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"A STATISTICAL RESEARCH ON THE IMPACT OF LEAN AND INDUSTRY 4.0 ON COMPANIES IN NORTHERN ITALY"

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Chapter 1: LEAN

1.1 Introduction to Lean

The Lean Production paradigm has become the major approach to create highly efficient processes in industry since the early 1990s. After the sudden end of the Computer Integrated Manufacturing (CIM) era, which finally was doomed to fail due to the unrulable complexity of the required automation technology, the Lean approach was successful because of its high effectiveness by reducing complexity and avoiding non-value-creating process steps.

Its simplicity and its up to 25 per cent higher productivity are some reasons why Lean Production has become status quo of production systems [1].

The focus of Lean is "to achieve a flow of material, information or customers that delivers exactly what customers want (perfect quality), in exact quantities (neither too much nor too little), exactly when needed (nor too early nor too late), exactly where required (in the right location) at the lowest possible cost" [2]. Lean, in other terms, concerns a production system that is oriented on learning of organization through continuous improvements. It took its origins in the Toyota Production System and has been recognized mainly as "doing more with less".

It aims at reducing unnecessary variations and steps in the work process by the elimination of waste: that is any action that does not add value to the product or services.

Originally, it was focused on the elimination of such wastes as defects of requiring rework, unnecessary processing steps, movement of materials or people, waiting time, excess inventory, and overproduction. Nowadays, it covers diverse aspects of the manufacturing starting from the initial stage of product life cycle such as product development, procurement and manufacturing over to distribution [3]. Lean principles are applied across all sectors, including finance, healthcare, IT, retailing, construction, agriculture and the public sector [2].

It is implemented as a philosophy and a set of tools and practices to achieve the highest quality, lowest cost, and shortest lead time. It is an effect of a complex, pro-quality management in all areas of enterprise activities [4].

Its definition is not that straightforward. Lean can be viewed, in fact, as three related, but still distinct, things:

1) *A philosophy of how to run operations properly*

   A way of thinking about how to smooth flow through processes by doing all the simple task well, on gradually doing them better, on meeting customers' needs and on squeezing out any sort of waste at every step of the chain.

2) *A method of planning and controlling operations*

   A concern on how items such as materials, information and customers may flow through the operations, and more specifically how managers can deal with them to better facilitate this flow. Uncoordinated flow causes unpredictability, and unpredictability causes waste in form of people holding back inventory, capacity or time, or for protecting them against it. A planned and controlled lean mechanism takes advantage of several methods in order to achieve a synchronized flow and a reduced waste. Above all, it uses the "pull", that is set on functioning by the Kanban system. Level scheduling and mixed modelling are further approaches applied to sustain this aim.

3) *A set of tools for improving operations performance*

   A collection of improvements tools and techniques that are the main mean to cut out waste and its impacts. The most important among them will be discussed throughout this chapters about lean. What matters is that the rise of lean ideas gave birth to a series of methodologies that have now become mainstream in the vast field of operations, and they shifted the viewing on the improvement itself as its main purpose.

Lean can be also considered as an extended just-in-time including all parties involved in supply chain, intra and inter-organization [5, 6].

It is a multi-dimensional approach that can work synergistically to create an efficient, high quality system to deliver products in accordance with the pace of customer demand with minimum waste [7,8].

1.2 Lean Implementation

Generally, the successful implementation of any management practice often relies on organizational characteristics. However, it should be emphasized that not all organizations can, or even should, implement the same set of practices.

The most often revealed practices commonly associated with lean production are [7]:

1) bottleneck removal (production smoothing)
2) cellular manufacturing
3) competitive benchmarking
4) continuous improvement programs
5) cross-functional work force
6) cycle time reductions
7) focused factory production
8) just-in-time/continuous flow production
9) lot size reductions
10) maintenance optimization
11) new process equipment/technologies
12) planning and scheduling strategies
13) preventive maintenance
14) process capability measurements
15) pull system/Kanban
16) quality management programs
17) quick changeover techniques (SMED)
18) reengineered production process
19) safety improvement programs
20) self-directed work teams
21) total quality management

These tools create a system as they contribute to the elimination of a particular type of waste, but they should be applied together in order to benefit of synergetic effects. The approaches are in fact often treated as “lean toolbox”, to highlight their importance when applied as a group of techniques. [4]

As far as the implementation process of lean production is concerned there are discussed diverse frameworks and related topics.

First of all, according to Ålström [9], it is evident that improvement activities are a main feature in the implementation. However, continuous improvement should be introduced late during the process to allow it to benefit from the earlier established other principles. Therefore, a small leap forward is to be considered necessary at the very beginning of each transactional phase.

Second, Storhagen [10] suggests that continuous improvement and change can be supported by job rotation and teamwork, which only in the beginning of the lean implementation allow taking the advantage of people contribution considerably. From this reasoning it follows also that employees' attitudes to quality should be concerning mainly material flow which contains only value adding operations [11]

Third, following Womack and Jones's "lean leap process", [3] there is a need to identify a change agent to create a new lean organization. A change agent would be the necessary reason for moving the organization on. Additionally, someone or a group of people should be the first to acquire lean knowledge to be then able to share it with the rest of organization and promote any transformation even before any value streams is mapped. It is therefore fundamental that a small group, inside the organization, is formed. It will be the group itself to transfer the knowledges acquired through training.

Last, lean thinking can be recognized as completed and successfully set on working when it is applied also to suppliers and customers, a global strategy is developed, and continuous improvement program is transitioned from a top-down to a bottom up.

Hobbs [12] proposed a step-by-step implementation of lean which hypothetically can reflect the five lean principles (see the following table).

Step Lean principle

Establish strategic vision -
Identify and establish teams -
Identify products Value
Identify processes Value stream
Review factory layout Flow
Select appropriate pull strategy Pull
Continuously improve Perfection

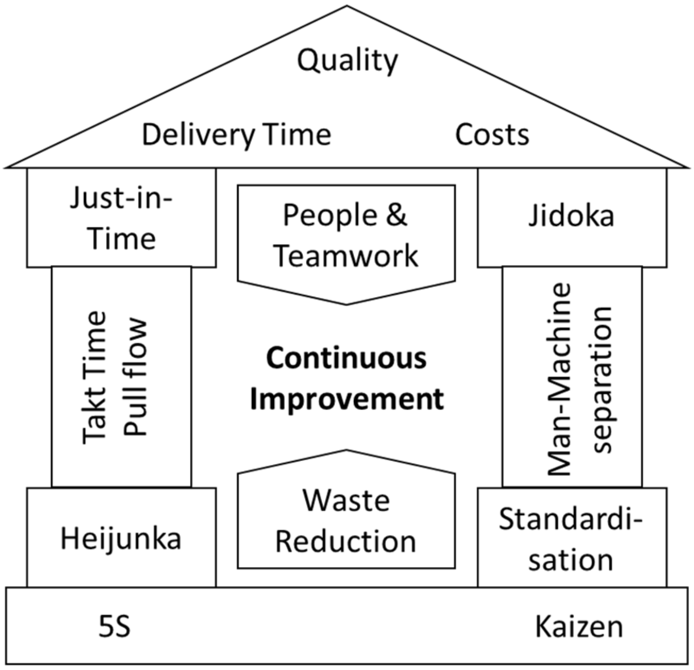
Important to be noticed is that steps three to seven are linked to the five lean principles, whereas it is difficult to assign the original lean principles to steps one and two. For this reason, Hines [13] proposes to extend the classical principles of lean to "people" as well, making according to his point of view the second step justified because of its place into the list. The first step can be instead suggested to be a starting point for any strategic implementation project, and thus it can be considered as "a pre-step".

A commonly associated practice to identify waste, to be set before starting any implementation, is "Gemba Walk", which consists into viewing the processes by staying into the actual place where things happen. If there is the will to understand how to improve something, there is also a strong need for managers or whoever is going to implement lean practices to visit the places where the waste is supposed to be seek out.

To reach excellence the Lean philosophy has to be integrated in the business culture by leadership and coaching to improve processes every day [14]. Starting from this Japanese management philosophy western companies began to develop their own production system and several implementation approaches [15, 16, 17]. The rate of successful Lean Production implementation varied depending on the company size. Nowadays most industrial company groups are following Lean principles, but the implementation rate is still low in small and medium sized companies [7, 18, 19].

1.3 Lean Production System

The Toyota Production System (TPS), and its synonym Lean Production, was developed by Toyota Motor Corporation in the 1970s. The TPS integrates a set of methods and tools with the management philosophy to completely eliminate the seven forms of waste (Muda) and produce profit through cost reduction [20]. The TPS defines everything that does not create value as waste including: overproduction, waiting for work, conveyance, extra or wrong work, inventory, motion or correction of mistakes [21].



(Fig. 1.1)

The House of Lean Production (Fig. 1) is the symbol for the Lean Production principles. The triangle roof emblematizes the systematic focus on the customer oriented key performance indicators (KPI) for quality, delivery time and costs [22, 23]. The roof is sustained by composing elements that are discussed singularly in the following points:

1) *5S*

   5S encompasses the five Japanese words: seiri (整理), seiton (整頓), seisō (清掃), seiketsu (清潔), and shitsuke (躾), that have been translated as "Sort", "Set In order", "Shine", "Standardize" and "Sustain". Each of these describes how to organize a work space for efficiency and effectiveness by identifying and storing the items used, maintaining the area and items, standardize procedures and sustaining the new order. In practice, this means that what is not needed should be eliminated and things should be positioned in such a way that they can be easily reached and found whenever they are necessary. Things such as objects and the workplace itself should be kept clean and tidy, no refuse should be found around. Perpetual neatness should be the principle applied to maintain cleanliness and order. A culture of commitment and pride should be created into the organization and shared among the workers in keeping the standard once set.

2) *Kaizen*

Kaizen (改善) is the Japanese word that stands for "improvement". Kaizen refers to all those activities that permit to continuously improve all functions and involve all employees from the CEO to the assembly line workers. It is an approach that also applies to all processes, such as purchasing and logistics as well as to the overall supply chain.[24] . It implies incremental improvements more than breakthrough changes. Kaizen considers human resources as a cornerstone to be utilized and trained for better reaching the organization's goals. As a ground there should be a strong "respect for humans" and therefore for employees. Kaizen encourages team-based problem solving, job enrichment, job rotation and multi-skilling. The intention is to decentralize and provide a higher degree of personal responsibility, engagement and ownership of the task. Self-discipline, flexibility and autonomy are just some of the "basic working practices" that can be found belonging to Kaizen.

3) *Just-in-Time (JIT)*

The Just-in-Time or JIT is a well-known inventory management system wherein the material, or the products are produced and acquired just when there is the need for these tasks to be carried out. The JIT system is adopted by the firms, to reduce the unnecessary burden of inventory whenever the demand is less than the inventory raised. The underlying objective is the one of increasing the inventory turnover and reduce the holding cost and any other costs associated with it. This approach to inventory requires a proper understanding between the manufacturer and the supplier in terms of the delivery and the quality of the material as well as on the overall reliability of the chain form the beginning to the end. JIT may sometimes result to take some risk as any misunderstanding or unexpected variation into some of the expected future condition could generate process halts or unpleasant consequences for the customers.

4) *Jidoka and Man-machine Separation*

Jidoka means "intelligent automation" or "humanized automation". Processes are automated so that to be sufficiently "aware" of themselves. Awareness permits to machines to: detect malfunctioning and products defects, stop themselves and alert operators. Companies agree on the importance of this element as it allows to prevent producing multiple defective items, delivering low quality products to customers as well as keep up the tack time. Jidoka has the potential to keep on benefit considerably of new coming technological applications and increase the impact on efficiency and effectiveness.

5) *Heijunka*

Heijunka is the technique of achieving even output flow by coordinated sequencing of very small production batches throughout the manufacturing line in a lean production or just in time (JIT) system. It is an approach based on level scheduling which keeps the mix and volume between stages at even rate over time. It prevents the productions process from being centered on a production of large batches. It makes sense from an inventory point of view as it protects accumulation within and between stages. Moreover, it helps minimizing variability into the production for facing demand. Small batches move along the process and diminish the overall level of work-in-process, regularity and rhythm permits to make planning and control activities easier and predictable.

6) *Standardization*

Standardized work is one of the most powerful but least used lean tools. It means doing things in the same way or, more formally, adopting a common sequence of activities, methods and use of equipment. It prevents arising of confusions, misunderstanding and unsimilar outputs. Standardization can give some significant advantage but hardly all processes can be standardized. Often companies have to draw a line between those processes that need to be standardized and those that do not. By documenting the current best practice, standardized work forms the baseline for kaizen or continuous improvement. As the standard is improved, the new standard becomes the basement for further improvements, and so on. Improving standardized work is a never-ending process. Basically, standardized work consists in the definition of three elements: the takt time, the rate at which products must be made in a process to meet customer demand; the precise work sequence in which an operator performs tasks within takt time; the standard inventory, including units in machines, required to keep the process operating smoothly.

7) *Takt Time*

Takt time is the rate of customer demand. It is the average time between the start of production of one unit and the start of production of the next unit, when these production starts are set to match the rate of customer demand. It is normally a terminology applied to paced processes like moving-belt assembly lines. It is the beat or tempo of working required to meet the demand on time. The work content within each build stage should be balanced, to ensure the takt time is maintained, and, if for any reason, operators finish a stage quicker than planned, or struggle to keep up, the engineering teams can then look at ways of rebalancing the production stages.

8) *Pull Flow*

Pull system is a lean technique for reducing the waste of any production process. Applying a pull system allows to start new work only when there is a customer demand for it and provides the opportunity to reduce overhead and optimize storage costs. Pull stands in against the push concept of production and encompasses well the use of flow. Compared to the traditional approaches flow does not place buffers of inventory between stages. Each stage will eventually work on the outputs of the preceding one. The isolation of stages thanks to buffer is avoided because it has to be paid for in terms of inventory or queues and slow throughput times as products, customers and information spend time waiting to be processed.

1.4 Advantages and Disadvantages of Lean Production

Companies implementing lean can benefit of some advantage as well as bear some additional risk not usually linked to traditional business' approaches. Some of the advantages are:

1) *Fewer Infrastructure*

   A manufacturer implementing lean production only uses the building space, equipment, tools, supplies and manpower necessary to meet near-term inventory demand from buyers. In contrast to mass production facilities, a building used with a lean production strategy doesn't have any wasted space. Only the room necessary to meet demand is required. Similarly, the business doesn't need unused equipment and tools sitting around. Labor shifts are also scheduled to ensure workers don't stand around without work to do.

2) *Less Waste*

   The goal of limited waste is a key focus of lean manufacturing relative to mass production. Companies don't want excess inventory sitting around waiting for customers to demand for it. This approach eliminates dated or obsolete inventory and the risk that certain items perish or expire. Eliminating waste is cost-effective. It is not necessary to have space or people to manage the extra inventory until it is purchased.

3) *Strong Customer Relationships*

   Lean production is an efficient approach to customer relationships. Unlike mass production, which attempts to meet the needs of all customers when demand occurs, lean production involves meeting the needs of loyal customers on a scheduled or predictable basis. Keeping your best customers happy and in good supply contributes to limited waste, while ensuring that your cash cow customers feel important to your business. It is also easier to customize products or flex production processes when you cater to select buyers.

Disadvantages may be summed up as follows:

1) *Equipment or Labor Failure*
   One of the central disadvantages of lean production is that you have little margin for error. If equipment breaks down or you need more-than-projected labor for certain processes, you may fall behind and lose your optimized efficiency advantages. In a mass production plant, workers simply slide over to another piece of equipment if something quits working. In a lean production facility, there aren't a lot of extra equipment and tools around.

2) *Missed Deliveries*
   Directly tied to the lack of flexibility or margin for error is the potential for missed delivery deadlines. Breakdowns can cause you to harm your primary customer relationships if you don't deliver as promised. Your wholesale or retail buyers need goods by deadlines to meet the demand from their customers. If you consistently fail to provide timely shipments, buyers look for suppliers that can. Sometimes, you don't even get a second chance on a major miss.

Moreover, it seems as if Lean Production reached its limit: strong deviations in market demands are in conflict with required levelled capacity utilization. Thus, a production which is decoupled from market demand is often needed [25, 26, 27]. This is in conflict with an also required order-oriented production and direct connection of production to market demands. Although Lean Production supports a higher variety of products, its fixed sequence of production and fixed cycle times are not suitable for individual single-item production. Besides, Lean Production was invented in the 1950s and thus does not take into account possibilities of modern ICT. In traditional Lean Production, changes in production processes, buffer stocks or cycle times require laborious adjustments of Kanban cards or Kanban bins [28]. Hence, Lean Production's suitability for future shorter product life cycles and individual single-item production is limited.

Chapter 2: INDUSTRY 4.0

2.1 Introduction to Industry 4.0

Since its conceptual introduction, Industry 4.0 has been a matter of discussion throughout companies, organizations, and universities [29]. Hundreds of academic publications, articles and conferences have targeted this term and related topics [30].

Currently, the term is associated to "smart factories". Mainly, these are plants and sites of production that exploit some or all the technologies and concepts belonging to this broad topic: horizontal and vertical system integration, industrial internet of things, autonomous robots, augmented reality, cloud computing, advanced analytics, big data, laser cutters, and 3D scanners.

"Industry 4.0" is nowadays significantly changing the manufacturing methods and the relationships between economic actors both within and out of the companies. Changes are becoming more and more relevant over the labor market and the broader spectrum of stakeholders of an organization [31].

The term "Industrie 4.0" has been officially introduced by the German Government in 2011. The state considered it to be "one of the key initiatives of its high-tech strategy", fundamental, to push the economic development of the country [30].

No formally respected definition exists for it. It has been defined as "the integration of complex physical machinery and devices with networked sensors and software, used to predict, control and plan for better business and societal outcomes" [32] or "a new level of value chain organization and management across the lifecycle of products" [33] or "a collective term for technologies and concepts of value chain organization" [30]. The overall concept of Industry 4.0 can be perceived as a strategy for being more competitive in the future. It focuses on the optimization of value chains due to autonomously controlled and dynamic production [34].

Industry 4.0 is an approach that set a network where both components and machines as well as workers are becoming smart and a part of a standardized thinking. A well proven and strict standardization permits to handle each piece essential to the business as a Lego-bricks to set up larger and more efficient systems.

Going through an historical prospective many author think about "Industry 4.0" as the Fourth Industrial Revolution, while other experts and researchers, do not consider it as a proper one. The latter group favors more the idea of this phenomenon as one of the last major upheaval in modern manufacturing, where the previous are recognized to be: the lean manufacturing in the 70’, the outsourcing wave in the 90’ and the automation proliferation following decade.

In any case a couple of differences could be potentially highlighted in comparison to the previous industrial revolutions: first, it would be the only industrial revolution predicted a priori and not observed only ex-post [29]; second, while previous revolutions were an actual leap forward, this one seems more to be an updated version of the third revolution [35].

An additional and relevant element is that Industry 4.0 differentiates itself from the Third Industrial Revolution, where the desire of improving efficiency resulted in workers losing their jobs, by the fact it does not necessarily imply that companies need to downsize their workforce.

2.2 Important Words for Understanding Industry 4.0

According to Henning Kagermann, Wolfgang Wahlster, and Johannes Helbig, authors of the "final report of the Industrie 4.0 Working Group" [33] for the German Federal Ministry of Education and Research, there are three main concepts that characterize Industry 4.0. These are: the Internet of Things (IoT), Cyber-Physical Systems (CPS), and Smart Factories.

1) *Internet of Things*

   Internet of Things (IoT) is the most important and necessary technological development at the base of Industry 4.0. Wrongly, it is now commonly used to refer to the fourth industrial revolution and its bundle of technologies [31]. Gartner, a leading research and advisory company, defines the Internet of Things as "the network of physical objects that contain embedded technology to communicate and sense or interact with their internal states or the external environment".

   For General Electrics [36], IoT is the result of the combination of physical technologies developed during the Industrial Revolution and the acknowledgeable advances of the Internet Revolution (in computer performances, in information technologies, and in communication technologies).

