output of the Panel Data Regression using fixed effects is shown in Table 19:

Total Number of Employees	Coef.	St.Err.	t-value	p-value	Sig
const	-1239,26	1392,19	-0,8902	0,3736	
EBIT	0,000119451	3,46389e-05	3,448	0,0006	***
LNTOTALASSETS	285,598	108,759	2,626	0,0088	***
LAGGEDEMPLOYEES	0,601745	0,0321313	18,73	1,95e-66	***
dt_2	17,4509	163,235	0,1069	0,9149	
dt_3	161,987	164,773	0,9831	0,3258	
dt_4	178,375	164,664	1,083	0,2790	
dt_5	184,254	166,987	1,103	0,2701	

*** *p<0.01, ** p<0.05, * p<0.1*

Table 19: Panel Data Regression Results of Model 3

(Source: Gretl statistical software)

While, the output of the Panel Data Regression using random effects is shown in Table 20:

Total Number of Employees	Coef.	St.Err.	t-value	p-value	Sig
const	-706,980	389,331	-1,816	0,0694	*
EBIT	3,79289e-05	2,56666e-05	1,478	0,1395	
LNTOTALASSETS	57,1513	30,1404	1,896	0,0579	*
LAGGEDEMPLOYEES	0,987049	0,00507512	194,5	0,0000	***
dt_2	67,9952	172,374	0,3945	0,6932	
dt_3	187,447	172,674	1,086	0,2777	
dt_4	137,513	172,678	0,7964	0,4258	
dt_5	134,669	172,739	0,7796	0,4356	

*** *p<0.01, ** p<0.05, * p<0.1*

Table 20: Panel Data Regression Results of Model 3

(Source: Gretl statistical software)

Thanks to the results obtained, it is possible to test the significance of the coefficients and to check how the control variables affect the dependent one.

In addition, after running Model 3, as done for Model 1 and Model 2, it will be easier to understand how the additional variable in Model 4, the independent variable (R&D

Expenditures), affect the dependent one (the Total Number of Employees), together with the control variables.

Looking at the significance of the single variables both in Table 19 and Table 20, when the p-values are considered, the control variables and the years' dummy variables are analyzed:

- In the fixed effects model (Table 19), the coefficients of all the control variables are positive and they are all highly significant ($\boldsymbol{\alpha} < 0.05$). This is in line with the literature since the expectations were to find all positive and significant relationships among every single control variable and the Total Number of Employees. While none of the years' dummy variables is significant ($\boldsymbol{\alpha} > 0.05$). Year 2017 is by default omitted by the software Gretl, in order to avoid *'The Dummy Variable Trap'*.
- In the random effects model (Table 20), the coefficients of all the control variables are positive but EBIT is not significant ($\boldsymbol{\alpha} > 0.05$) and LN of Total Assets reaches a little significance ($\boldsymbol{\alpha} < 0.1$). While none of the years' dummy variables is significant ($\boldsymbol{\alpha} > 0.05$) but this does not affect the validity of the study. Year 2017 is by default omitted by the software Gretl, in order to avoid *'The Dummy Variable Trap'*.

Comparing the two models, it is possible to underline how the results in Table 19 are more statistically significant than the ones in Table 20 so, in contrast of what I have done in Model 1 and Model 2, in Model 3 I will analyze the fixed effects model.

Regarding the results in Table 19, the following figure represents the residuals against the fitted values with the aim to check for potential issues of heteroskedasticity:

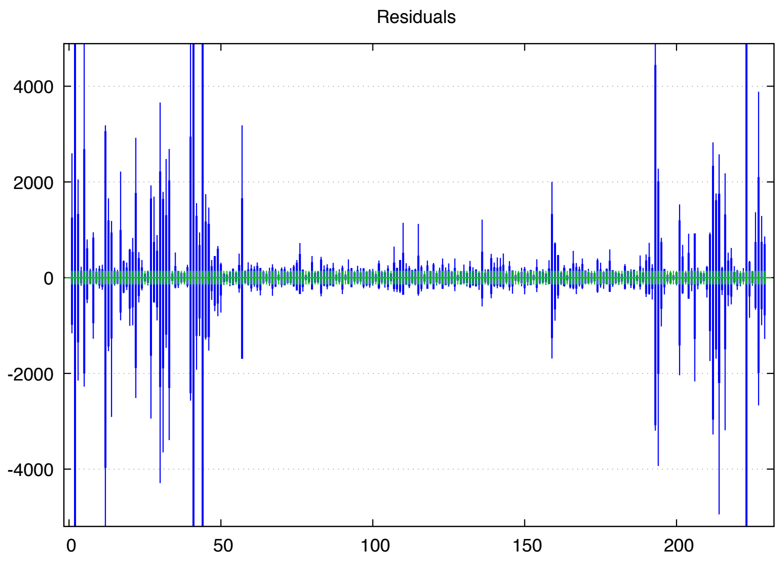

Figure 19: Residuals versus Fitted Plot of Model 3

(Source: Gretl statistical software)

The output of the regression in Figure 19 shows that a minor issue of heteroskedasticity can exist, since the variance seems to increase with the predicted values.