   IoT has important consequences for the industrial settings. Its industrial applications can be summed up into the expanded terminology of Industrial Internet of Things (IIoT). Through IIoT it is possible to establish a useful network of connections among a myriad of different machines. "Intelligent Machines" become capable of a kind of default reasoning, thanks to the fact that they can use the information they create and receive through the network. The communication can reasonably even be external to the plant or organization and potentially at long distance with any device.

   IIoT empowers the whole worlds of analytics, data management and results applications. Much more information can be gathered, analyzed and the resulted decisional application can be easily putted into action by a press bottom. Visibility and countability of performance data can result in a significative improvement of efficiency.

On the base of IIoT technologies, workers can be connected wherever they are and whenever they want and most of the operation of teamworking, design, management or maintenance can be run at distance on a fully informed on-time basis.

2) *Cyber-Physical Systems*

The Cyber-Physical Systems are an important feature of Industry 4.0 and can be defined as "integrations of computation, networking, and physical processes; where physical processes affect computations and vice-versa" [37].

They are computer systems capable of continuously interacting with the physical system in which they operate. Their system is composed of physical elements each with a computational capacity, that closely combines the so-called "three Cs": computational capacity, communication and control capacity.

What makes them different from normal physical systems is the integration of Information and Communication Technologies capabilities.

The improvements in sensor technology, miniaturization and energy efficiency have been contributing to the possible applications of most CPS. Sensors are hardware devices that produce a measurable response to a change in a physical condition as analog signals then to be converted into digital signals by the analog-to-digital converters.

3) *Smart Factories*

Smart factories are highly digitized and connected production facilities that rely on technologies such as artificial intelligence, robotics, analytics, big data and the internet of things and can run largely autonomously with the ability to self-correct. These are characterized by:

"Smart Networking" - its leveraging on cyber-physical systems permits to keep interconnected on a continuous basis automated systems, equipment, software and supplies.

“Mobility and Ubiquity” - thanks to digitalization and constant flow of information provided by the sensors that constantly monitor machines, it is possible to perform an important amount of activities such as preventive maintenance at distance.

“Flexibility” – new commands, changes or automated adaptations of format and configuration advantages the factory to produce different kinds and amount of goods.

“Integration with the customers” – customers’’ expectations and products’ characteristics can easily be inputted into the production system, with no considerable effort.

“New business model underground” - industry 4.0 technologies allow to make up new blue-ocean strategies to interface with the customers’ segments and provide the highest value possible. New configurations of products are even possible, based on data gathered directly from the customers’ base. The Smart Factories can potentially decrease the distance between the costumers and the company, increasing the importance of single customization and customers’ product auto-design.

2.3 Characteristics of 4.0 Companies

Gilchrist [37] identifies four main features that characterize companies that completely embrace the Industry 4.0's applications. These characteristics differentiate 4.0 businesses from the traditional ones as the network effect and the control over technologies and products will create numerous advantages and consequences. These are explained in the following subsections:

1) *Vertical Integration of Smart Production Systems.*
   The Smart Factories are at the core of each Industry 4.0's company. They make sense only if they are interconnected by IoT to the downstream distributors and upstream suppliers. This is due to the fact that most of their applications comes from the advantages provided by the necessary and underlying relationship with the others. The integrations with the suppliers allow to coordinate and react rapidly to changes in the production. Inventory and stock levels become problems that can be set partially aside once suppliers have all the information and the minimum time span ensured to provide materials and components on time. Distributors integrated into the systems can communicate better the changes in demand and even the pattern of consumptions of good for improving both the delivery of finished product as well as the definition of future market trends. The direct connection with the customers' base permits to suit customer-specific and personalized goods and services. Customers will no more have to burden with finding the right product to their needs, because their needs will be the pull reasoning at the production stage for their even singular product assembly.

2) *Horizontal Integration Through the global Value Chain Networks.*
   Companies belonging to the same holding can work more properly and as a tightened group. A coordination, even on a global base, from inbound logistics through warehousing, production, marketing and sales to outbound logistics and downstream services is the point of an integration at this level. Different companies set around the globe can coordinate their activities thanks to the tracking methodologies of smart products and smart machines. IoT can share information and therefore characterized these companies for avoiding wasteful duplication of inventory, production activities and even management's decisions.

3) *Through-Engineering across the Entire Value Chain.*

   Components and products can be controlled during their lifecycle from the very beginning to the end-user for engineering useful consequences for both the companies and the various stakeholders. Any part or product is logged and can be accessed at any time, ensuring constant traceability. Companies of this kind can arrange new solutions for facing old and new socio-economic problems. Data can be used for improving both financial and operating performance but also to develops counter-measure to arising themes such as pollution and waste-recycling.

4) *Acceleration of Manufacturing.*

   Companies can exploit the technological outcomes for fastening operations. Artificial intelligence (AI), advanced robotics and sensor technology have the potential to increase autonomy further still and to speed up individualization and flexibilization. Those organizations that start to move into this direction will benefit from the incoming new technologies as they will have the proper underground to have them implemented. Once new technologies will be feasible in order to be applied for improving auto correction and full human-machine distinction the manufacturing process could be accelerate and improved.

2.4 Benefits of Industry 4.0

Digitalization permits a company to meet individual customer requirements. Requirements such as design, configuration, ordering, planning, manufacture, and operation phases. The Internet of Things allows customers to be involved in most industrial activities [38], while the 3D printers enable the production of a wider range of products with a relative lower price, even at single batches. The prototyping and product development activities gets simpler and cheaper than before [39].

The continuous control operated by the cyber-physical systems opens to the possibility of getting to know about possible problems and related solutions for better managing quality, time, risk and speed. Thanks to the connection with other parties in the supply chain, delivery and volume flexibility can be set as an assumption to most realities [37] impacting on inventory and units' stocks. 3D Scanners can be used for reverse-engineering [40], while 3D printing and laser cutting traduce digital models into real and physical objects [41].

With predictive analytics, it is possible to prepare for future inconveniences, thus obtaining a superior level of flexibility [42].

The adoption of the Industrial Internet of Things, and thus of cyber-physical systems, allows companies to optimize decision-making. Managers and workers have the possibility to access whenever they want information. Cloud computing and big data analytics perform real-time analysis of data, presenting it in a way that is useful for and easily understandable by users [37].

Moreover, collaborative robots allow companies to cope with ageing population, a phenomenon that is concerning the most advanced economies as Italy and Japan. People can be employed for a longer time regardless of their natural decadence as they can count on technologies and specific designed robots to carry out the most heavy and dangerous tasks.

The adoption of digital technologies will reduce the demand for traditional assembly and production jobs, but considering the incoming needs for new skilled specialist some authors believe that the demand will more than out weight the losses.

2.5 Other Relevant Technologies

In order to provide a list of all the most important and enabling technologies to be considered for "Industry 4.0" several reports and papers were used, like the one of Gilchrist [37], Albert's [43], Drath and Horch's [29], and others authors.

Two relevant technologies and application have already been a matter of discussion in the previous chapters: Cyber-physical systems and the Industrial Internet of Things. The other remaining technologies important for Industry 4.0 are the following, each is explained by a short definition:

1) *Robots*

   "Actuated mechanisms programmable in two or more axes with a degree of autonomy, moving within their environment, to perform intended tasks", where autonomy is the "ability to perform intended tasks based on current state and sensing, without human intervention [44].

2) *Automated Guided Vehicles (AGV)*

   "Autonomous vehicles capable of transporting, weightlifting, detecting, etc." [45]. These are usually robots that follow along marked long lines or wires on the floor. They can also use more sophisticated technologies as radio waves, vision cameras, magnets, or lasers for navigation. They are most often used in industrial applications to transport heavy materials around a large industrial building, such as a factory or warehouse.

3) *Additive Manufacturing: 3D Printing*

   "The process of joining materials to make objects from 3D model data, usually layer upon layer, as opposed to subtractive manufacturing methodologies" and the "fabrication of objects through the deposition of a material using a print head, nozzle, or another printer technology" [39].

4) *Laser Cutters*

   "A unit that produces optical-frequency radiation in intense, controllable quantities of energy" [46]. These are machines that use a laser to cut materials, and are typically used for industrial manufacturing applications. Computers with numerical control are necessary to direct the material or the laser beam generated, by inputting a model which delimits the area of the cut.

5) *3D Scanners*

A 3D scanner performs the opposite operation of a 3D printer: the are in fact kind of "Reverse Engineering" tools [40]. Their purpose is usually the one of creating a 3D model of an object. A point cloud of geometric values is virtually created on the surface of the subject. These points are then used as basics information for extrapolating the shape of the subject by a process called reconstruction.

6) *Augmented Reality*

This term comprehends a set of wearable devices or, more generally, all the devices that can enhance the information that is available to the user in physical environments (rather than on digital laboratories, as it happens for virtual reality). The objects that reside in the real world are enhanced by computer-generated perceptual information, sometimes across multiple sensory modalities, including visual, auditory, haptic, somatosensory and olfactory. Augmented reality is related to two largely synonymous terms: mixed reality and computer-mediated reality.

7) *Big Data Analytics*

Complex process of examining large and varied data sets, or big data, to uncover information such as hidden patterns, unknown correlations, market trends and customer preferences that can help organizations make informed business decisions. Big data is a field that treats ways to analyze, systematically extract information from, or otherwise deal with data sets that are too large or complex to be dealt with by traditional data-processing application software. Big data often includes data with sizes that exceed the capacity of traditional usual software to process within an acceptable time and value.

8) *Cloud Computing*

Through cloud services, companies can access additional CPUs, storage units, software, infrastructures and analytics tools and pay only what they need [37]. Cloud computing is the on-demand availability of computer system resources, especially data storage and computing power, without direct active management by the user. The term is generally used to describe data centers available to many users over the Internet. Large clouds, predominant today, often have functions distributed over multiple locations from central servers.

9) *Machine Learning*
"Development of algorithms to instruct computers to autonomously perform instructions for which they have not been programmed" [47]. They are more precisely computer systems that can perform a specific task without using explicit instructions, relying on patterns and inference instead. Machine learning is seen as a subset of artificial intelligence. Algorithms build a mathematical model based on sample data, known as "training data", in order to make predictions or decisions without being explicitly programmed to perform the task.

Chapter 3: Lean 4.0

Already in the early 1990s, first approaches for integrating automation technology into Lean Production arose and were called Lean Automation. Nowadays, there new areas of application for Lean Automation are flourishing due to the potential of Industry 4.0 technologies.

This chapter provides an overview over existing possibilities and examples of the combination of automation technology and Lean Production. Besides, different cases and a framework will outline how Industry 4.0 can add value to Lean Production in future.

3.1 Lean Automation as Combination of Two Disciplines

Lean Automation picks up the idea of combining automation technology with Lean Production. The term made his appearance in the mid-1990s, shortly after the peak of Computer Integrated Manufacturing (CIM) [48, 49, 50].

In the last decade, science did not take Lean Automation in great consideration. However, in the context of Industry 4.0 new solutions are available for combining automation technology with Lean Production, which are described below.

The digitalization of the Kanban system is known already since several years. Conventional, physical cards for an order-oriented production control are replaced by virtual Kanban [51]. Thanks to the empowerment of this so called “e-Kanban system”, missing or empty bins are recognized automatically via sensors. The e-Kanban system sends a virtual Kanban to trigger replenishment. By using ICT lost Kanban are not causing mistakes in production control as long as inventory in manufacturing execution system matches real inventory. In addition, adjustments of Kanban due to changes in batch sizes, processes or cycle times are easily possible [27].

In 2013. Würth Industrie Services GmbH & Co. KG presented the optical order system “iBin” as an extension for Kanban bins. A camera in the module detects the charging level of the bin and iBin reports wireless the status to an inventory control system. In addition, iBin also manages to send orders automatically to suppliers. As a result, buffer stock can be reduced and spare parts can be scheduled order-oriented [52].

As shown above, the combination of automation technology and Lean Production can be beneficial. Contrary to common belief, Lean Production does not exclude automation. In 1960s, Ono stated that process should be automatized and supervised by qualified employees; he called this principle "Autonomation" [26]. This process of "fusion" of informatic technologies and human supervision corresponds to Industry 4.0, by which humans - supported by innovative technology - take the same role [53, 54].

3.2 Advantages of Combining both

Following Dombrowski et al., the existing literature is structured into two perspectives: either LM is considered as a prerequisite for introducing I4.0 tools or I4.0 tools are regarded as promoters of LM [55]. Another widely acknowledged perspective is that the combination of both topics yields in positive synergies. The latter is added as a third, more general perspective.

Table 2 provides a useful outline of literature supporting these perceptions. After outlining these three views limitations of extant research are analyzed.

LM as enabler towards I4.0 [56, 57, 58, 59, 60, 61, 62, 63, 64, 65]
I4.0 advances LM [66, 67, 68, 69, 70]
Positive correlation between LM & I4.0 [71, 72, 73]

1) *Lean Management as Enabler towards Industry 4.0*

   Several authors consider LM as a *condition sine qua non* for a successful introduction of I4.0 solutions [56, 57, 58]. This is supported by the hypothesis from Bill Gates that automating inefficient processes will magnify their inefficiency. Summarizing, the visions can be recapitulated as follows:

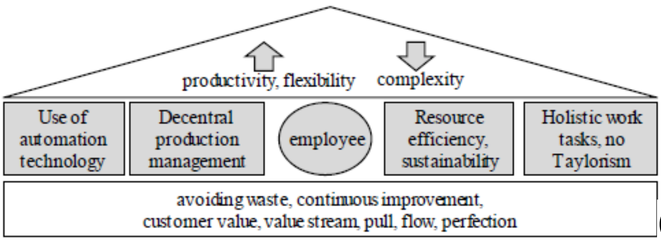
   - Standardized, transparent, and reproducible processes are of fundamental significance for introducing I4.0 [56, 59, 60].
   - Decision-makers require LM competence for considering customer value and avoiding waste [57].
   - By reducing product and process complexity LM enables the efficient and economic use of I4.0 tools [56, 64]. Hence, lean processes are regarded as a basis for the efficient and economic implementation of I4.0. However, Nyhuis et al. annotate that LM and I4.0 implementation may influence each other iteratively. Thus, the progression is not necessarily purely sequential. [74, 75]

2) *Industry 4.0 advances Lean Management*

   Wagner et al. as well as Pokorni et al. state that lean processes allow a stabilization and finishing of the production process by applying I4.0 [66, 67]. While Ruettimann et al. highlight the ability to advance the flexibility of modern lean production systems, Kolberg and Zuehlke state that I4.0 can enhance LM [68, 69]. Hence, I4.0 contributes to addressing limitations of LM. Exemplary, the economic production of goods in a lot size of one is a way to enhance production economies beyond traditional economies of scale. The availability of real-time data provides transparency and information quality. [62] Moreover, I4.0 is promising to cope with a fluctuating market demand superior to a levelled production in LM. Eventually, the increased flexibility through I4.0 delivers a good instrument to face the rising complexity.

3) *2.3. Correlation between Lean Management and Industry 4.0*

Mrugalska and Wyrwicka support the statement that I4.0 and lean can coexist and support each other [73]. In accordance, Vogel-Heuser et al. reject a contradiction between I4.0 and LM [72]. Moreover, committing into I4.0 can help to overcome existing limits for implementing lean [71]. Referring to the combining of LM and I4.0, the existing literature created terms like lean 4.0, lean automation, smart lean manufacturing, and lean industry 4.0. As shown, the majority of authors agrees with the general compatibility of LM and I4.0. The general agreement could be due to the similarities concerning targets like the reduction of complexity, central pillars, and lean principles as a common ground (see Fig. 1). Accordingly, both paradigms are managed in a decentral way. Kanban in LM as well as self-organizing systems in I4.0 distribute responsibility in subsystems [56, 75]. Moreover, LM and I4.0 focus on a pivotal role of employees [56].



(Fig 3.1)

3.3 Use Cases for Applying Industry 4.0 Solutions

The identified enablers can be applied to several methods of Lean Production. The following section, presented in Mayr, describes examples of possible combinations [108].

1) *Smart Operator*

   Within the Andon method, by which employees in case of a failure should be notified as soon as possible, the Smart Operator could reduce time from failure occurrence until failure notification. Equipped with smart watches, employees receive error messages and error locations almost in real time. Differently from wide-spread signal lamps, recognizing failures does no more depend on location of employees. In addition, CPS equipped with proper sensors recognize failures and automatically activate fault-repair actions on other CPS. Information about cycle times within the visual field of employees support just-in-time proceeding of goods. In addition, new employees get individualized information about necessary tasks to get along in timed productions [108].

2) *Smart Product*

   In a mindset of continuous improvement processes, also called Kaizen in Japanese, Smart Products could collect product data for the analysis during and after its production. In contrast to manual data acquisition for value stream mapping, the implementation of SP could make possible to gather individualized information per product and production line automatically. On the one hand, this way of data acquisition is less labour-intensive and data are more precise. Furthermore, a Smart Product could contain Kanban information to control production processes. An example of a completely de-central controlled production based on Smart Products was demonstrated by SmartFactoryKL at Hannover Messe 2014 in Germany [108]. The working stations were able to produce autonomously, following a work schedule on the product.

3) *Smart Machine*

   According to Poka Yoke, technical installations help employees to avoid mistakes [26]. With their computing capacity and connectable sensors, CPS could be fast and flexible integrations in fault-prone processes for supporting. Optically identical components can be identified e.g. via QR codes or RFID. Industry 4.0 could furthermore support Lean Production's requirement for an adaptable, modular production [108]. Since several years, SmartFactoryKL exhibits uses modular working stations based on standardized physical and IT interfaces, which can be flexibly reconfigured to new production lines via Plug'n'Produce. According to the Single-Minute-exchange-of-Die (SMED) principle, setup time should be reduced to less than ten minutes. Plug'n'Produce transfers SMED from a single working station to whole production lines [108].

4) *Smart Planner*

Due to its characteristics, such as focus on one-piece flow and highest possible product variety, Lean Production is not suitable for individual single-item productions. With the Smart Planner, traditional Kanban systems with fixed amount of Kanban, fixed cycle times and fixed round trips for transporting goods turn into dynamical productions automatically adopting to current production programs. Decentralized, in working stations, integrated CPS could negotiate cycle times and thus find the optimum between highest possible capacity utilization per working station and a continuous flow of goods [108]. Appling this approach to Lean Production, it could allow Lean Production to be implemented not only as concerns mass and batch production, but also in job shop production.

Takeda already describes a comprehensive framework for the integration of automation technology [76]. However, this concept does not consider modern ICT, especially innovative assistance systems [108]. A comprehensive, integrated framework which describes where and how CPS can be integrated is still missing [77, 78].

Industry 4.0	**Lean Production**	
	Principle: Just-In-Time	**Principle: Jidoka**
	Method: Kanban system	**Method: Andon**
Smart Operator	Employee gets information about remaining cycle time via augmented reality	Wearable computing systems receive failures and display it in real time to the employee
Smart Product	Smart Product contains information of Kanban to realize an order-oriented production	-
Smart Machine	Machines offer a standardized interface for receiving and sending Kanban	Machines send failures directly to Smart Operators and call other systems for fault-repair actions
Smart Planner	IT systems reconfigure production lines and update Kanban according to the new configuration	-

(Fig. 3.2)

3.4 Conceptual Conjunction of I4.0 Tools and Lean Methods

As a result of an extensive review of existing literature and reasonable assessments of the authors, Table 3 portrays a matrix to illustrate which I4.0 tools can represent a valuable support the analyzed lean methods. The I4.0 tools are selected based on reviewing academic as well as corporate publications [108].