In addition, also a not so relevant issue of non-normality is shown in Figure 20:

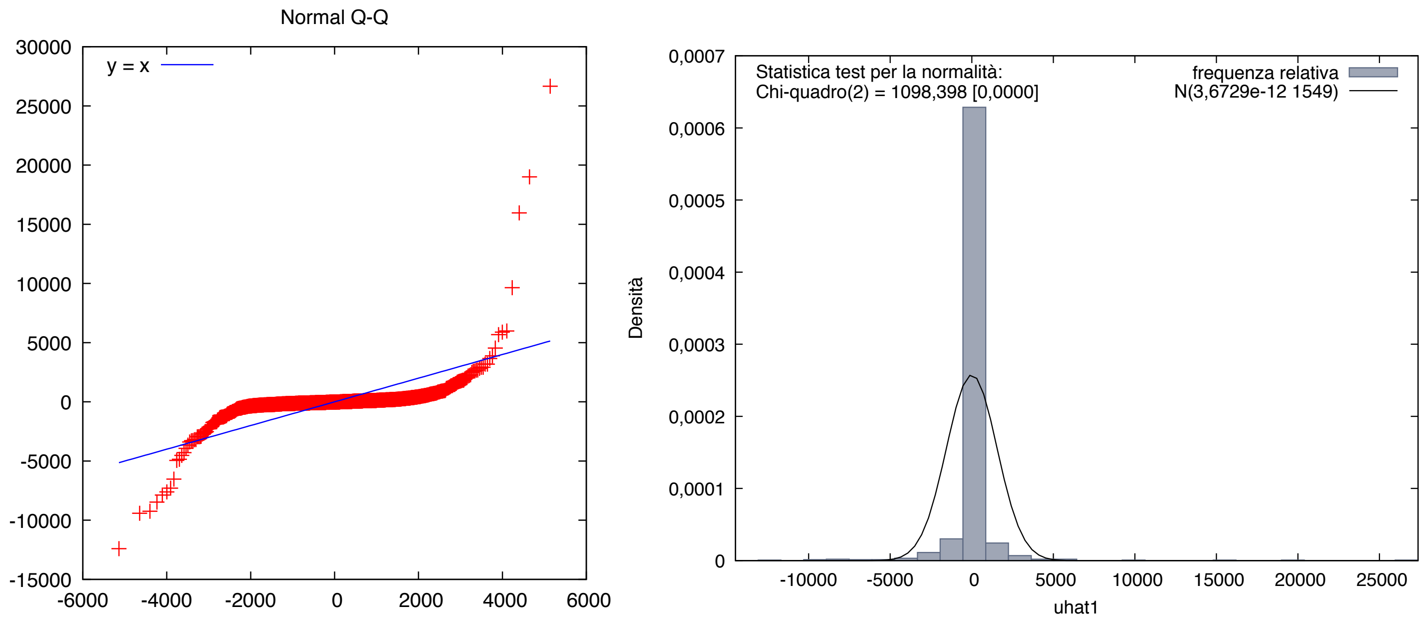

Figure 20: Normal Distribution of Model 3

(Source: Gretl statistical software)

Furthermore, the overall significance of the fixed effects model indicates that the control variables are jointly significant in their relationship with the Total Number of Employees.

4.4 Model 4

In Model 4, the statistical relationship between R&D Expenditures and Total Number of Employees is tested for the five years period considered (2013-2017), using data coming from the 229 companies that belong to ‘discrete technology’ sectors.
In this way, it is possible to demonstrate the validity of the third hypothesis underlined in Chapter 2.
The variables of the sample of the 229 US ‘discrete technology’ companies employed in Model 4 are the following and the respective descriptive statistics are showed in Table 21:

- Total Number of Employees is the dependent variable which assumes values between 2 and 134.000;

- LN of Total Assets (LNTA) is a control variable which assumes values between 5.896 and 19.672;

- Operating Profit (EBIT) is a control variable which assumes values between -7.672.000 and 40.301.000;

- Lagged Employees is a control variable which assumes values between 2 and 128.100;

- R&D Expenditures is the independent variable which assumes values between 0 and 10.594.000;

Variable	Obs	Mean	Std.Dev.	Min	Max
Total Number of Employees	1145	6.545	17.459	2	134.000
EBIT	1145	669.428	3.008.332	-7.672.000	40.301.000
LNTA	1145	12.980	2.493	5.896	19.672
Lagged Employees	1145	6.463	17.410	2	128.100
R&D Expenditures	1145	337.335	1.150.446	0	10.594.000

Table 21: Descriptive Statistics of variables of Model 4

(Source: Personal Representation)

So, a panel data regression will be run in order to test if the p-values of the variables confirm or not that the relationship between the dependent and the independent variables is significant. In addition, in the statistical analysis, the time effect is considered, including years' dummy variables.

As already explained, a fixed effects model or a random effects model could be considered.
In order to choose between a fixed effects model or a random effects model, for the correctness of the panel data regression, both are shown in the next two figures and a comparison between them is made with the aim to select and analyze only the most significant one.

The following is the equation of the regression with fixed effects:

$$\textit{Total Number of Employees (t)} = \beta 0 + \beta 1 * \textit{EBIT (t)} + \beta 2 * \textit{LN(TA (t))} + \beta 3 * \textit{Lagged Employees (t)} + \beta 4 * \textit{R\&D Expenditures (t)} + \beta 5 * \textit{Iyears} + \varepsilon$$

The output of the Panel Data Regression using fixed effects is shown in Table 22:

Total Number of Employees	Coef.	St.Err.	t-value	p-value	Sig
const	-1551,14	1381,33	-1,123	0,2618	
EBIT	9,51615e-05	3,47948e-05	2,735	0,0064	***
LNTOTALASSETS	287,812	107,759	2,671	0,0077	***
LAGGEDEMPLOYEES	0,591714	0,0319232	18,54	2,69e-65	***
RDExpenditures	0,00123259	0,000290719	4,240	2,47e-05	***
dt_2	-11,6741	161,878	-0,07212	0,9425	
dt_3	93,1484	164,061	0,5678	0,5703	
dt_4	105,035	164,062	0,6402	0,5222	
dt_5	97,7800	166,702	0,5866	0,5576	

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Table 22: Panel Data Regression Results of Model 4

(Source: Gretl statistical software)

While, the output of the Panel Data Regression using random effects is shown in Table 23:

Total Number of Employees	Coef.	St.Err.	t-value	p-value	Sig
const	-687,016	395,211	-1,738	0,0821	*
EBIT	3,14472e-05	2,84860e-05	1,104	0,2696	
LNTOTALASSETS	55,5780	30,6395	1,814	0,0697	*
LAGGEDEMPLOYEES	0,985665	0,00545351	180,7	0,0000	***
RDExpenditures	4,84003e-05	8,02915e-05	0,6028	0,5466	
dt_2	66,9007	172,079	0,3888	0,6974	
dt_3	183,464	172,507	1,064	0,2875	
dt_4	133,435	172,521	0,7734	0,4393	
dt_5	130,904	172,555	0,7586	0,4481	

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Table 23: Panel Data Regression Results of Model 4

(Source: Gretl statistical software)

Thanks to the results obtained, it is possible to test the significance of the coefficients and to check the positive and significant relationship between the dependent and the independent variables.

Looking at the significance of the single variables both in Table 22 and Table 23, when the p-values are considered, the control variables, the years' dummy variables and the added variable, R&D Expenditures, are analyzed:

- In the fixed effects model (Table 22), the coefficients of all the control variables are positive and they are all highly significant ($\alpha < 0.05$), as already verified in Model 3. This is in line with the literature since the expectations were to find all positive and significant relationships among every single control variable and the Total Number of Employees. While none of the years' dummy variables is significant ($\alpha > 0.05$). Year 2017 is by default omitted by the software Gretl, in order to avoid *'The Dummy Variable Trap'*. In addition, the newly added variable, R&D Expenditures, is positive and significant ($\alpha < 0.05$).

- In the random effects model (Table 23), the coefficients of all the control variables are positive but EBIT is not significant ($\alpha > 0.05$) and LN of Total Assets reaches a little significance ($\alpha < 0.1$). While none of the years' dummy variables is significant ($\alpha > 0.05$) but this does not affect the validity of the study. Year 2017 is by default omitted by the software Gretl, in order to avoid *'The Dummy Variable Trap'*. In addition, the newly added variable, R&D Expenditures, is positive and significant ($\alpha < 0.05$).

Comparing the two models, it is possible to underline how the results in Table 22 are more statistically significant than the ones in Table 23 so, in contrast of what I have done in Model 1 and Model 2, in Model 4 as in Model 3, I will analyze the fixed effects model.