1) *Just-in-Time/just-in-Sequence*

   4.0 The lean method JIT/just-in-sequence (JIS) aims to deliver the right product, at the right time, place and quality in the right quantity for the right costs. Several I4.0 tools, as described in Table 3, allow to reach the objective. Automated guided vehicles (AGV), for instance, can transport objects within the material flow automatically. This minimizes human mistakes as well as empty trips [108]. Besides, material is supplied to workstations in accordance to the requirements. In case of obstacles the transportation system will reroute the vehicle to an alternative path. [75, 79] Furthermore, intelligent bins and smart products also pursue self-optimization: a digital object memory stores every necessary manufacturing parameter; combining it with monitoring the condition of the transported goods, the memory is used to navigate the AGV efficiently. This self-organization helps to build robust logistics networks for production. [57] In addition, Auto-ID technology, such as RFID, can be applied to track material in real-time and to localize objects in the value chain precisely. This results in reduced search time as well as improved process transparency. Additionally, part recognition allows the identification of incorrect components. The advantage is the possibility to remove parts, according to the idea of poka-yoke. Moreover, the automated selection of RFID tags enables continuous stock monitoring which eventually results in reduced inventory levels. Besides, it facilitates an automated replenishment process from suppliers. [66, 80] The JIT/JIS 4.0 method additionally applies big data and data analytics techniques. The opportunity to analyze detailed real-time process information provides insights into parameters, helps to identify trends, and allows to deduce rules for the production system [81]. Furthermore, a continuous material flow is supported by reducing machine downtimes through predictive maintenance actions [82]. In general, data analysis has the potential to contribute to an improved system performance of the whole supply chain [66]. Overall, JIT/JIS 4.0 convinces with higher transparency, shorter lead times and improved flexibility. Apart from this, supply chain actors benefit from a better cooperation and an improved resistance against disturbances [108].

2) *Heijunka 4.0*

The objective of heijunka is to set the production program to a constant rate. By solely producing what the costumers need, waste in the form of overproduction is reduced. Some I4.0 tools contribute to improving heijunka [108]. Data analytics, for instance, enhances the forecast quality. Planning is realized thanks to the data history in combination with a better understanding of customer needs through an in-depth analysis of the market. [57, 79] Besides, new software tools using advanced analytics can be utilized to support the planning process itself. For instance, the software AnaPro levels the production program automatically based on product specification, structure of the technological process, workplace and sales [83]. Applying heijunka 4.0 benefits in a reduced effort for levelling the production program. Planning is automated and short-dated adjustments can be integrated smoothly.

3) *Kanban 4.0*

Kanban aims to retain a continuous material flow by maintaining a predefined stock level to guarantee an uninterrupted supply of material [108]. I4.0 can help to improve this lean method. Using simulation methods, or a virtual real-time representation of physical objects based on a CAD model (digital twin), new kanban loops can be planned with more farsightedness and seamlessly integrated into the existing production environment [108]. Simulation ensures the identification of ideal kanban parameters like lot size, stock or delivery frequency. Moreover, external changes can be included while the system refreshes parameters autonomously. [69] By applying Auto-ID, a constant monitoring of work in process is possible. Hence, transparency of material movements is increased. This allows a comparison of target and actual values to remove unnecessary stock. [71] Additionally, a holistic linkage and improved exchange of data in production result in a self-organizing system. Thus, stock level can be reduced to a minimum. The application of AGV can further contribute to a JIT delivery to the workplace: it makes possible to provide refill in the exact moment when new material is required. Consequently, the material supply at shop floor level can be realized by using a one container system. [75] Hence, the need to fill several containers with the same material is omitted. To summarize the value of the kanban 4.0 method, the authors conclude that by applying I4.0 tools, stock levels can be minimized and transparency will consequently increase. As a direct consequence, the required space declines: the final advantage can be summarized in cost savings. Besides, reduced inventory simplifies the detection of bottlenecks in the production processes [108]. Therefore, causes of problems can be identified and encountered.

4) *Value Stream Mapping*

4.0 VSM enhances the transparency of the material and information flow within the value creation chain to identify waste [108]. Subsequently, an improved target state is defined in value stream design. This optimization is aimed at shortening lead time and facilitating a flow through production [84]. I4.0 permits the implementation of a connected manufacturing environment where data can be transmitted in real-time. While applying Auto-ID enables the instant localization of objects, big data and data analytics facilitate the consolidation of information. Consolidated key performance indicators enable decision making based on facts [79]. By deploying human-computer interaction (HCI), devices which allow to receive information, trigger actions and control processes (e.g. tablet, smartphone, and head mounted displays), information becomes remotely retrievable for stakeholders. Machine performance, for instance, can be analyzed by maintenance staff to reduce downtime or used by managers to pursue process optimization [108]. Hereby, VSM 4.0 is a tool for daily operations management. Machine learning and data analytics support the creation of a value stream design. Target states are generated automatically and validated before implementation [82]. This approach supports a continuous improvement process. The main benefit of VSM 4.0 is the improvement in transparency through a real-time display of value streams [108]. This helps to individuate waste within production processes and leads, leading to a lean value creation. Besides, the effort to carry out VSM is reduced and decisions are based on real-time data.

5) *Total productive Maintenance*

4.0 Smart factories result in an increasing number of maintenance objects. Additionally, their technical complexity is rising and an unplanned breakdown results in high costs [85, 86]. Autonomous maintenance represents an adequate instrument which permits the shift of responsibility and authority for routine maintenance tasks from technicians to operators. The resulting free volume of maintenance experts is secured to performing preventive maintenance measures, under the form of planned maintenance. Moreover, shorter product lifecycles, higher product variety and increasing product complexity account for a rising amount of production start-ups. Consequently, early equipment management refers to the introduction of new products and aims at realizing short ramp-up periods [87, 88]. Several

I4.0 tools support operators in taking on more responsibility. Especially the combination of virtual representation technologies like virtual reality (VR) and augmented reality (AR) as well as head-mounted displays facilitates training as well as maintenance instructions [89]. As maintenance typically involves non-recurring and context sensitive activities, interaction with maintenance experts becomes crucial. By displaying virtual elements, operators can receive remote guidance [90]. Moreover, smart products and CM technology allow for load, wear, and defects to be monitored during machine operation [108]. The early detection, isolation, and identification of faults results in less downtime and prevention of consequential damages. [91] Based on cross-linked machines predictive analytics is a helpful tool for planned maintenance as it allows to analyze the correlation between condition parameters and the probability of defaults. Unlike conventional CM, predictive analytics uses complex algorithms to predict defects based on large data sets (big data). Eventually, predictive analytics is expected to scale up the accuracy of lifetime expectancy prognosis. [92] Lucke et al. propose a smart maintenance system to increase availability and to reduce maintenance costs as well as energy consumption [85]. In early product and equipment management, digitalization can contribute to eliminating media discontinuity between the planning and design phases on one hand and the production phase on the other hand. Plug and play allows the autonomous integration of a technical system based on a modular design and a service-oriented architecture. Thus, production plants can easily be adapted and customized. The services are provided via standardized interfaces and operate independently of hardware-specific characteristics [65, 93]. Moreover, virtual commissioning contributes to a fast start-up curve as digital twins allow a realistic simulation of production plants. More precisely, hardware-in-the-loop simulation enables testing of real PLC code on real controls against a simulated plant model [94, 95].

6) Single Minute Exchange of Die

4.0 SMED aims at reducing downtime and cost caused by setup processes. Short setup times Increase flexibility and facilitate the production of small lot sizes while achieving short lead times and maintaining a low level of stock. This becomes especially important as the amount of product variants is evolving [96]. Nyhuis et al. identify I4.0 technologies for information transfer and provision as enablers for a lot size of one [74]. Nevertheless, they reject a general linkage between I4.0 and a lot size of one based on the differentiation between digital and physical setup activities. While I4.0 provides a considerable potential for optimizing the former, physical setup times generally remain [74]. Apart from AR and plug and play, additive manufacturing (AM) is likely to achieve the highest impact on setup time. As AM processes are not directly connected to the type of product, varying work-pieces can be produced with minimum setup times. Times for selection, search and adjustment of tools and work-pieces are omitted. Nevertheless, small adaptions, temperature adjustments and cleaning operations will still incur [108]. Hence, Feldmann and Gorji argue that SMED can also be applied to AM. However, as setup times are already technologically reduced to a minimum, the impact is expected to be rather small. [97] Overall, neither the methodological approach, nor the philosophical principles are questioned through I4.0 [91]. As a whole, SMED will remain of fundamental importance for reducing the physical setup time.

7) *Visual Management*

The purpose of VM is to enhance transparency. Thus, deviations can be recognized at an early stage to implement countermeasures accordingly. This is achieved by transferring targets, standards, and specifications into a visual representation [108]. The importance of VM is rising proportionally to the increase of the amount of available data. Methods for implementing VM are 5S, zoning and Andon. [98] 5S is a systematic approach aimed to the organization of the workplace and its purpose is to improve clarity through keeping the workspace clean and arranging tools in a reasonable way. Hence, waste is eliminated on workplace level [108]. Auto-ID and AR can assist in carrying out 5S more efficiently. RFID ensures the identification and the localization of objects which reduces search time [80]. Furthermore, RFID tags can store instructions for cleaning tools and objects appropriately. Applying AR may replace physical shadow boards, as virtual elements guide operators where to place tools. Moreover, integrating gamification through AR might motivate personnel by gaining credits for cleaning or placing tools correctly [99,108]. The zoning process allows marking destinations by using visual instruments: this includes paths, manufacturing cells, and departments. A company-wide utilization of colors increases the information value [98]. Zoning implies several drawbacks. Firstly, signs and tapes need to be adjusted physically by operators. Secondly, this concept is not suitable for flexible navigation. HCI and AR can represent the solution to overcome this lacking flexibility. Koch et al., Neges et al. describe a system for navigation by means of AR which is based on natural markers like warning signs [100, 101]. Alternatively, RFID can be a valid alternative for indoor navigation, however, compared to Wi-Fi or Bluetooth, it is not commonly installed option on smartphones and tablets [102]. Andon is applied for visualizing status and disruptions in production and thus supports the lean principle jidoka. Additionally, Andon boards display actual and target values revealing deviations [98]. Unlike traditional Andon lamps HCI devices like tablets, smartphones, head-mounted displays and smart watches enable a targeted notification for users. Hence, notifications are displayed in real-time regardless of the distance between operator and machine. Smart watches represent an ergonomic and time-saving option, allowing to assess the need for action with a glance at the operator's wrist [69, 73]. For digital Andon boards, several suppliers provide solutions to visualize complex data and processes in real-time. Examples of relevant data are machine condition, production progress, order status and capacity utilization. Retrieving this information from mobile devices supports a location-independent access and use [108].

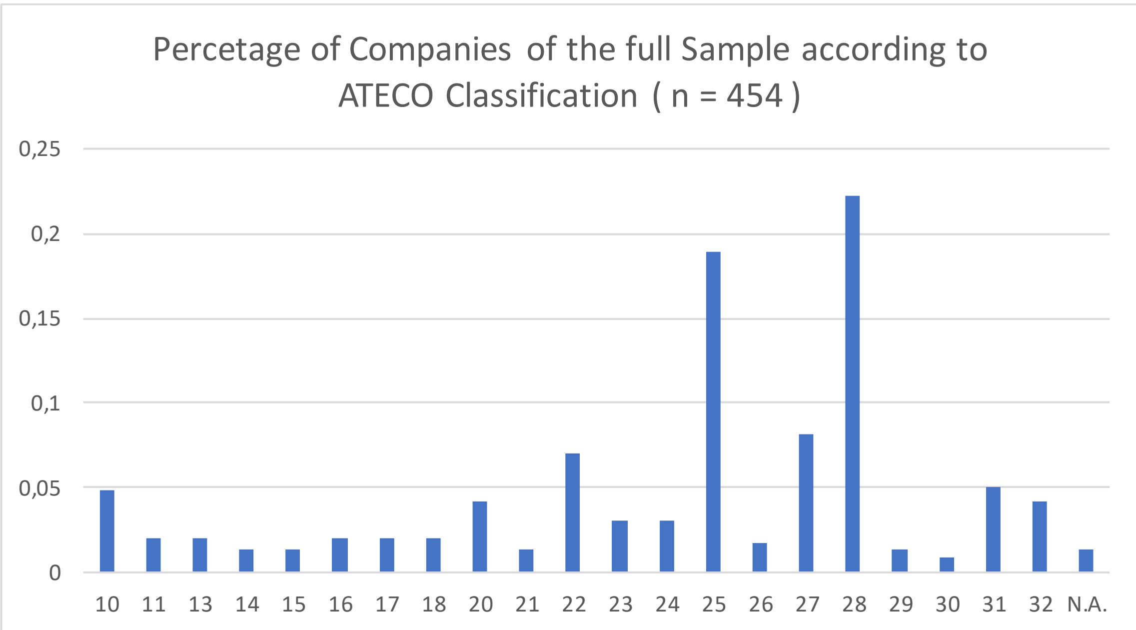
8) *Poka-Yoke 4.0*

Poka-yoke describes mechanisms that help operators to avoid mistakes: it fosters the detection and elimination of abnormal conditions so to prevent defective products from leaving the process [108]. This is especially important in industries with a wide variety of products. Poka-yoke can be either realized by generating forced sequences or by reviewing the process during its execution and stoppage in the event of errors [103]. Auto-ID ensures the correct identification and assignment. A digital product memory allows to request required components and helps to identify incorrect deliveries. This prevents adding value to defective parts [73, 108] By using smart sensors and machine learning, machines can automatically detect and solve irregularities ensuring optimal product quality [104]. Eventually, AR and head-mounted displays, as well as RFID-readers can be adopted if the objective is to achieve zero-error picking [105, 106, 108]. Despite the fact that strictly speaking CM is not a test method, Lettau describes the use of CM measurement technology for the end-of-line-test of electric drives production [107].

Chapter 4: Descriptive Statistics of the Sample

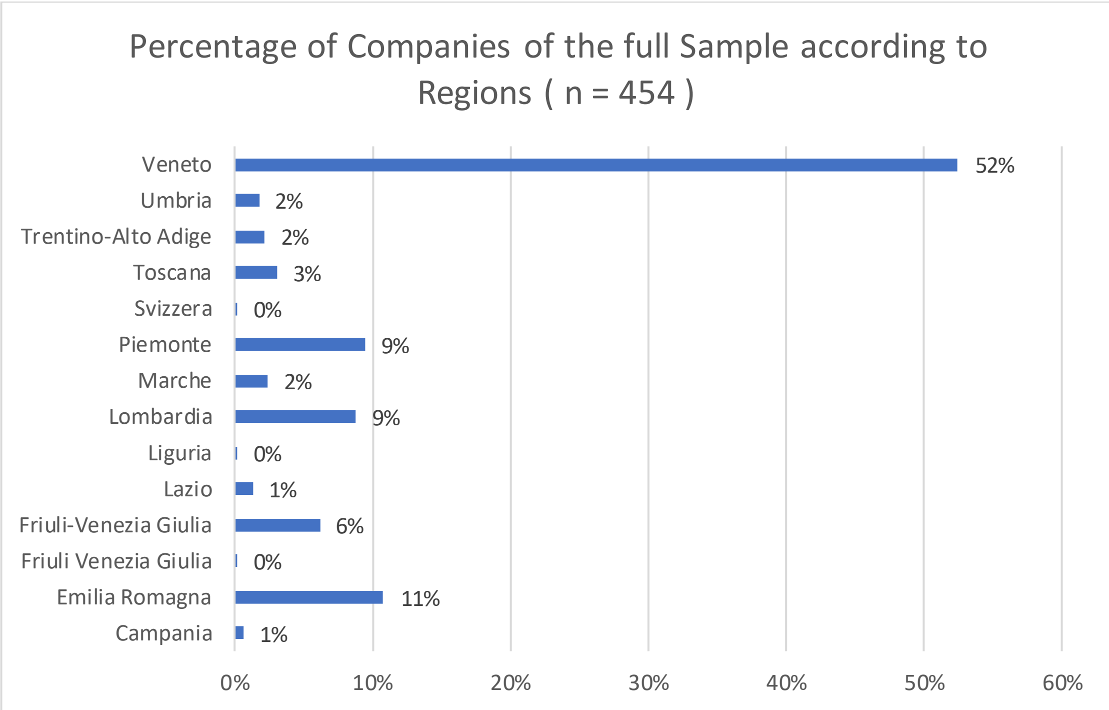
4.1 Full Sample

Figure 4.1 shows in which sectors respondents operate. Following ATECO 2007 codes, companies were grouped into 21 main industries. The ATECO classification is used by the Italian National Statistical Institute (ISTAT) to classify businesses according to their activity sector. Such classification derives from the Statistical Classification of Economic Activities in the European Community, and it consists in six-digit code to specify the industry in which each firm operates. For analyses purposes, it was given importance to the first 2 digits (concerning the macro-area of activity). The most important sectors according to this classification result to be the one related to ATECO 2 digits: 22 Manufacture of rubber and plastic products, 25 Manufacturing of metal goods and 28 Manufacturing of Machineries and NCA goods.



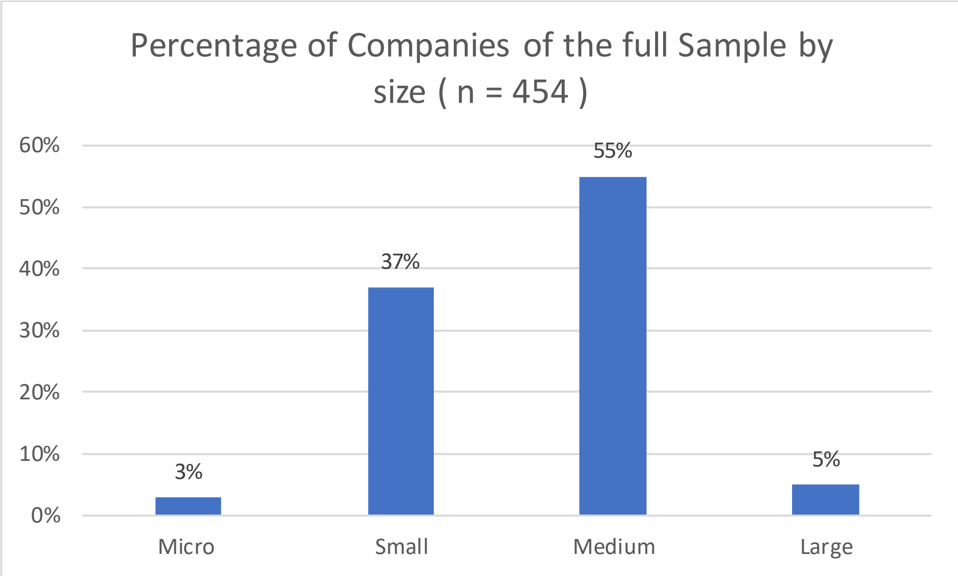
(Fig. 4.1)

Observing the geographical distribution of respondents (Fig. 4.2), it can be observed how Veneto seems to be the most important region for this database. The 52% of the companies are located in this region. It follows Emilia Romagna with 11%, Piemonte 9%, Lombardia 9% and Friuli-Venezia Giulia 6%. Other regions were included into the database of northern Italy because of the presence of plants, nevertheless they do not count much into the total amount. The dataset results unbalanced into the realistic representation of the distribution of companies on the Italian territory, but it is still to be considered valid for the inferential statistic that will follow in the subsequent chapters.