Regarding the results in Table 22, the following figure represents the residuals against the fitted values with the aim to check for potential issues of heteroskedasticity:

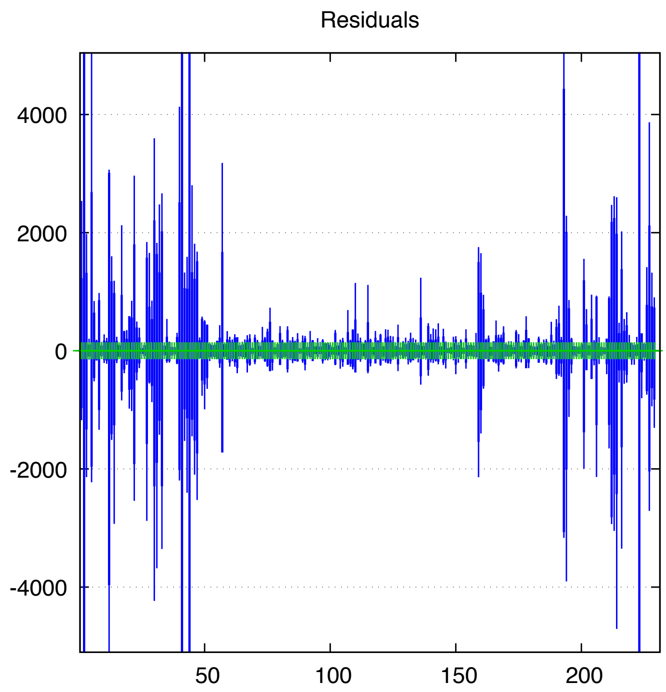

Figure 22: Residuals versus Fitted Plot of Model 4

Source: Gretl statistical software)

The output of the regression in Figure 22 shows that a minor issue of heteroskedasticity can exist, since the variance seems to increase with the predicted values.

In addition, also a not so relevant issue of non-normality is shown in Figure 23:

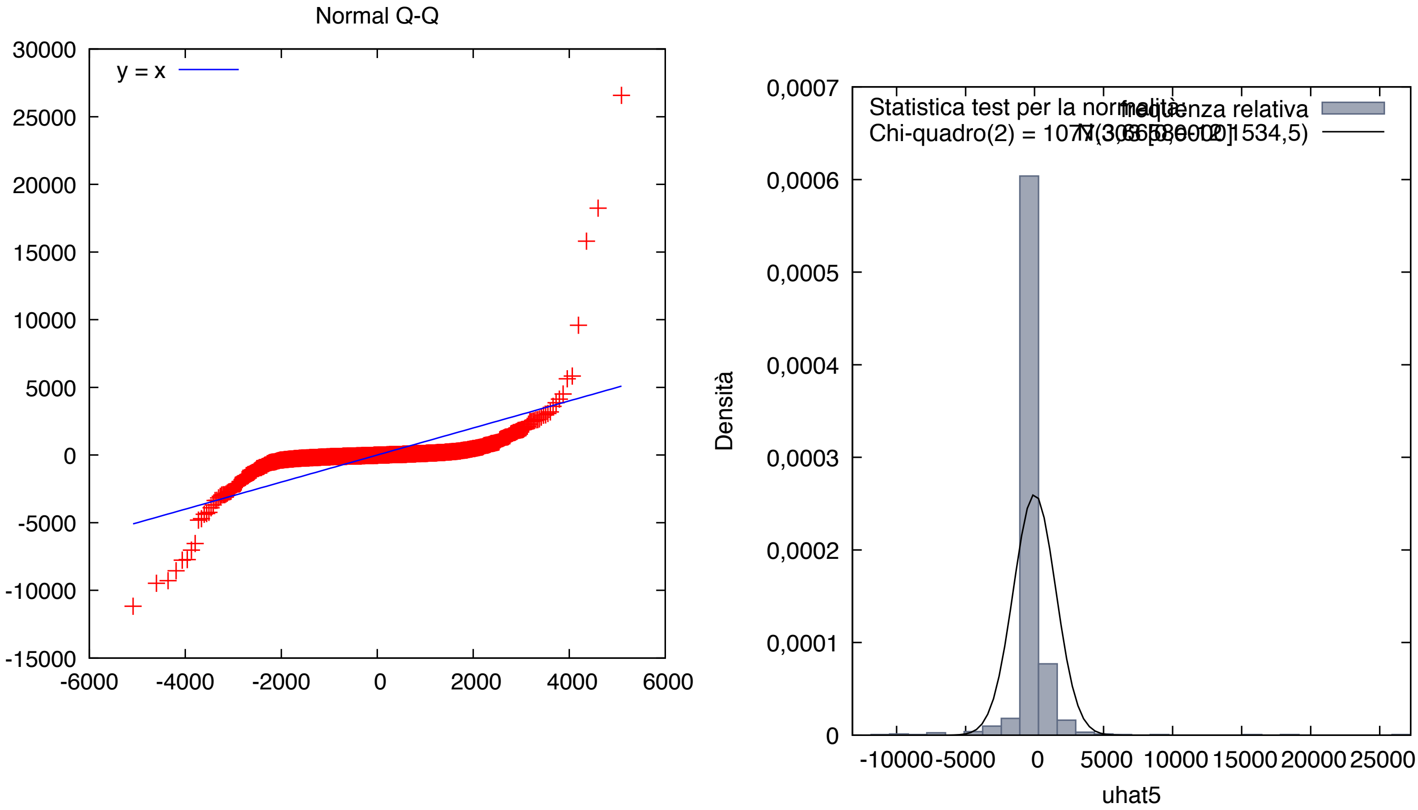

Figure 23: Normal Distribution of Model 4

(Source: Gretl statistical software)

Furthermore, the overall significance of the fixed effects model indicates that the control variables are jointly significant in their relationship with the Total Number of Employees and also R&D Expenditures affect the Total Number of Employees in a positive and significant way, so demonstrating that US manufacturing firms classified as ’discrete technology’ companies, are characterized by a positive and significant employment impact of R&D Expenditures (Hypothesis 3).
Looking at the coefficients’ estimates in Model 4, it can be stated that, on average, and holding the other coefficients constant:

- When EBIT increases by 1 unit, the change in the Total Number of Employees is equal to an increase of 0 % units;

- When LN of Total Assets increases by 1 unit, the change in the Total Number of Employees is equal to an increase of 2.87 % units;
- When Lagged Employees increases by 1 unit, the change in the Total Number of Employees is equal to 0.06 % units;
- When R&D Expenditures increase by 1 unit, the change in the Total Number of Employees is so little (0 % units);

So it is possible to conclude that there is a statistical significant and positive relationship between R&D Expenditures and Total Number of Employees not only for companies that belong to ‘complex technology’ sectors but also for companies that belong to ‘discrete technology’ sectors.

4.5 Final Results

As already said, this empirical analysis has been conducted with the aim to study the statistical relationship between Innovation and Employment on a sample of 532 US manufacturing companies, divided into ‘complex technology’ and ‘discrete technology’ sectors, over a time period of five years (2013-2017).
To conduct the analysis, Research and Development Expenditures and the Total Number of Employees at the firm level have been employed and the time-effect has also been considered in all the models built.

In particular, in order to answer the research question **(Is the positive impact of R&D Expenditures on employment limited solely to the US high-tech manufacturing firms, classified as ‘complex technology’ companies?)**, four statistical models have been constructed and their final results are presented and described in this paragraph.

In Model 1 and in Model 3, the statistical relationship between the control variables and the dependent variable has been tested, using data coming from the 303 companies that belong to ‘complex technology’ sectors in Model 1, and using data

coming from the 229 companies that belong to ‘discrete technology’ sectors in Model 3.
While, in the other two models, an answer to the established hypotheses has been provided.

In Model 2, Research and Development Expenditures’ data have been added to the control variables with the aim to test the statistical relationship between the dependent and the independent variables, using data coming from the 303 US manufacturing companies that belong to ‘complex technology’ sectors.
Model 2 provided statistical evidence that, on average and maintaining the other variables constant, Research and Development Expenditures at time t are statistically and positively related with the Total Number of Employees, so demonstrating the first hypothesis (H1: US High-Tech Manufacturing companies are characterized by a positive and significant employment impact of R&D Expenditures) and also the second hypothesis (H2: US High-Tech Manufacturing firms, classified as ’complex technology’ companies, are characterized by a positive and significant employment impact of R&D Expenditures).

In model 4, Research and Development Expenditures’ have been added to the control variables with the aim to test the statistical relationship between the dependent and the independent variables, using data coming from the 229 US manufacturing companies that belong to ‘discrete technology’ sectors. Model 4 provided statistical evidence that, on average and maintaining the other variables constant, Research and Development Expenditures at time t are statistically and positively related with the Total Number of Employees, so demonstrating the third hypothesis (H3: US Manufacturing firms, classified as ’discrete technology’ companies, are characterized by a positive and significant employment impact of R&D Expenditures).

So there is enough statistical evidence to conclude that Research and Development Expenditures at time t affect the Total Number of Employees at the firm level in a positive and significant way for all the companies included in the sample, both for ‘complex technology’ sectors and ‘discrete technology’ sectors.

This is coherent with the existing literature regarding US high-tech manufacturing companies and, in addition, these results are able to fill the gap in the literature, because *“It would have been interesting to include ‘discrete technology’ sectors in our study, but unfortunately we did not have a comparable number of observations for these sectors. This remains a challenge for future work” (Coad and Rao)*, so demonstrating that the relationship between Innovation and Employment is positive and significant also for those companies classified as ‘discrete technology’ firms. Further explanations and recommendations are provided in Chapter 5.

5. CONCLUSIONS

The objective of this research was to investigate the relationship between Innovation and Employment for US manufacturing companies during a time period of five years (2013-2017).

In particular, this study analyzes how R&D Expenditures at time t affect the Total Number of Employees at the firm level.

As already underlined, innovation is often considered as the driver of employment growth but the debate on the potential adverse consequences of innovation on employment is still open.