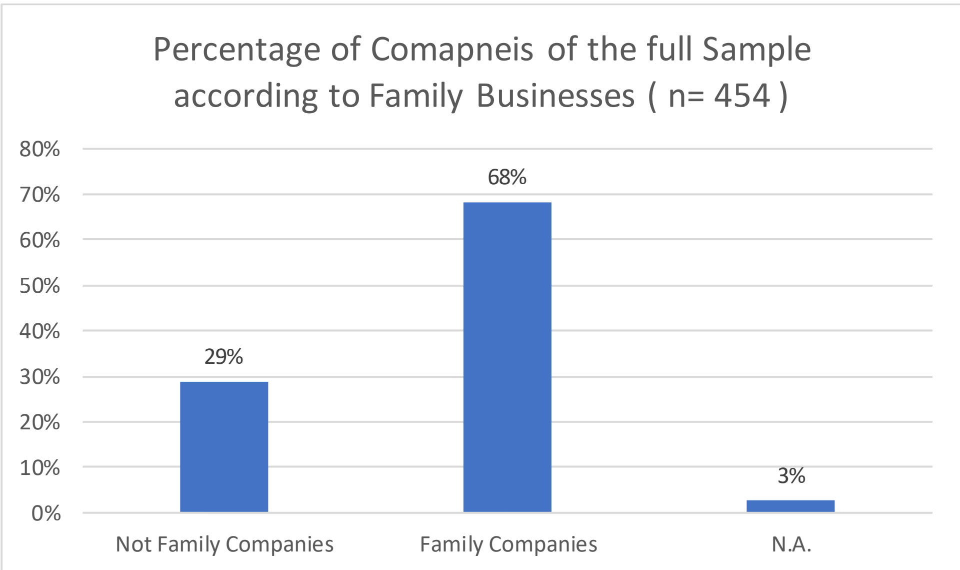
(Fig. 4.2)

Following a division by number of employees it was possible to define companies by their size. 55% and 37% of them appertain to the medium-small segment, 5% are large companies, while only 3% can fit the micro ones.



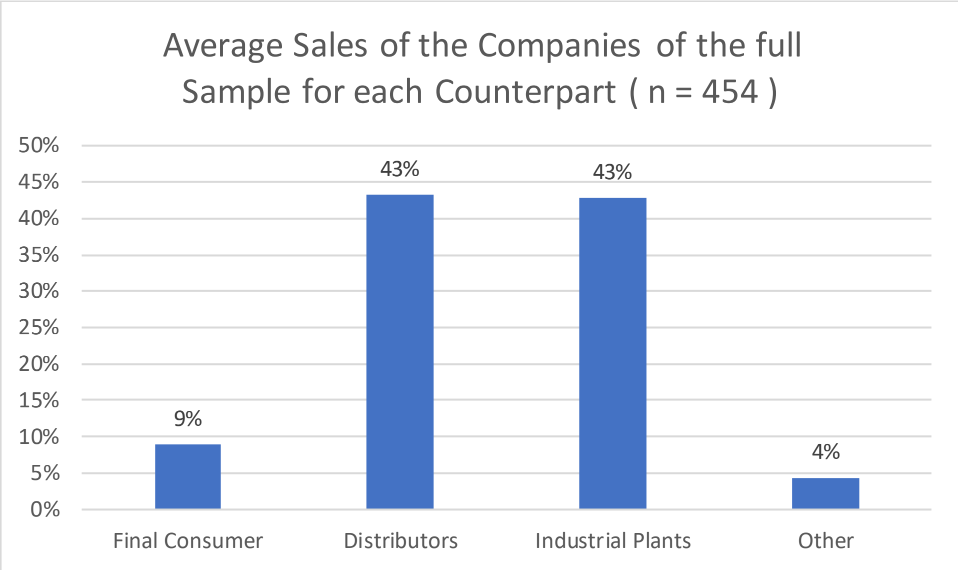
(Fig. 4.3)

As expected, most of the companies belongs to the category of the Family Businesses 68%. The real percentage of companies on the Italian soil would be even higher, but the questionnaire was probably set and filled by an important number of not family businesses 29%.



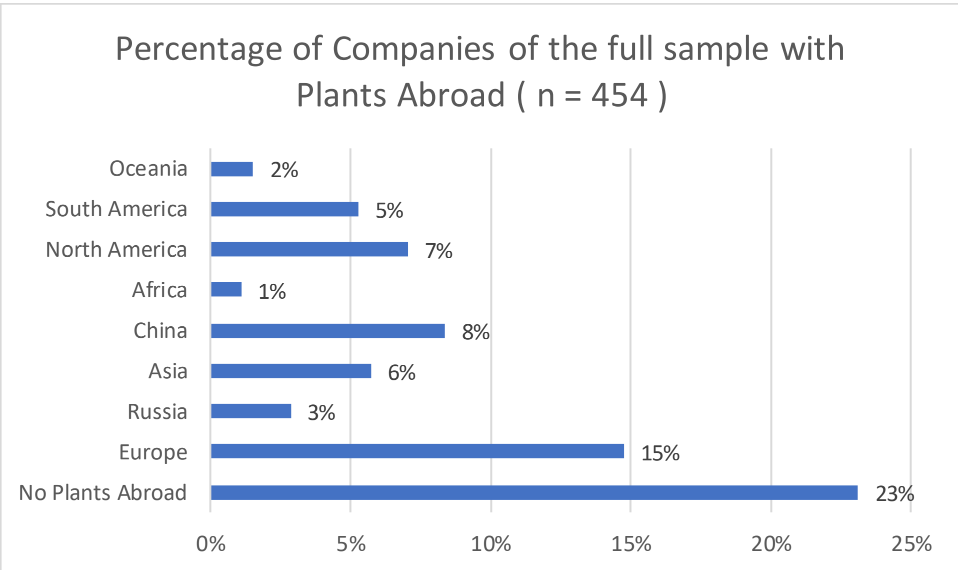
(Fig. 4.4)

The sales of the companies have been subdivided into 4 categories for understanding how they are created. Fig. 4.5 shows how most of the sales belongs to the B2B segments 83%.



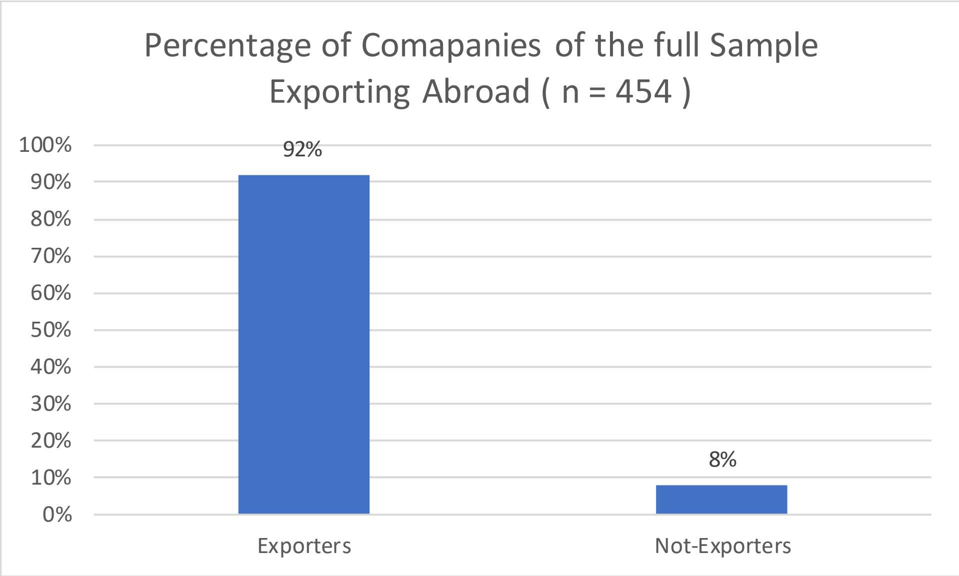
(Fig. 4.5)

77% of the companies have plants abroad. These are mainly set into other European countries 15%, China 8% and North America 7%. Less than a quarter do not have any plant abroad and limit their production activity on the Italian boarder only. (Fig. 4.6)



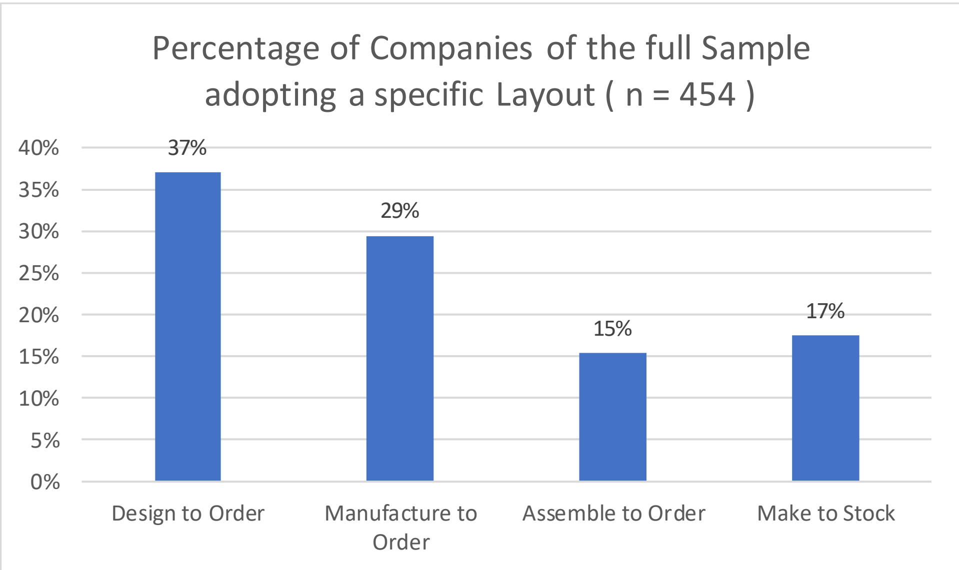
(Fig. 4.6)

More or less the totality of the companies exports actively abroad 92% (Fig. 4.7), and therefore benefit of a much broader market and customer base for benefiting the financial performance.



(Fig. 4.7)

Fig. 4.8 shows how Design to Order 37% seems to be the most applied specific layout by the Italian companies of the dataset. Followed by Manufacture to Order 29%, Make to Stock 17% and Assemble to Order 15%.



(Fig. 4.8)

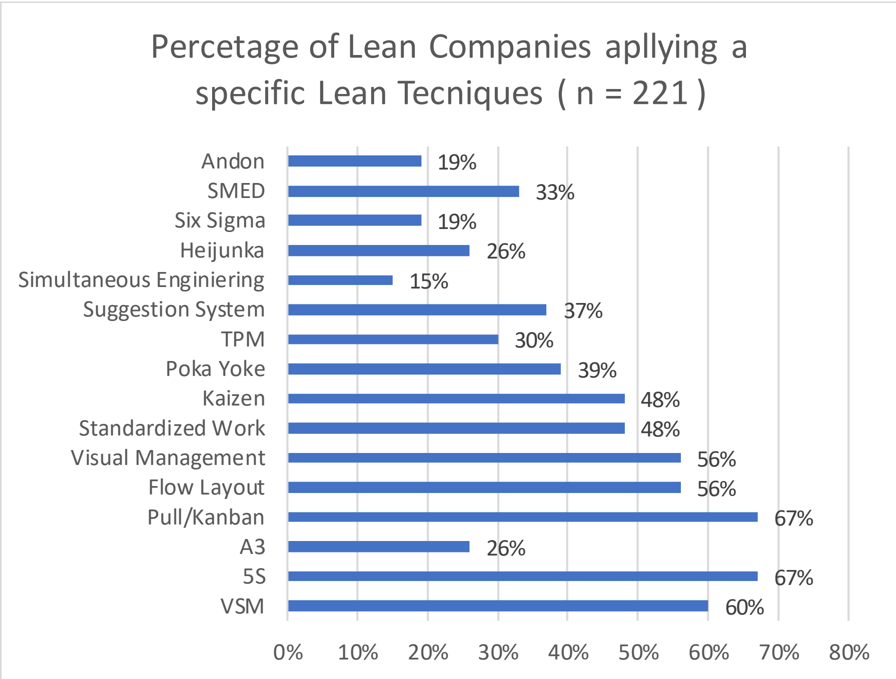
The following table report how the companies belonging to the full sample can be divided by dichotomous sets that will be employed in the following chapter throughout the statistical analysis. On the right side it is possible to see that 205 companies are industry 4.0, 94 are not industry 4.0 and 155 did not place themselves into any of the two not answering to the questionnaire in the proper section. On the bottom it is possible to read that 221 companies are lean, 233 are not lean and all answered the related question.

Looking at the intersection 115 companies are both industry 4.0 and lean, 90 are industry 4.0 and not lean, 27 are not industry 4.0 and lean and finally 67 are not industry and not lean.

	Lean	Not Lean	N.A.	TOTAL
Industry 4.0	115	90	0	205
Not Industry 4.0	27	67	0	94
N.A.	79	76	0	155
TOTAL	221	233	0	454

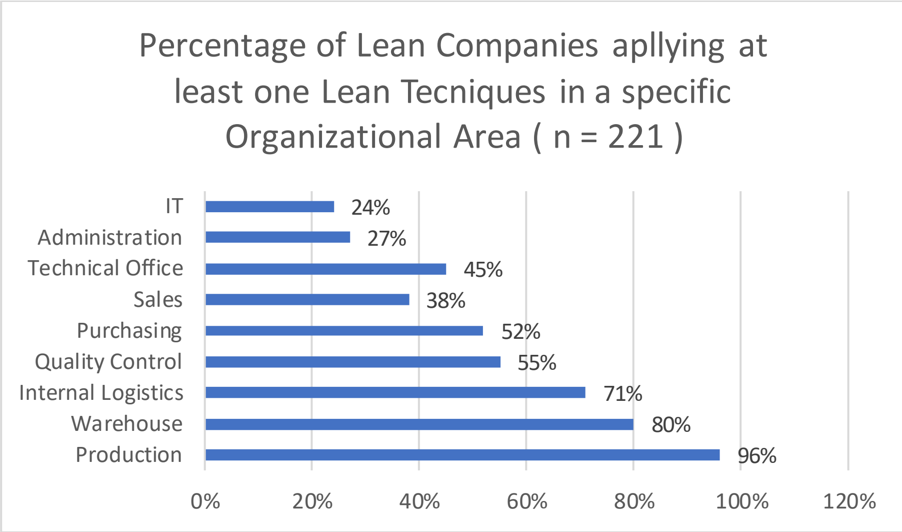
4.2 Lean

Fig. 4.9 represent the percentage of lean companies that apply a single specific lean technique. Pull / Kanban and 5S are applied in the 67% of the cases. These two together with Value Stream Mapping, Flow Layout and Visual Management are the most important. These may be due to the fact that there are elements when applying the lean principles that are more necessary.



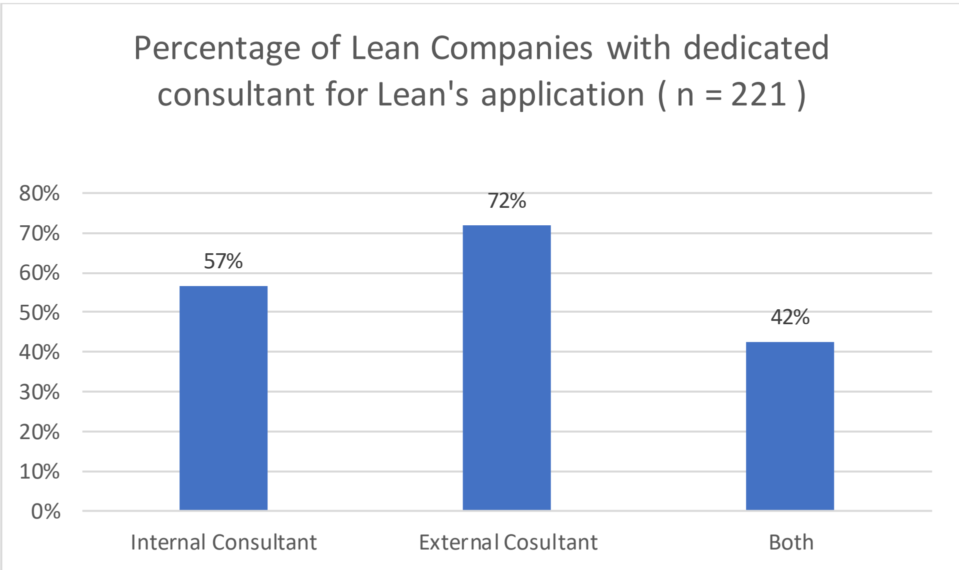
(Fig. 4.9)

Lean companies tend to concentrate as expected most of the lean practices into the organizational areas of production 96%, warehouse 80% and internal logistics 71%. Whereas only a quarter of the companies manage to apply lean to IT and administration (Fig. 4.10).



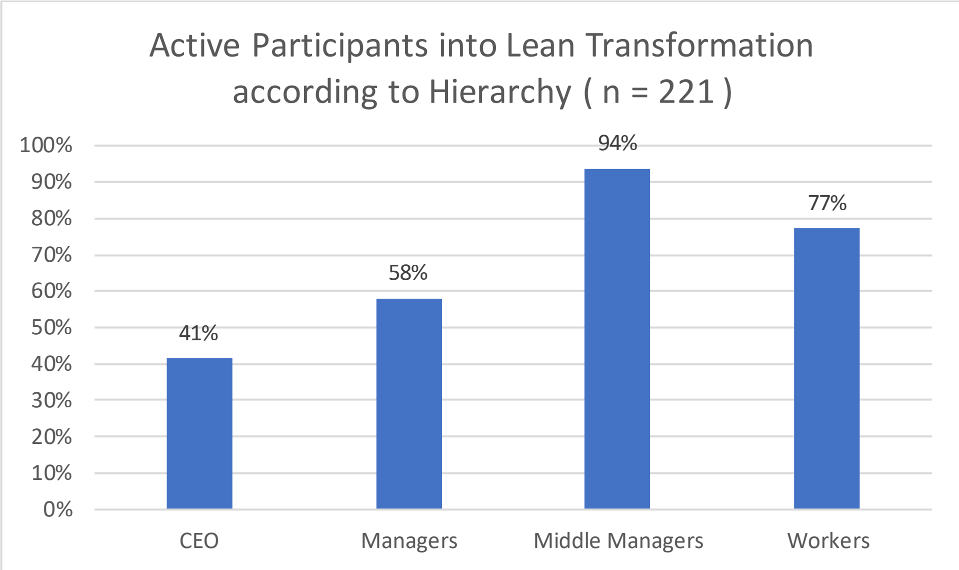
(Fig. 4.10)

Fig. 4.11 shows how lean companies utilized dedicated figures to convey the lean implementation into the organization. 72% hire an external consultant, 52% employ an internal consultant, while 42% make use of both.



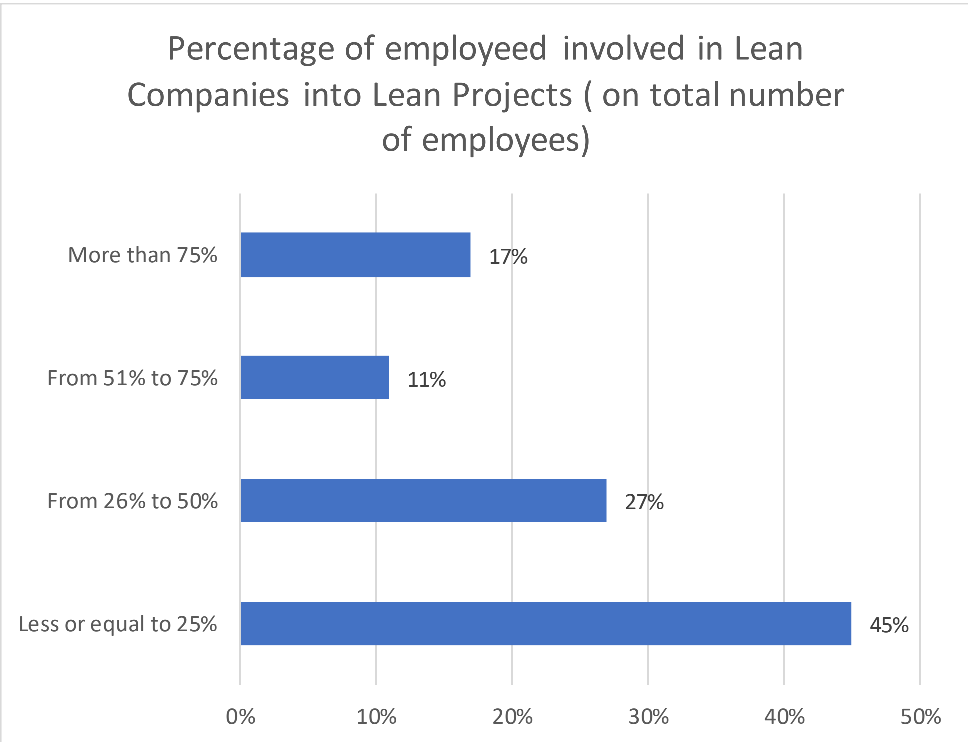
(Fig. 4.11)

Middle managers and workers are the most active participants into the lean transformation with respectively 94% and 77%. This is reasonable as those figures that stay close to each activity have the power and the knowledge to make those adjustment for applying the principles of lean. Nevertheless, Managers and CEO seems to contribute to the cause.



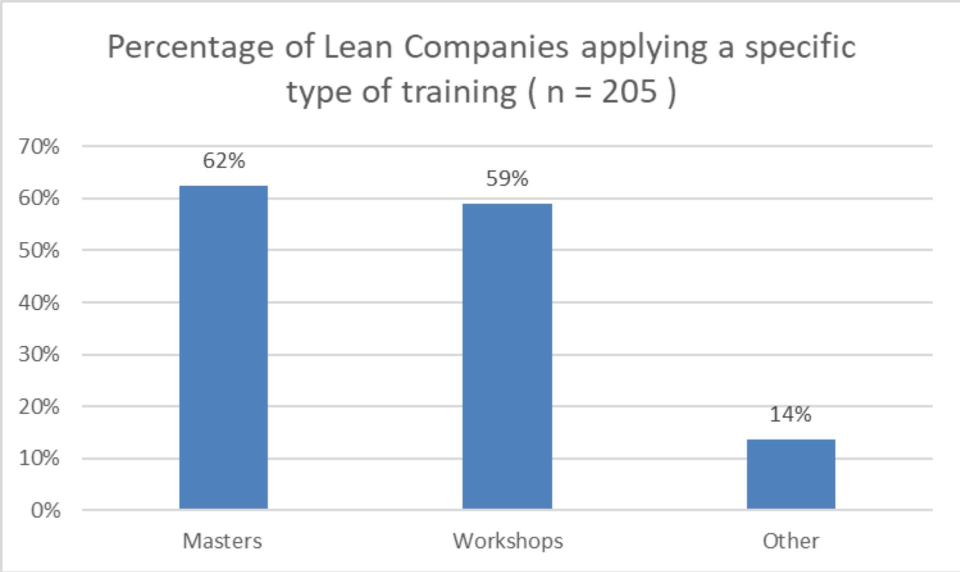
(Fig. 4.12)

The percentages in the fig. 4.12 highlight how much of the workforce is employed into lean projects. 45% of the companies employ less than 25% of the workforce, only a few companies can state to have the lean principles diffuse among almost the totality of the organization.



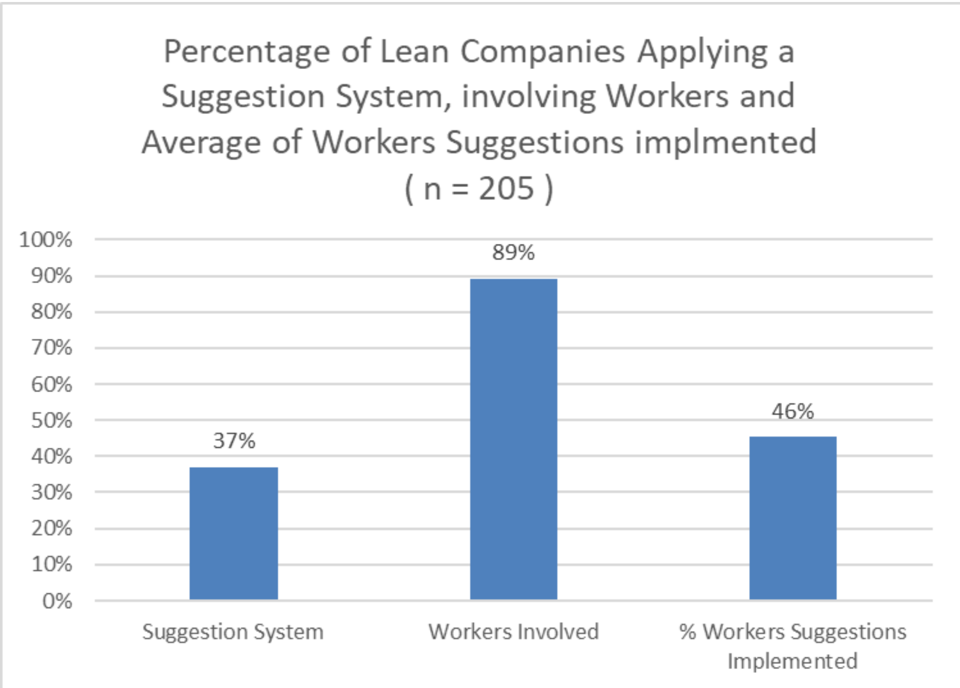
(Fig. 4.13)

Companies seems to prefer master courses and workshops for training the workforce over lean specific topics.



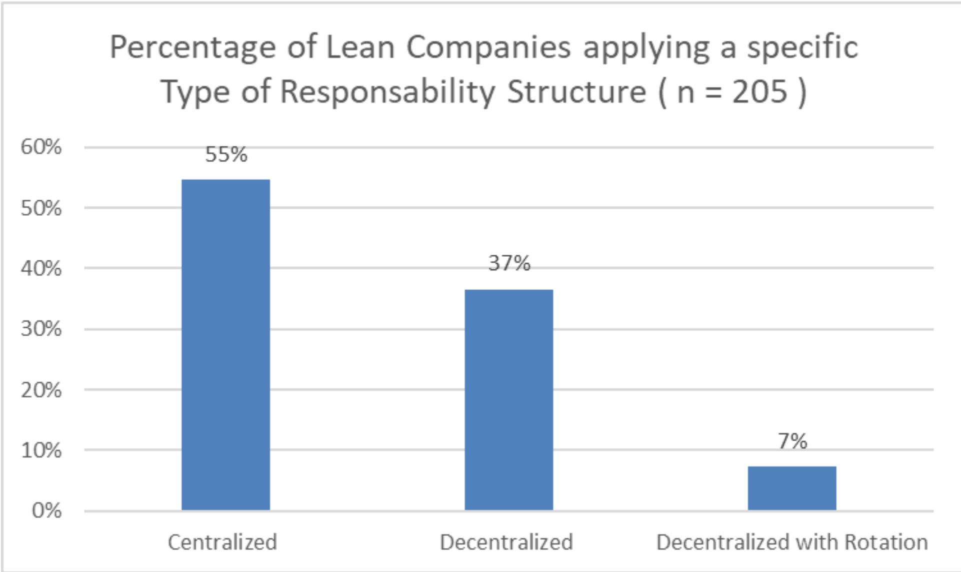
(Fig. 4.14)

37% of the lean companies apply a suggestion system and involve the 89% of the workers, with a percentage of implementation of the suggestion of the 46%.



(Fig. 4.15)

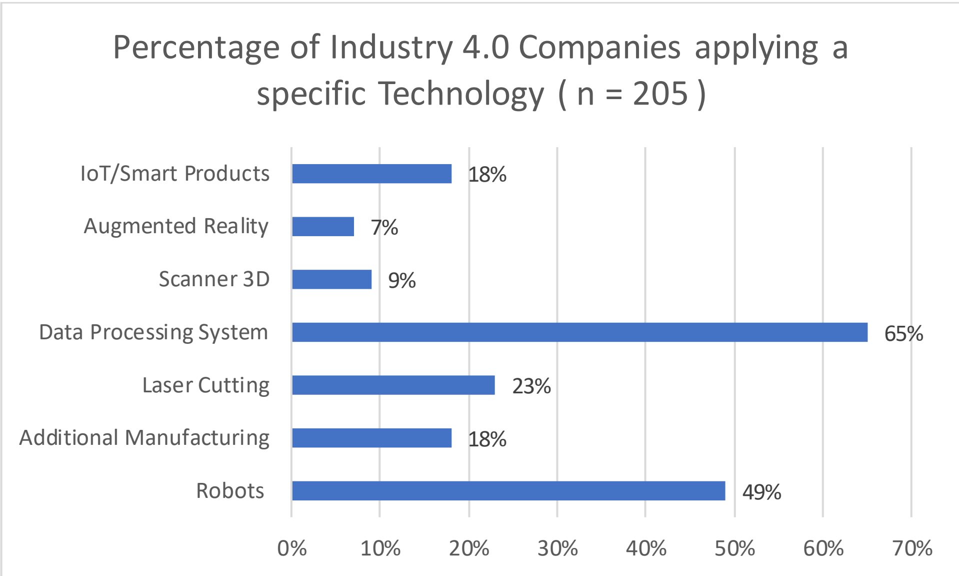
Not many companies apply a decentralized structure of control over the activities which would be in the best interest of the lean implementation. Only 37% of them follow this pattern.



(Fig. 4.16)

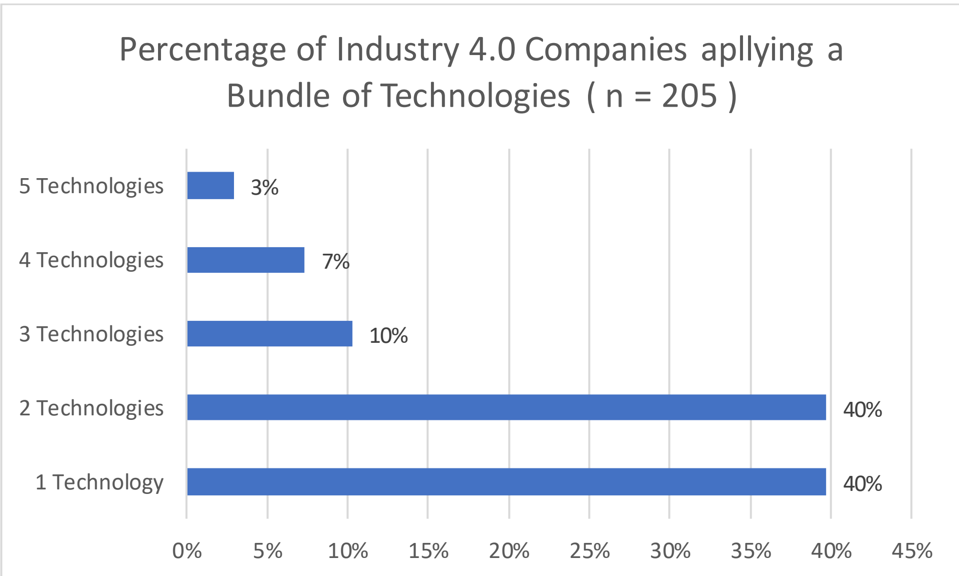
4.3 Industry 4.0

The most applied specific industry 4.0 technology is the data processing system 65%. It follows robotics 49% and laser cutting 18%. Only 18% of the companies declare to have an IoT infrastructure.



(Fig. 4.17)

Most of the industry 4.0 companies apply only 1 technology or 2 technologies into their activities, respectively 40% and 40%. Those that have more than 3 technologies sum up to 20%.



(Fig. 4.18)

Chapter 5: Graphical Performance Comparison between dichotomous Sets

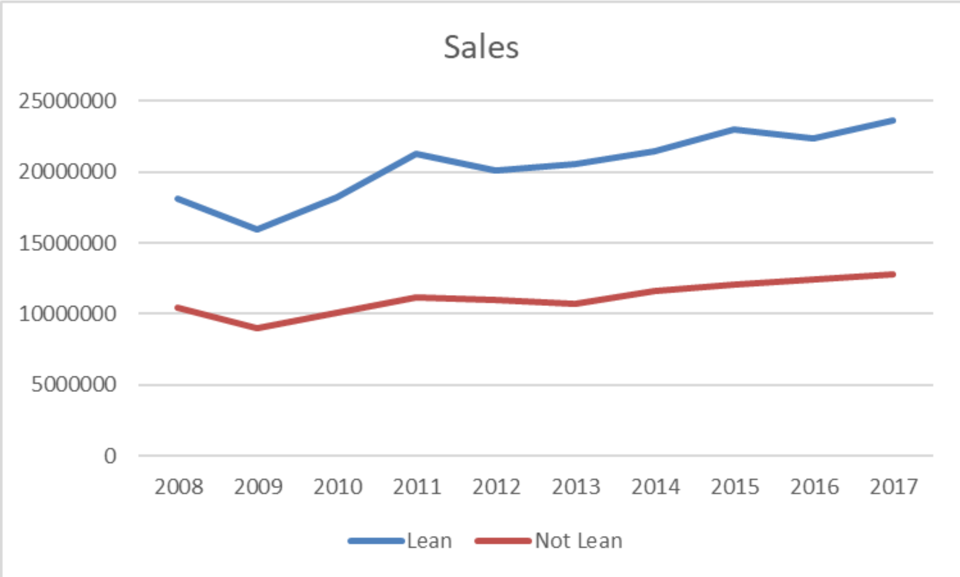
This chapter presents graphical data related to the dichotomous sets presented in chapter 4. Data have been elaborated on a time laps of 10 years, from 2008 to 2017. The most important variable downloaded by the online resource of AIDA database have been checked to find out possible graphical differences between the groups. These variables are presented with no particular order, but following each dichotomy there will be reference to their role when it comes at judging different performance aspects related to different business' metrics.

5.1 Lean Companies VS Not Lean Companies

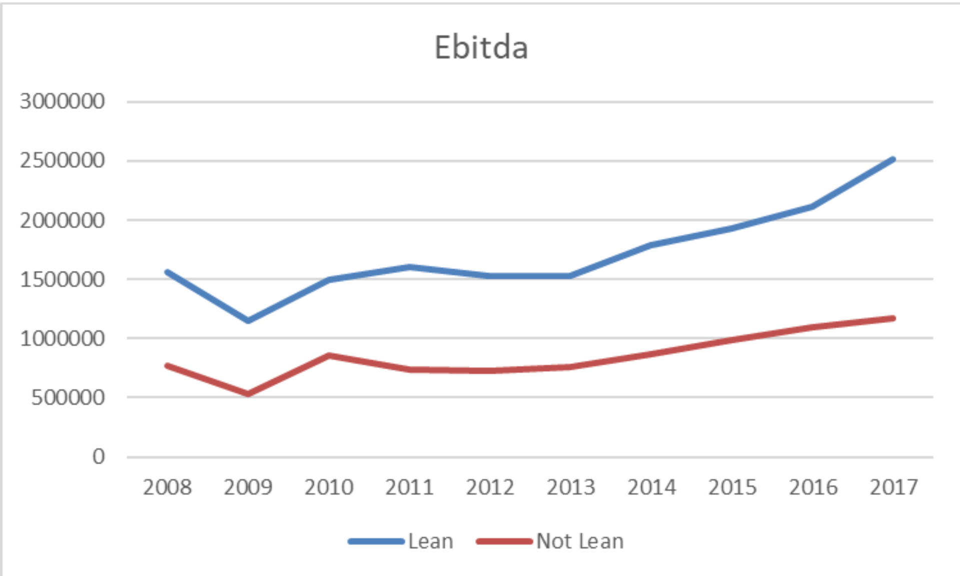
Lean companies show better data and indexes related to their profitability in comparison to not lean companies: sales (Fig. 5.1) and EBITDA (Fig. 5.2) are more than double during the whole 10-year period, while the EBITDA/Sales (Fig. 5.3) index shows how the firsts perform slightly better, less that an averaged 1% more, than the seconds, considering the result before any influence due to the interest of debt and fixed capital investments. Lean companies manage to departure from the opposite group for what regards ROE (Fig. 5.4), ROA (Fig. 5.5), ROI (Fig. 5.6), ROS (Fig. 5.7). Distances between 1-2% in these indexes represent a sensible difference in financial profitability performance form an investor point of view.

Productivity indexes do not define a competitive edge of lean companies on not lean companies: lean companies have more employees (Fig. 5.9) than the counterpart, more or less 100% more. Sale pro capite are lower (Fig. 5.10), and they cost even scarcely more (Fig. 5.12). Average days of inventory (Fig. 5.8) do not define clear pattern, but it is possible to notice some level of divergence in the value added pro capite (Fig. 5.11) for the lean companies on the not lean.

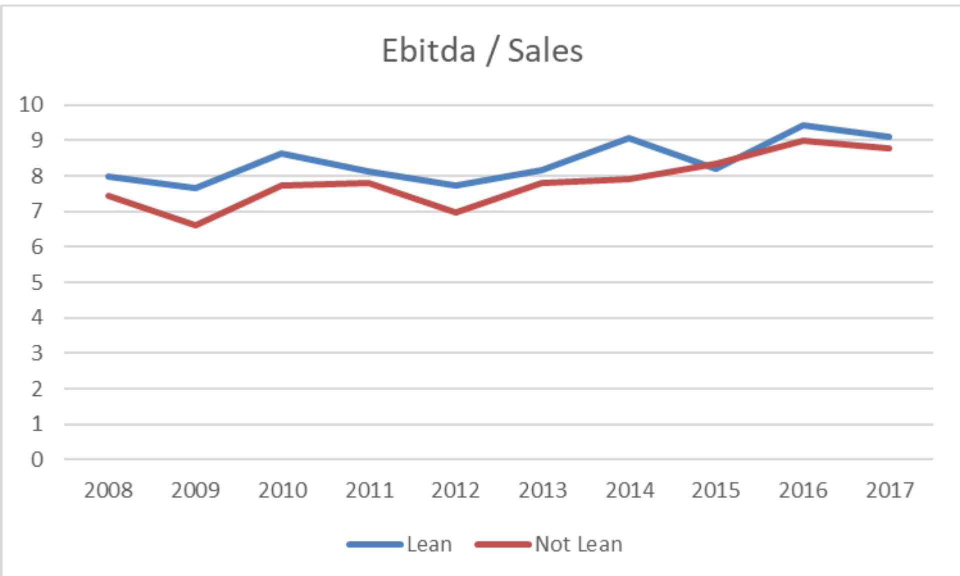
Form a capital structure prospective lean companies have leveraged less (Fig. 5.13), and the relative weight of debt on EBITDA (Fig. 5.14) has been visible more linear and lighter. The amount of short-term debt (Fig. 5.15) and long-term debt seems to have been similar to both groups once looking at the nominal value in percentage.