In fact, as underlined by Van Roy, Vértesy and Vivarelli (2018), "*economic theory does not have a clear-cut answer about the employment effect of innovation so there is a strong need for empirical analyses able to test the final employment impact of technological change*".

So the empirical analysis has been conducted with the aim to contribute to the existing literature by providing, as most empirical studies have already done, statistical evidence that the relationship between R&D Expenditures and the Total Number of Employees at the firm level is significant and positive in all the four models built and so for all the 532 companies of the sample.

In addition, adopting different periods of time was useful to verify how the relationship between R&D Expenditures and the Total Number of Employees change during the years.

Even if the study has been conducted in the most efficient and accurate way possible, some limitations must be analyzed:

- the time period considered in the analysis includes only five years (2013-2017). Maybe a longer time period could add more statistical information about the relationship between R&D Expenditures and Total Number of Employees.

- for the construction of the sample, the high-tech companies have been selected according to the SIC Classification. At the same time, high-tech companies could also be classified according to R&D Intensity and so considering only companies with average values of R&D Intensity higher than 7%; this diverse classification could lead to different final results therefore it would be suggested, for future studies, to adopt different criteria for the classification of high-tech companies.

- R&D Expenditures have been considered as the independent variable but scholars sometimes use also the number of patents or citations based on patent data as another common measure for innovation. For this reason, if patents are used as the independent variable, the study could lead to different results.

- as already underlined, Coad and Rao (2007) conducted this same study generating a firm and year specific 'innovativeness' index by extracting the common variance in a firm's patenting and R&D expenditure histories, demonstrating that firm-level innovative activity leads to employment creation; while, in this research, only R&D Expenditures have been used as the indicator of innovation within firms.

- the final employment impact of innovation depends also on institutional mechanisms which can be very different at the micro and macro levels and can vary in different economic contexts, such as in different countries or in different sectors within the same country (Vivarelli, 2007);

- employment is influenced by many other factors such as the macroeconomic and cyclical conditions, the labour market dynamics, the time in working time and so on.

However, even if these limitations subsist, this study provides relevant and added information on the relationship between R&D Expenditures and Total Number of Employees at the firm level for US high-tech manufacturing companies, classified as 'complex technology' sectors, and also for those classified as US 'discrete technology' manufacturing companies.

Regarding some suggestions for future works, it will be interesting to analyze how skills and tasks within the work environment affect the relationship between Innovation and Employment.
In fact, as explained in Chapter 2, there is a particular branch of labor economics literature that is composed by studies which are mainly focused on the qualitative employment effects of innovation rather than on the quantitative ones.
The literature regarding the qualitative consequences of innovation and so the studies regarding the impact of innovation over skills and tasks should increase, featuring that technological change is not skill-neutral.

In addition, also some studies based on a distinction between the innovation type could lead to a better understanding of the employment effect of innovation so a suggestion for future works is to consider this aspect.
In fact, as explained by Harrison et al. (2008, 2014), since innovations have different purposes and can have different employment effects, the distinction between the innovation type leads to a better understanding of the employment effect of innovation.

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SUMMARY

During the last twenty years, lots of new technologies became available in the market, leading to important changes within business processes of many companies.
In particular, the diffusion of a new paradigm, based on information and communications technologies (ICTs) and automation, has caused some adjustments of the employment levels and structure in all the economy (Van Roy, Vértesy, Vivarelli, 2018).
Innovation is often considered as the driver of employment growth but the debate on the potential adverse consequences of innovation on employment is still open.
In fact, as underlined by Van Roy, Vértesy and Vivarelli (2018), "*economic theory does not have a clear-cut answer about the employment effect of innovation so there is a strong need for empirical analyses able to test the final employment impact of technological change*".
For this reason, an increasing number of scholars decided to study the employment effects of innovation.

When talking about the relationship between innovation and employment, the first distinction that has to be made is the one between the likely labor-friendly impact of product innovation and the possible labor-saving effect of process innovation.
Product innovation means introducing a good or a service that is new or significantly improved while process innovation is the implementation of new or significantly improved processes for the production or the delivery of products (OECD 2005).

Most empirical studies showed a clear and positive relationship between the introduction of new products and the growth of income and employment at the firm level; instead the empirical results on process innovations are ambiguous.
In this research, only product innovations will be considered because, as Van Roy, Dániel Vértesy and Marco Vivarelli (2018) explained in their paper, "*there is less debate about the positive employment effect of product innovations, that are generally*

understood to lead to the opening of new markets, or to an increased variety within the existing ones".

So this study aims at enriching the empirical microeconomic literature regarding the relationship between innovation and employment and it will investigate how R&D Expenditures, used as an empirical proxy for the economic value of innovation efforts (Pandit, Wasley and Zach, 2011), affect the Total Number of Employees at the firm level.