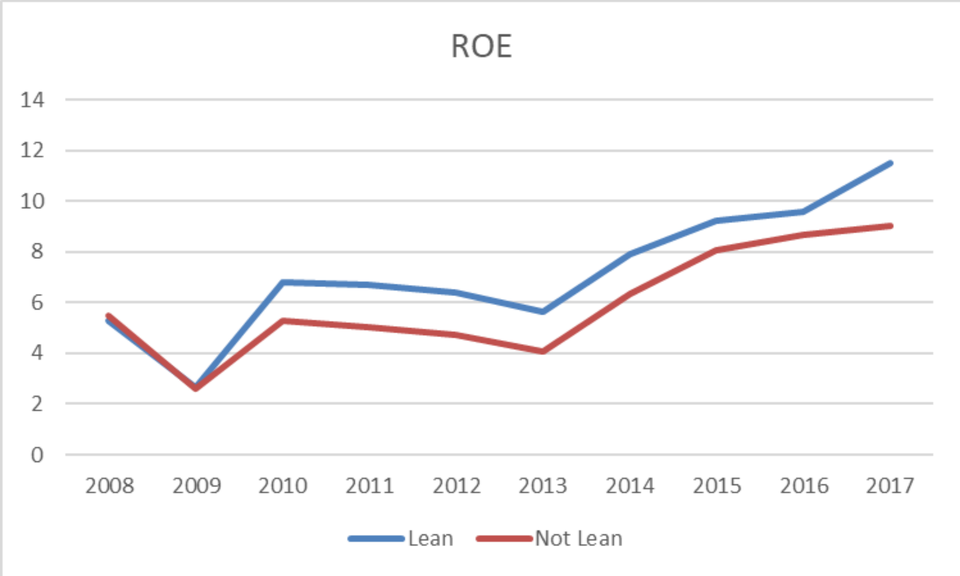
(Fig. 5.1)



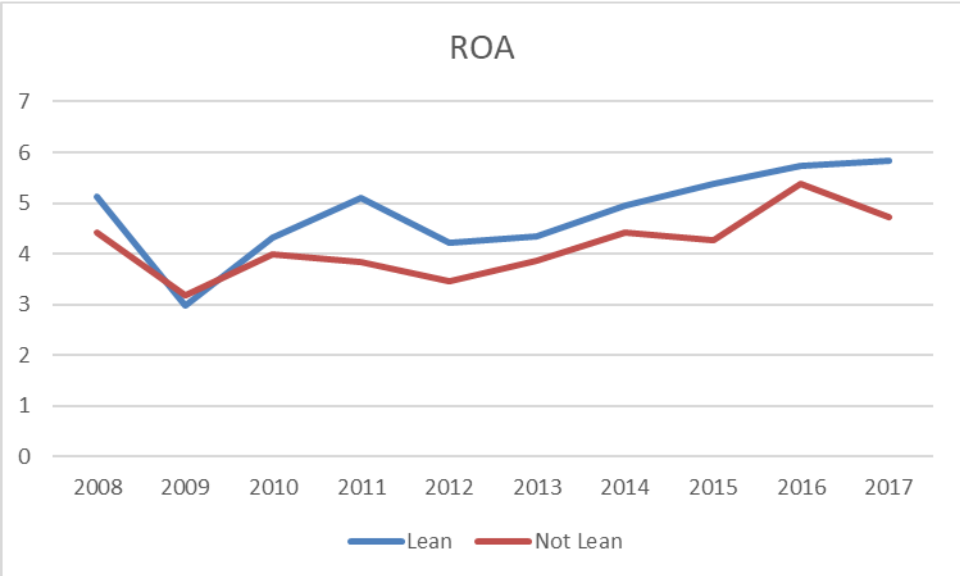
(Fig. 5.2)



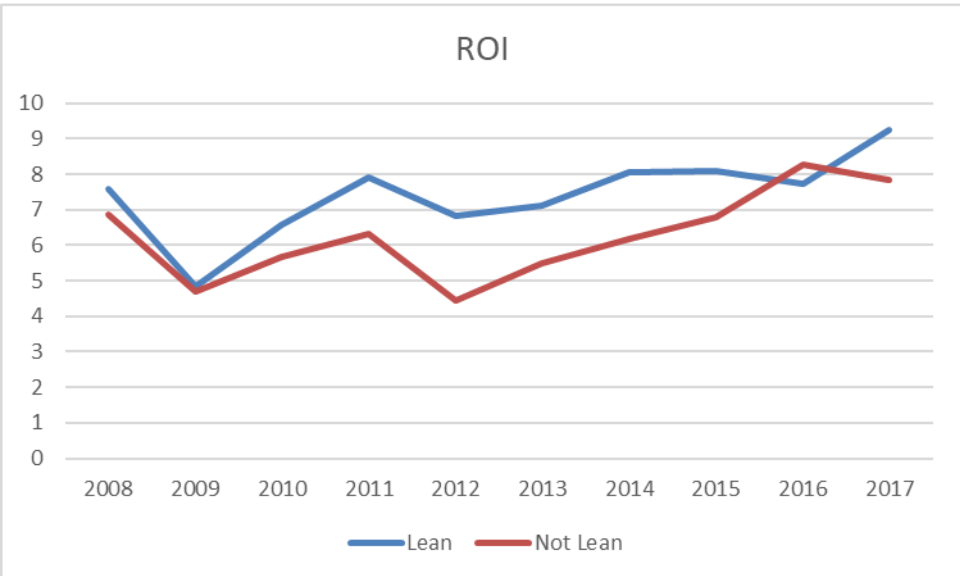
(Fig. 5.3)



(Fig. 5.4)



(Fig. 5.5)



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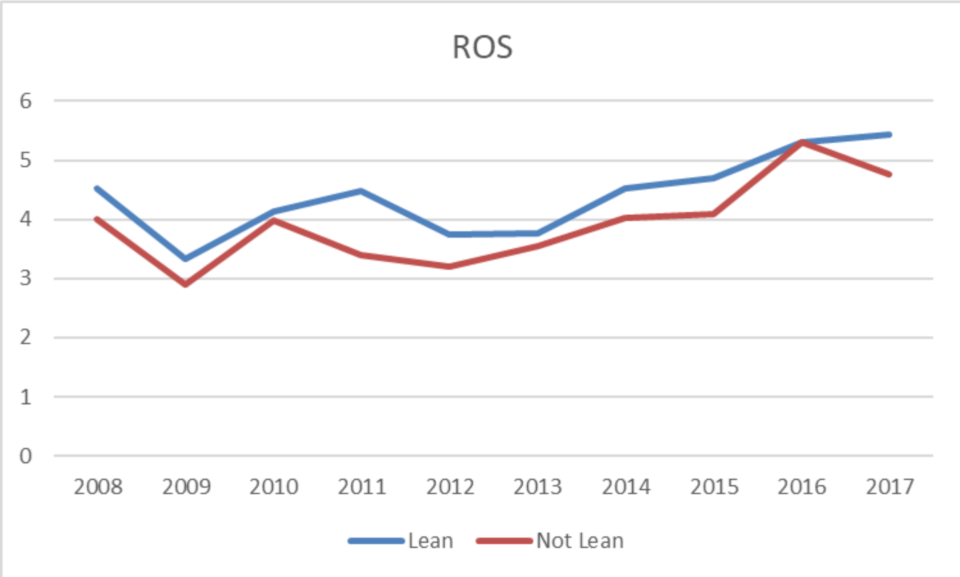
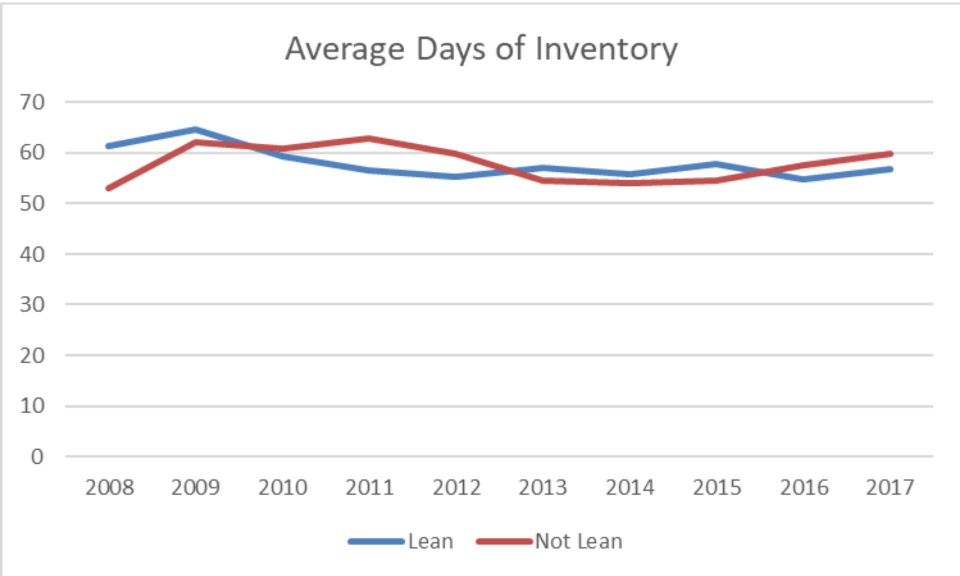


(Fig. 5.7)



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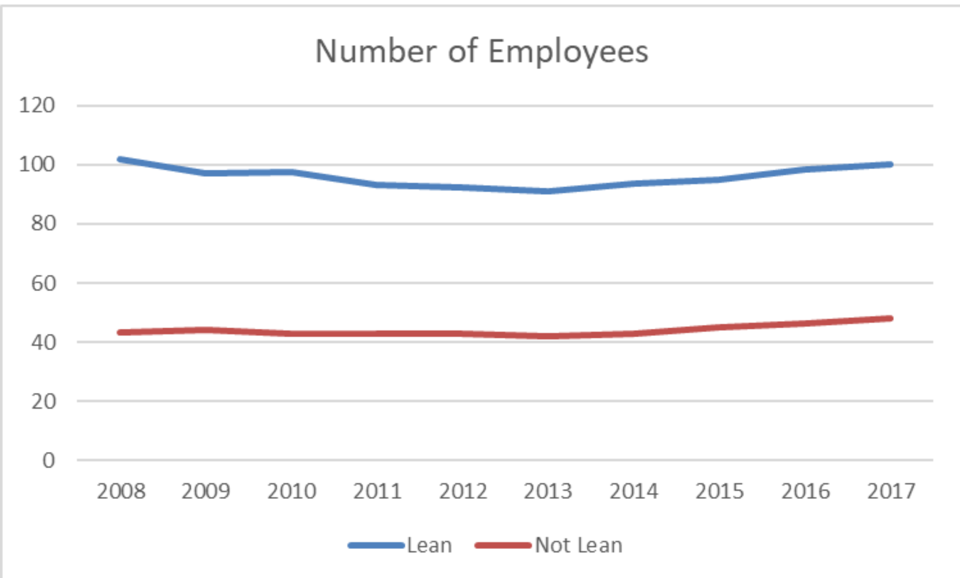
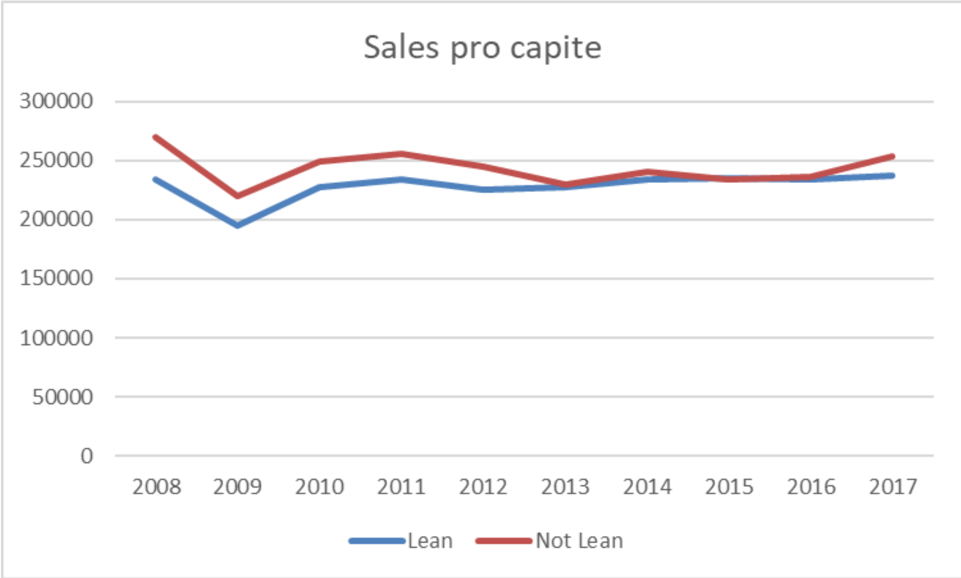
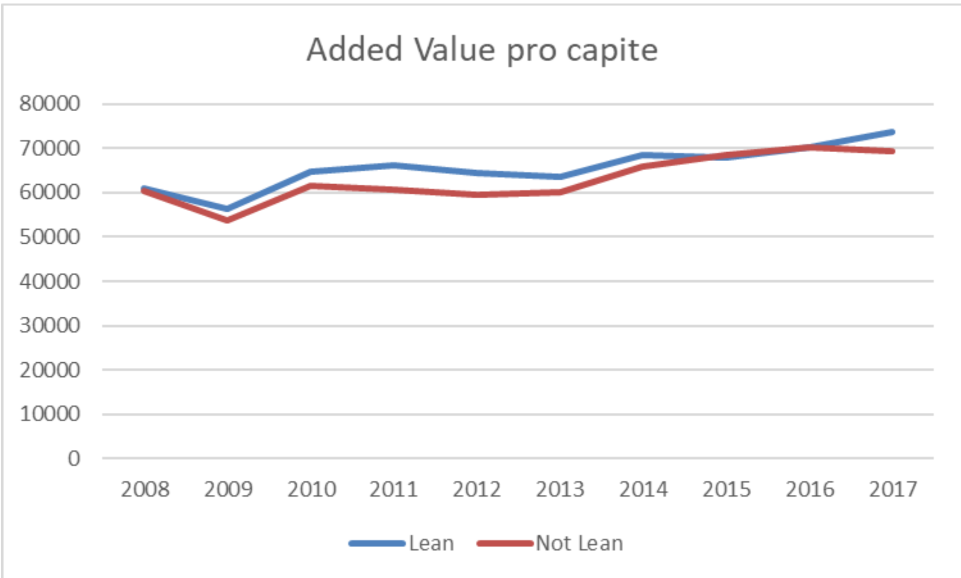


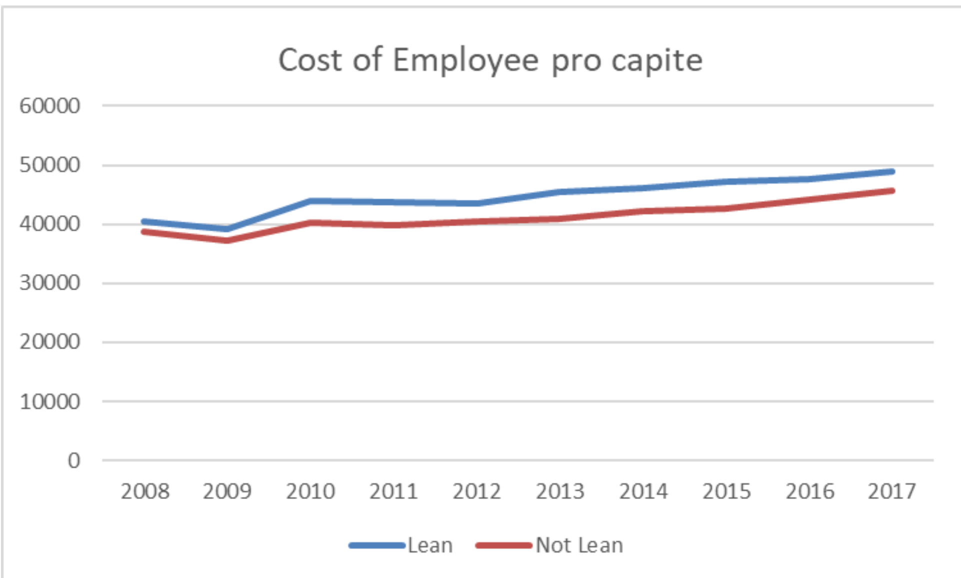
(Fig. 5.9)



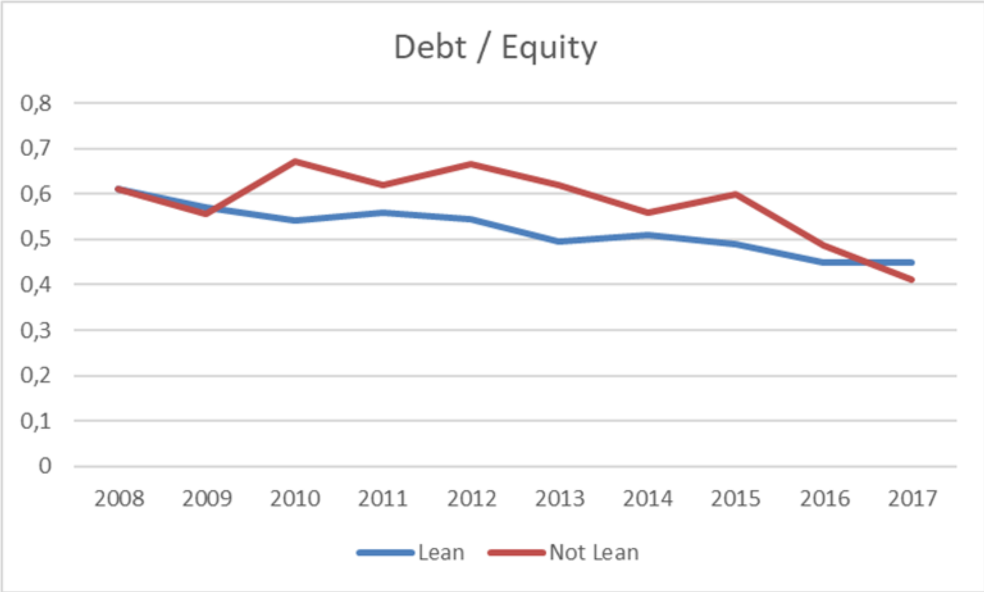
(Fig. 5.10)



(Fig. 5.11)



(Fig. 5.12)



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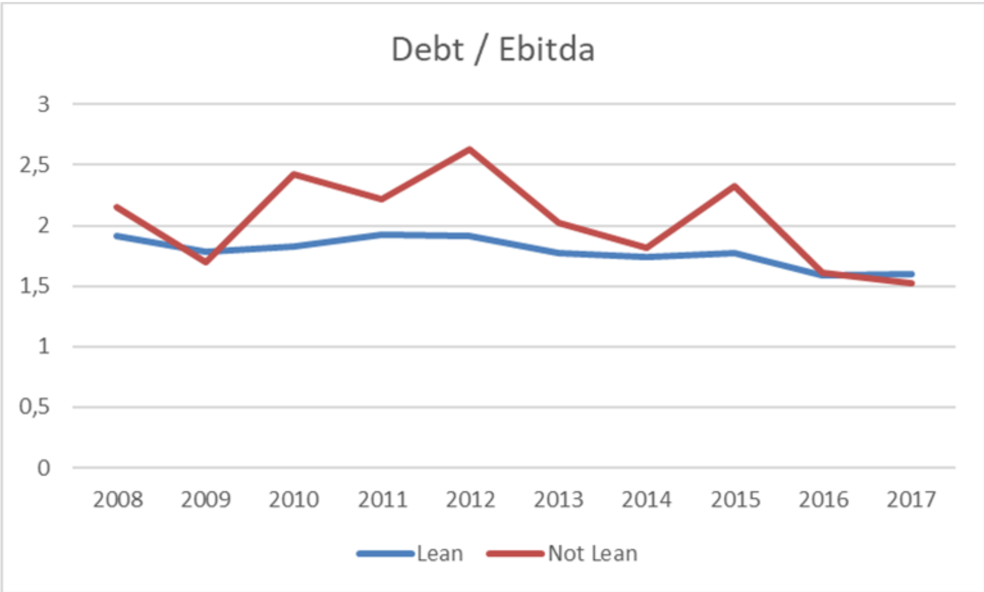
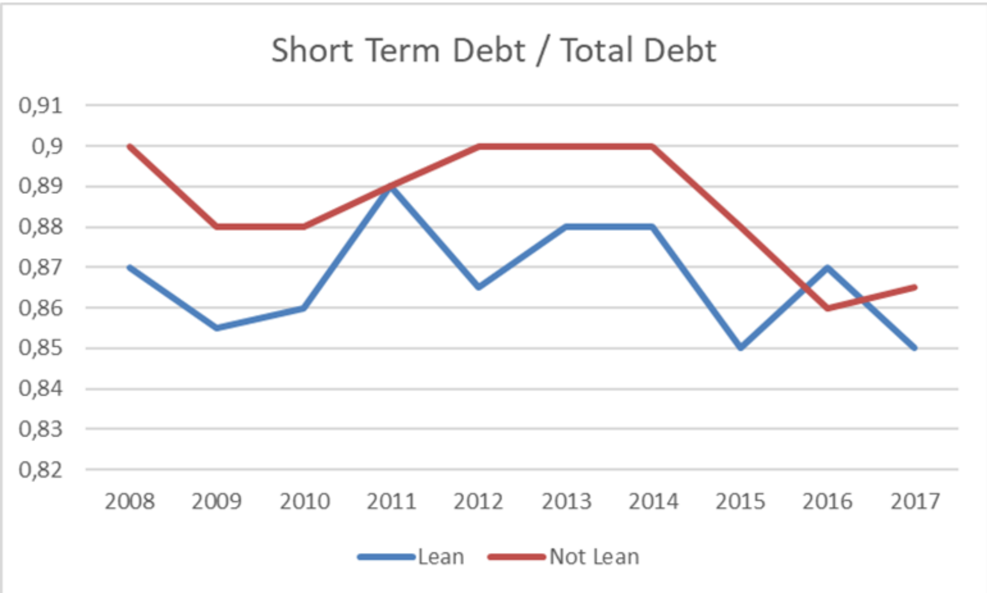


(Fig. 5.14)



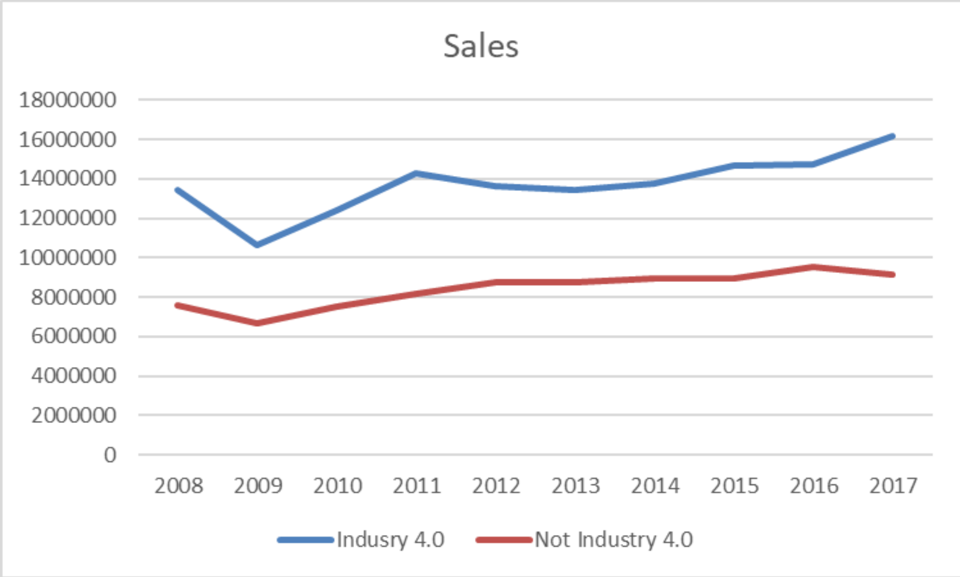
(Fig. 5.15)

5.2 Industry 4.0 Companies VS Not Industry 4.0 Companies

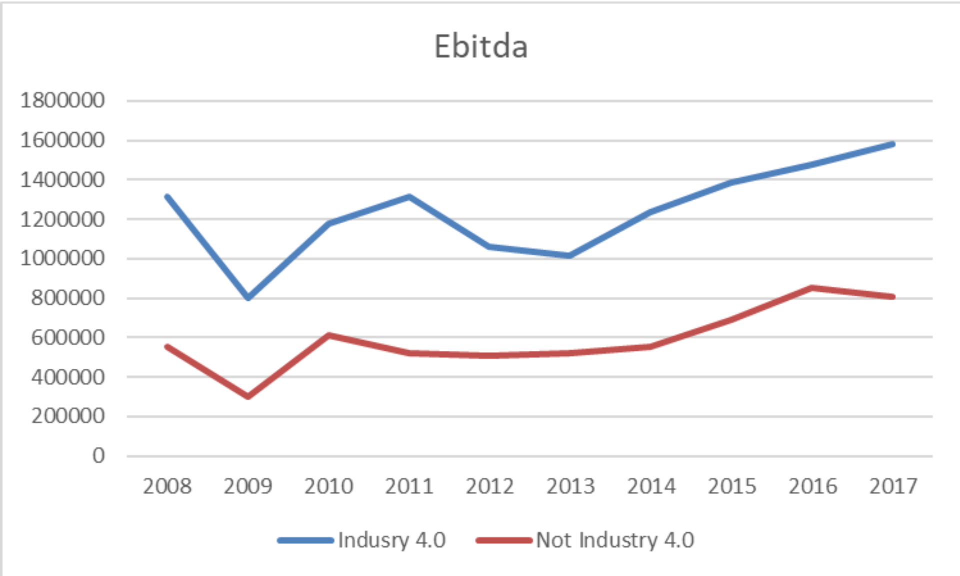
Industry 4.0 companies display better results related to their profitability in comparison to not industry 4.0 companies: sales (Fig. 5.16) and EBITDA (Fig. 5.17) are more than double during the whole 10-year period. The EBITDA/Sales (Fig. 5.18) index spots how the first group perform slightly better, less that an averaged 1% more, than the second. This is an outcome to be considered as a representation before any influence due to the interest of debt and fixed capital investments. Industry 4.0 companies manage to create some significant width from the opposite group in the results provided by the indexes of ROE (Fig. 5.19), ROA (Fig. 5.20), ROI (Fig. 5.21), ROS (Fig. 5.22). A 1-2% difference in these indexes of financial profitability performance is important form an investor point of view.

Productivity indexes do not define a competitive edge of industry 4.0 companies on not industry 4.0 companies: industry 4.0 companies have more employees (Fig. 5.24) than the counterpart. Sale pro capite are lower in the first year of the time span (Fig. 5.25), and the workers cost even scarcely more (Fig. 5.27). Average days of inventory (Fig. 5.23) defines a clear pattern, where industry 4.0 companies manage the inventory better that the counter group. Some level of visible distance is notable also in the value added pro capite (Fig. 5.24) for the industry 4.0 companies on the not industry 4.0 companies.

Form a capital structure prospective industry 4.0 companies have had a lower leveraged (Fig. 5.28) and a relative lighter burden of debt on EBITDA (Fig. 5.29) in the major part of the 10-year period. The amount of short-term debt (Fig. 5.30) and long-term debt seems to have been similar to both groups once looking at the nominal value in percentage. But it is notable how trends are looking to get some inversion in the last year of 2017, as all these 3 indexes show some not negligible tendency at switching places.



(Fig. 5.16)



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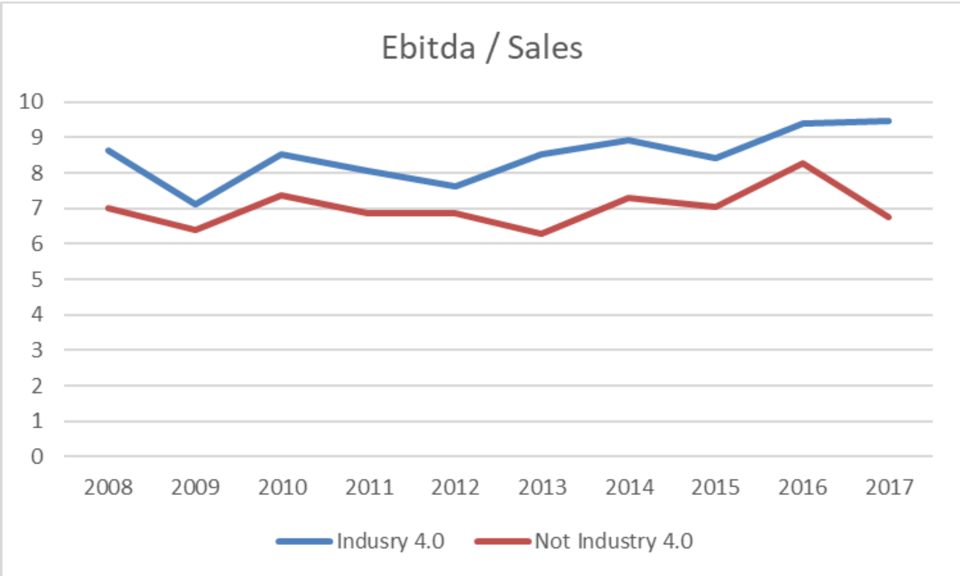

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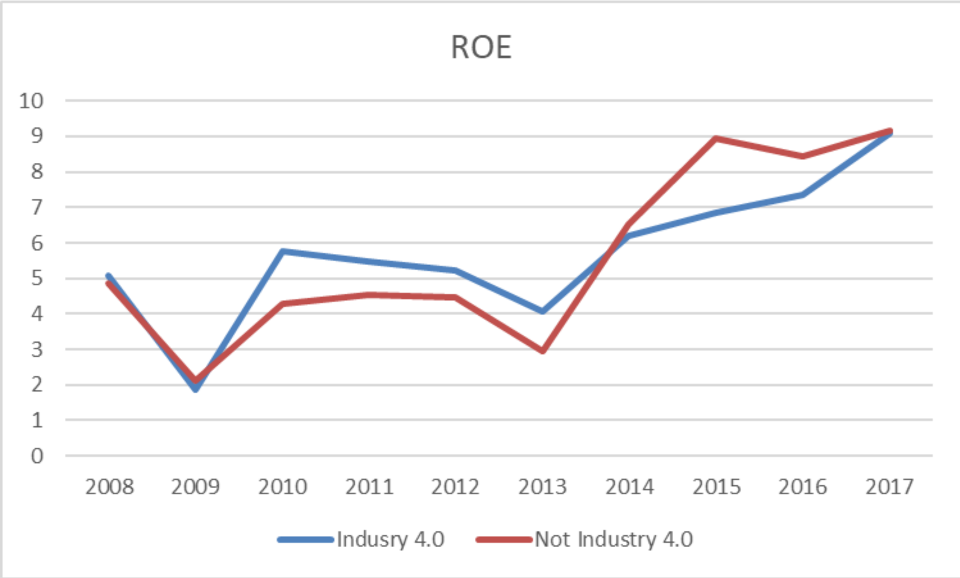

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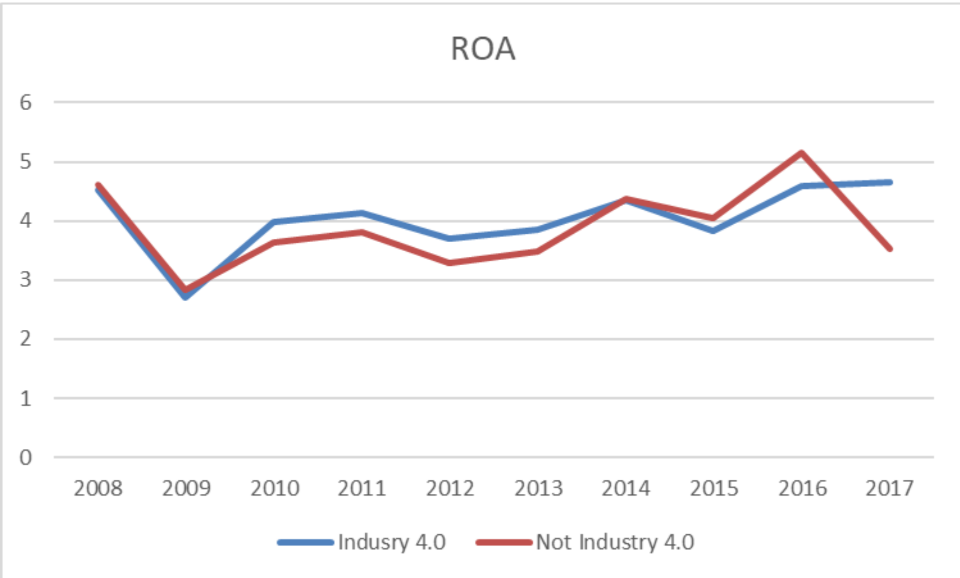

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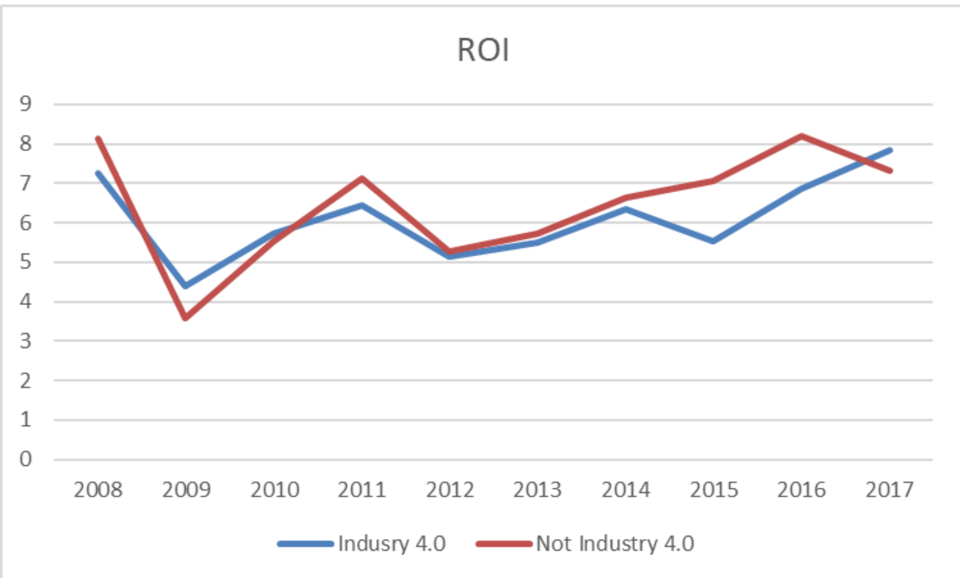

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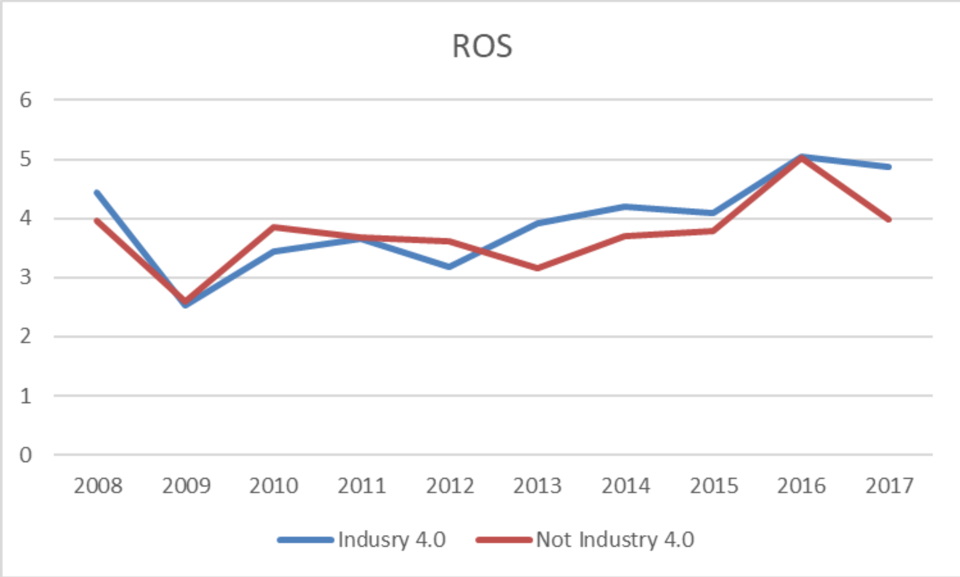

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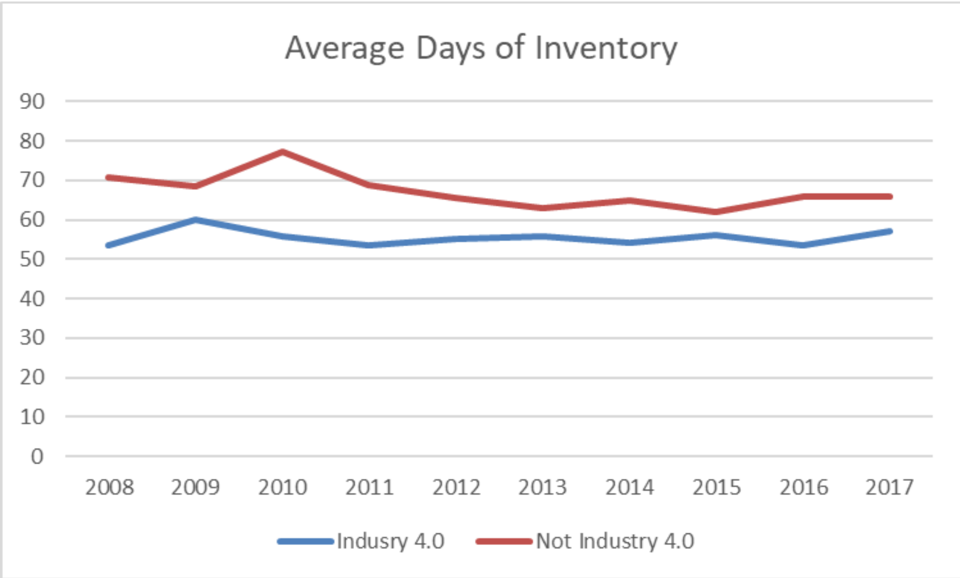

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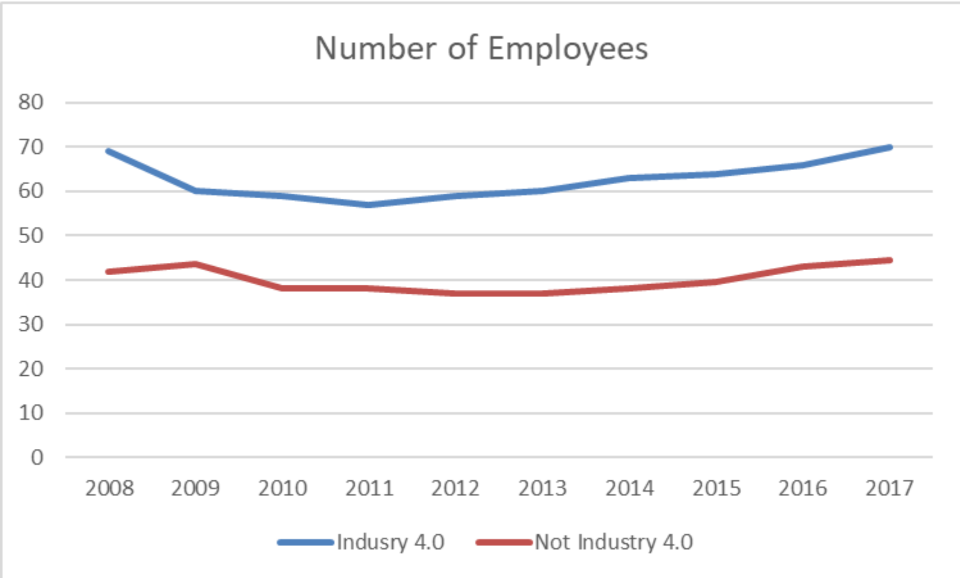

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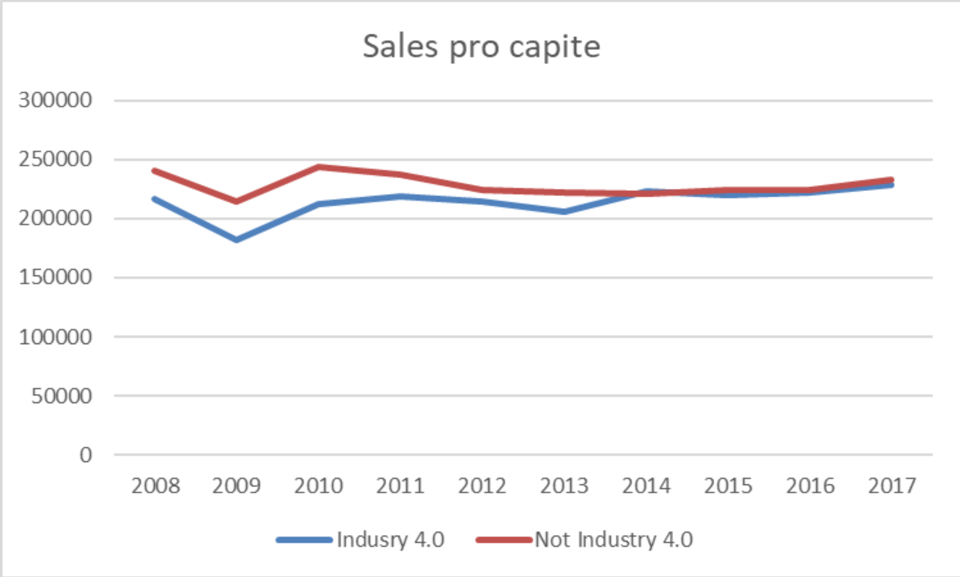