However, data on R&D spending are not always available or they are limited because many companies have strict confidentiality policies (Kleinknecht, 1993).
For this reason, only firms incorporated in the United States of America will be analyzed because, under US accounting laws and regulations, annual R&D Expenditures' public disclosure by companies is required.

In addition, according to the existing literature (see Francesco Bogliacino, Mariacristina Piva and Marco Vivarelli, 2012), product innovations are mainly and significantly connected with R&D Expenditures, especially in some sectors such as the high-tech manufacturing one.
High-Tech sector because it is one of the fastest growing sectors and so it is critical for innovation, productivity and growth.

In fact, firms included in the high-tech manufacturing and services sectors belong to dynamic and emerging sectors where a strong correlation between R&D and product innovation is even more likely than average (Francesco Bogliacino, Mariacristina Piva and Marco Vivarelli, 2012).

Many statistical researches demonstrated that product innovations have a positive impact on employment, but not so many studies have been conducted on US firms.

In addition, *in the previous literature, empirical analysis has very rarely been carried out according to sectoral belonging (Francesco Bogliacino, Mariacristina Piva and Marco Vivarelli, 2012)*.
So this thesis will be significant because both it takes into account US firms and it is mainly carried out according to the high-tech sector.

The empirical analysis is conducted with the aim to contribute to the existing literature by providing, as most empirical studies have already done, statistical evidence that the relationship between R&D Expenditures and the Total Number of Employees at the firm level is significant and positive for all the companies of the sample.

In particular, a sample of 532 US manufacturing companies over a time period of five years, from 2013 to 2017, is analyzed and split into two different groups, according to the distinction made by Hall (2004) and Cohen et al. (2000): 'complex technology' companies and 'discrete technology' companies.
The distinction between 'discrete technology' manufacturing companies (SIC between 19 and 33) and 'complex technology' manufacturing companies (SIC between 34 and 39) has been introduced by Hall (2004) and Cohen et al. (2000): they defined 'complex product' industries those industries where each product relies on many patents held by a number of other firms, while the 'discrete product' industries are those industries where each product relies on only a few patents.
In addition, 'Complex technology' sectors are the ones characterized by high patenting and high R&D expenditure.

Following what Coad and Rao (2011) have already done, for the empirical analysis concerning the high-tech manufacturing companies, four sectors of firms will be taken into account.
These four sectors are classified under the 'complex technology' class (SIC 35-36-37-38), because these sectors are characterized by high patenting and high

R&D expenditure so there is a bigger possibility to get relatively accurate measures of firm-level innovation.
But, at the same time, the relationship between innovation and employment will be studied not only for 'complex technology' sectors but also for companies that belong to 'discrete technology' sectors (SIC 20-21-22-23-24-25-26-27-28-29-30-31-32).

So, within the sample, 303 are the high-tech manufacturing companies that belong to 'complex technology' sectors (SIC between 34 and 39), and 229 are the manufacturing companies that belong to 'discrete technology' sectors (SIC between 19 and 33).

Therefore, four statistical models are built and a panel data regression is run for each model.
To conduct the analysis, Research and Development Expenditures and the Total Number of Employees at the firm level have been employed and the time-effect has also been considered in all the models built.

The empirical analysis will test if firm-level innovative activity leads to employment creation not only for 'complex technology' sectors but also for 'discrete technology' sectors, always taking into account R&D Expenditures.
So this thesis will be challenging and very helpful because it will fill a gap in the literature since, as explained by Coad and Rao, *"it would have been interesting to include 'discrete technology' sectors in our study, but unfortunately we did not have a comparable number of observations for these sectors. This remains a challenge for future work"*.

In doing so, this study will address a **Research Question** *(Is the positive impact of R&D Expenditures on Employment limited solely to the US high-tech manufacturing firms, classified as 'complex technology' companies?)* that will be declined in **3 different hypotheses**: 1) US high-tech manufacturing companies are characterized by a positive and significant employment impact of R&D Expenditures; 2) US high-tech manufacturing firms, classified as ’complex technology’ companies, are characterized by a positive and significant employment impact of R&D Expenditures; 3) US manufacturing firms, classified as ’discrete technology’ companies, are characterized by a positive and significant employment impact of R&D Expenditures.

In Model 1 and in Model 3, the statistical relationship between the control variables and the dependent variable has been tested, using data coming from the 303 companies that belong to ‘complex technology’ sectors in Model 1, and using data coming from the 229 companies that belong to ‘discrete technology’ sectors in Model 3.

While, in the other two models, an answer to the established hypotheses has been provided.

In Model 2, Research and Development Expenditures’ data have been added to the control variables with the aim to test the statistical relationship between the dependent and the independent variables, using data coming from the 303 US manufacturing companies that belong to ‘complex technology’ sectors.

Model 2 provided statistical evidence that, on average and maintaining the other variables constant, Research and Development Expenditures at time t are statistically and positively related with the Total Number of Employees, so demonstrating the first hypothesis (H1: US High-Tech Manufacturing companies are characterized by a positive and significant employment impact of R&D Expenditures) and also the second hypothesis (H2: US High-Tech Manufacturing firms, classified as ’complex technology’ companies, are characterized by a positive and significant employment impact of R&D Expenditures).

In model 4, Research and Development Expenditures’ have been added to the control variables with the aim to test the statistical relationship between the dependent and the independent variables, using data coming from the 229 US manufacturing companies that belong to ‘discrete technology’ sectors. Model 4 provided statistical evidence that, on average and maintaining the other variables constant, Research and Development Expenditures at time t are statistically and positively related with the Total Number of Employees, so demonstrating the third hypothesis (H3: US

Manufacturing firms, classified as ’discrete technology’ companies, are characterized by a positive and significant employment impact of R&D Expenditures).

So the final results show that an increase in R&D Expenditures has a positive and significant impact on the Total Number of Employees both for ‘complex technology’ companies and ‘discrete technology’ companies and so there is enough statistical evidence to conclude that Research and Development Expenditures at time t affect the Total Number of Employees at the firm level in a positive and significant way for all the companies included in the sample, both for ‘complex technology’ sectors and ‘discrete technology’ sectors.

This study is important because from one side it confirms the positive and significant relationship between innovation and employment in firms that belong to ‘complex technology’ sectors, as already showed by many scholars in the existing literature, and from the other side it demonstrates the positivity and the significance of this relationship also in firms that belong to ‘discrete technology’ sectors.

It is possible to conclude saying that, even if the study has been conducted in the most efficient and accurate way possible, some limitations must be analyzed:

- the time period considered in the analysis includes only five years (2013-2017). Maybe a longer time period could add more statistical information about the relationship between R&D Expenditures and Total Number of Employees.

- for the construction of the sample, the high-tech companies have been selected according to the SIC Classification. At the same time, high-tech companies could also be classified according to R&D Intensity and so considering only companies with average values of R&D Intensity higher than 7%; this diverse classification could lead to different final results therefore it would be suggested, for future studies, to adopt different criteria for the classification of high-tech companies.

- R&D Expenditures have been considered as the independent variable but scholars sometimes use also the number of patents or citations based on patent data as another common measure for innovation. For this reason, if patents are used as the independent variable, the study could lead to different results.

- as already underlined, Coad and Rao (2007) conducted this same study generating a firm and year specific 'innovativeness' index by extracting the common variance in a firm's patenting and R&D expenditure histories, demonstrating that firm-level innovative activity leads to employment creation; while, in this research, only R&D Expenditures have been used as the indicator of innovation within firms.

- the final employment impact of innovation depends also on institutional mechanisms which can be very different at the micro and macro levels and can vary in different economic contexts, such as in different countries or in different sectors within the same country (Vivarelli, 2007);

- employment is influenced by many other factors such as the macroeconomic and cyclical conditions, the labour market dynamics, the time in working time and so on.

However, even if these limitations subsist, this study provides relevant and added information on the relationship between R&D Expenditures and Total Number of Employees at the firm level for US high-tech manufacturing companies, classified as 'complex technology' sectors, and also for those classified as US 'discrete technology' manufacturing companies.

Regarding some suggestions for future works, it will be interesting to analyze how skills and tasks within the work environment affect the relationship between Innovation and Employment.
In fact, as explained in Chapter 2, there is a particular branch of labor economics literature that is composed by studies which are mainly focused on the qualitative employment effects of innovation rather than on the quantitative ones.

The literature regarding the qualitative consequences of innovation and so the studies regarding the impact of innovation over skills and tasks should increase, featuring that technological change is not skill-neutral.

In addition, also some studies based on a distinction between the innovation type could lead to a better understanding of the employment effect of innovation so a suggestion for future works is to consider this aspect.
In fact, as explained by Harrison et al. (2008, 2014), since innovations have different purposes and can have different employment effects, the distinction between the innovation type leads to a better understanding of the employment effect of innovation.

Finally, this thesis is structured in five different chapters, including the introduction.
Chapter 2 will go through a deep analysis of the available literature, examining what scholars have already found about the relationship between innovation and employment, and the last paragraph will be dedicated to the development of the research hypotheses.
Chapter 3, moving from the Literature Review to the Research Methodology, will provide a detailed description of the methodology through which the research has been conducted, underlying how the relationship between innovation and employment has been addressed. First of all the construction of the sample data and the criteria adopted will be illustrated, then the variables employed in the empirical analysis will be deeply described and finally the statistical methodology used to reach the conclusions will be presented.
Chapter 4 will describe the process used for the construction of the four models and it will also provide the statistical results with the relative demonstration of the three hypotheses.
Chapter 5 will focus on the conclusions with a specific section regarding the implications and the limitations of the study and with another section concerning some suggestions for future researches.