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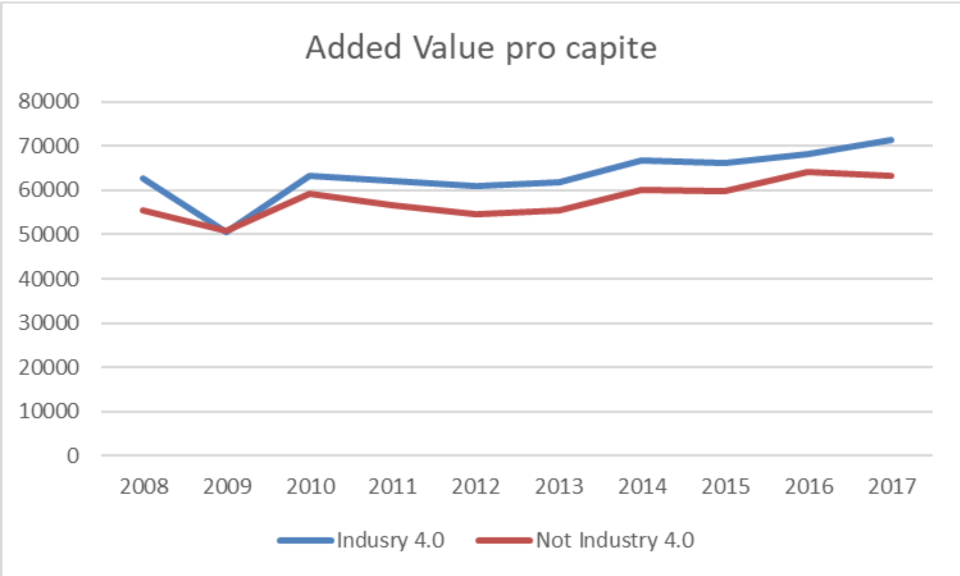

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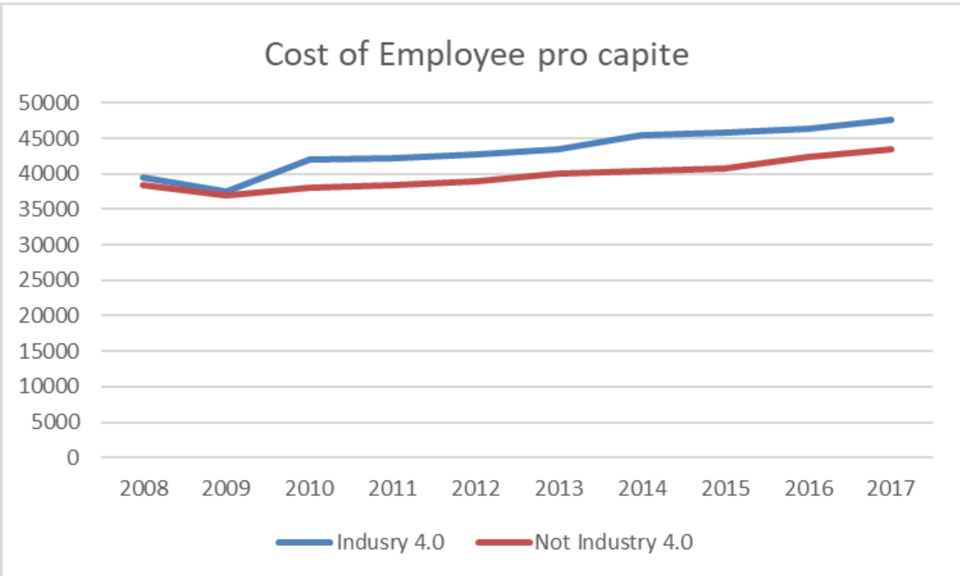

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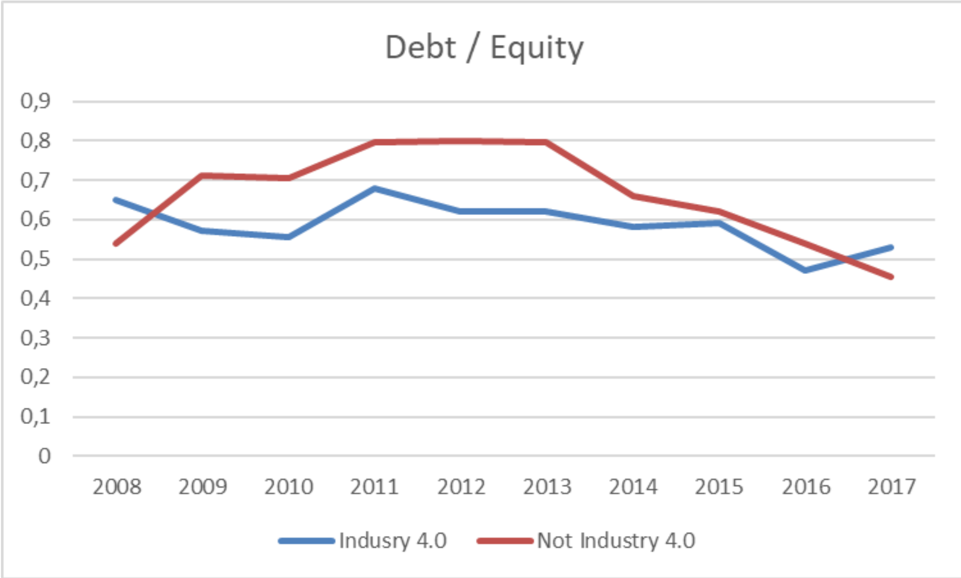

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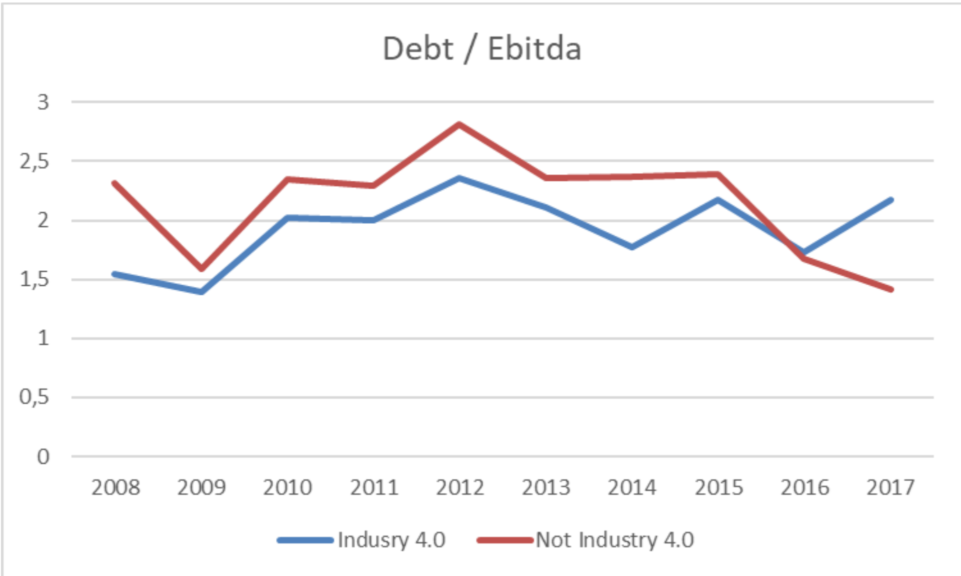

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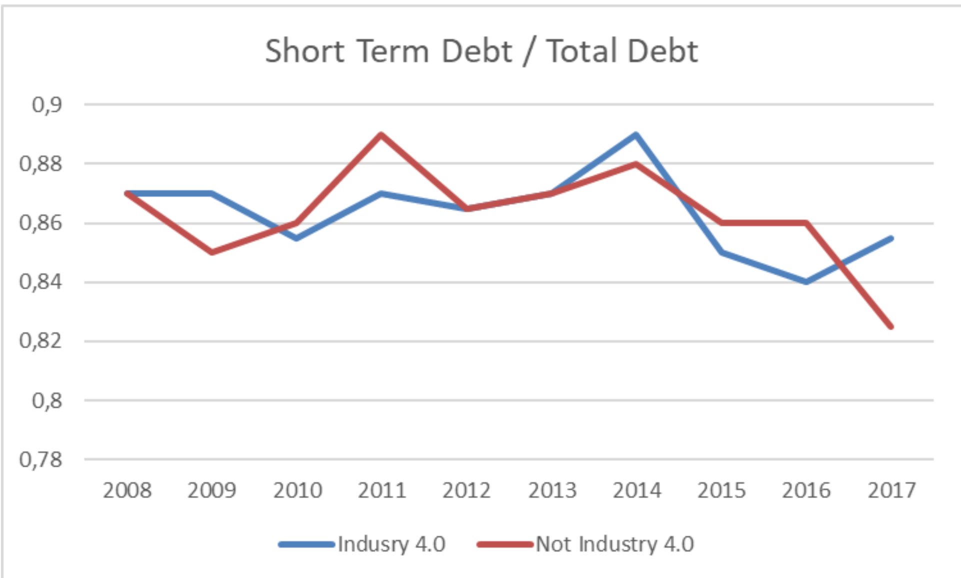


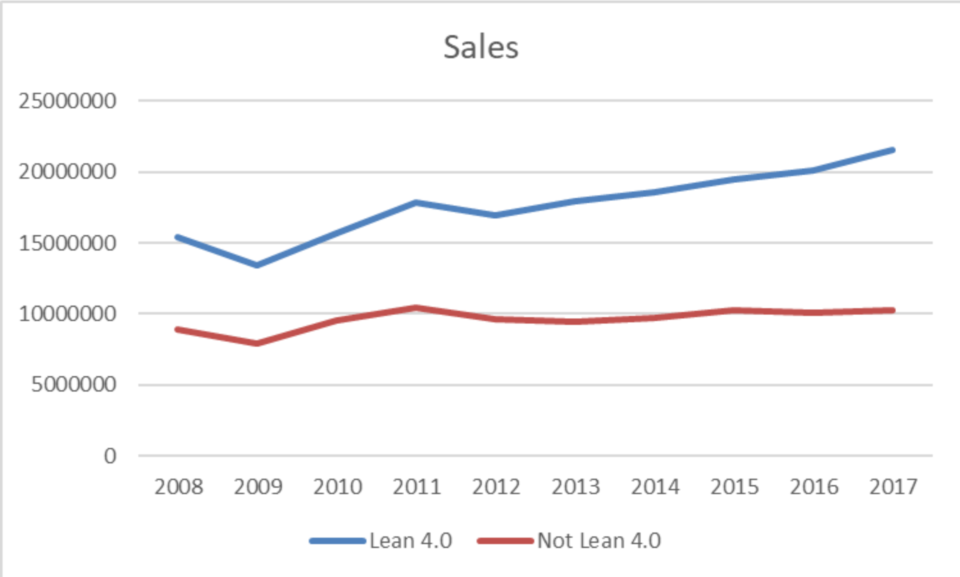
(Fig. 5.30)

5.3 Lean 4.0 Companies VS Not Lean 4.0 Companies

Lean 4.0 companies exhibit some good result related to their profitability in comparison to not lean 4.0 companies: sales (Fig. 5.31) and EBITDA (Fig. 5.32) are more than double during the whole 10-year period and the EBITDA/Sales (Fig. 5.33) index can show how the first group perform on averaged 1% better than the second. But Lean 4.0 companies do not manage to define a clear-cut distinction when it comes at looking at indexes of ROE (Fig. 5.34), ROA (Fig. 5.35), ROI (Fig. 5.36), ROS (Fig. 5.37). Lines showing performance between the groups keeps on overlapping.

Productivity indexes do not prove much competitive edge of lean 4.0 companies on not lean 4.0 companies: lean 4.0 companies have more employees (Fig. 5.39) than the counterpart. Sale pro capite are lower in the first year of the time span (Fig. 5.40), and the workers cost partially more (Fig. 5.44). Average days of inventory (Fig. 5.38) seems to suggest some level of better management by lean 4.0 companies, even if the central years of the time span see not lean 4.0 companies reaching the same performance level. The value added pro capite (Fig. 5.39) for the industry 4.0 companies on the not industry 4.0 companies overlaps like the profitability indexes.

Form a capital structure prospective are the not lean 4.0 companies that have had a lower leveraged (Fig. 5.43) and a relative lighter burden of debt on EBITDA (Fig. 5.44). Again, the amount of short-term debt (Fig. 5.45) and long-term debt seems to have been similar to both groups once looking at the nominal value in percentage. It is important to highlight how trends are getting the discrepancy even wither in the last year of 2017, as all these 3 indexes shows some not negligible tendency.



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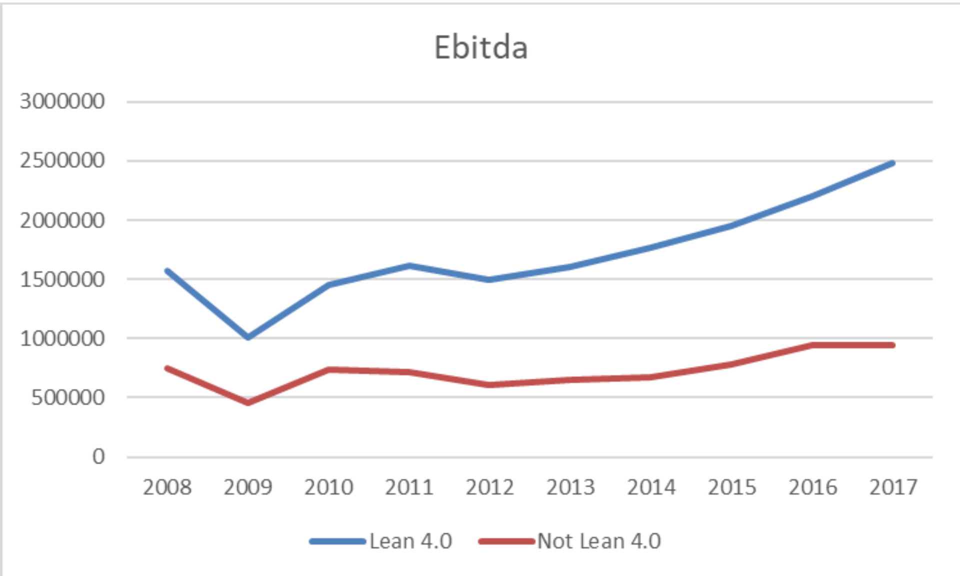
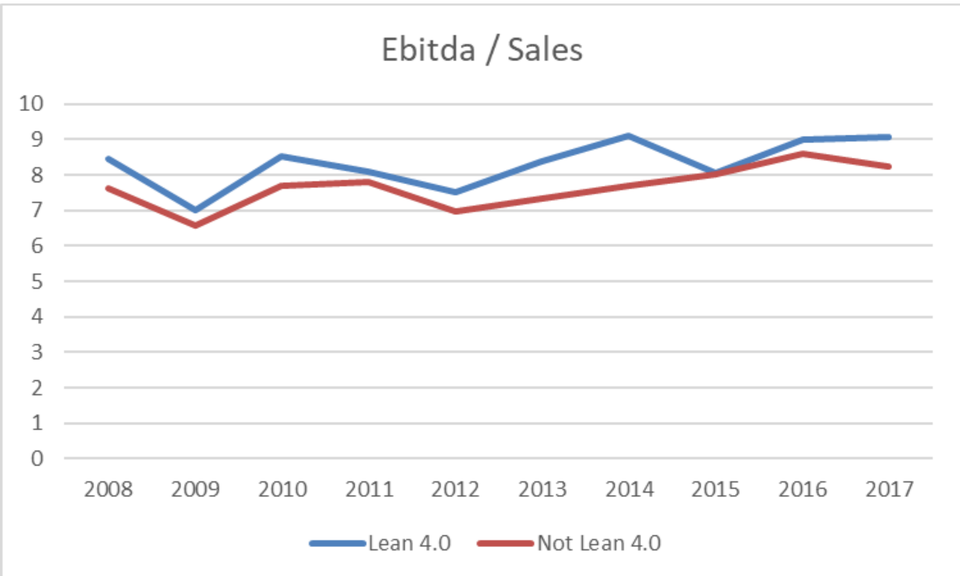


(Fig. 5.32)



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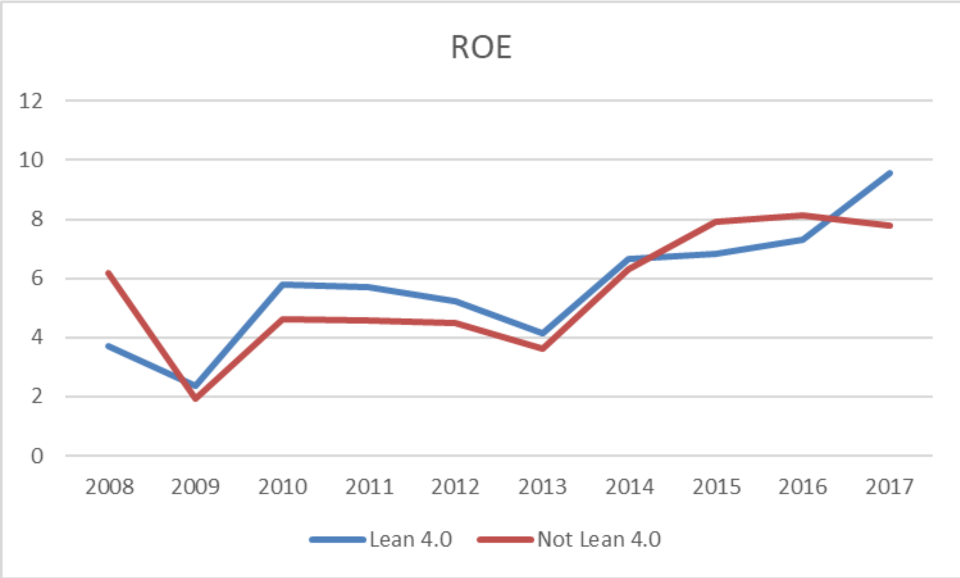

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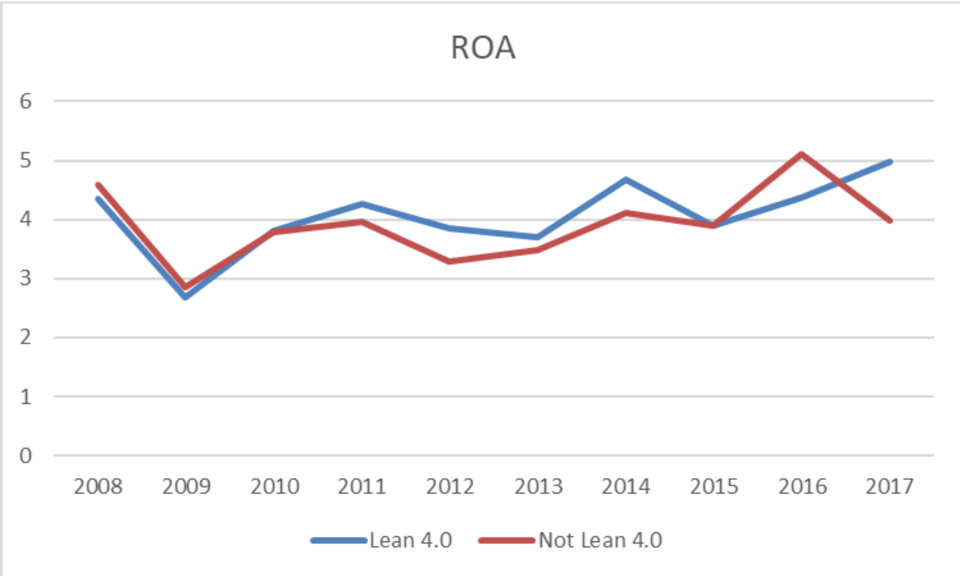

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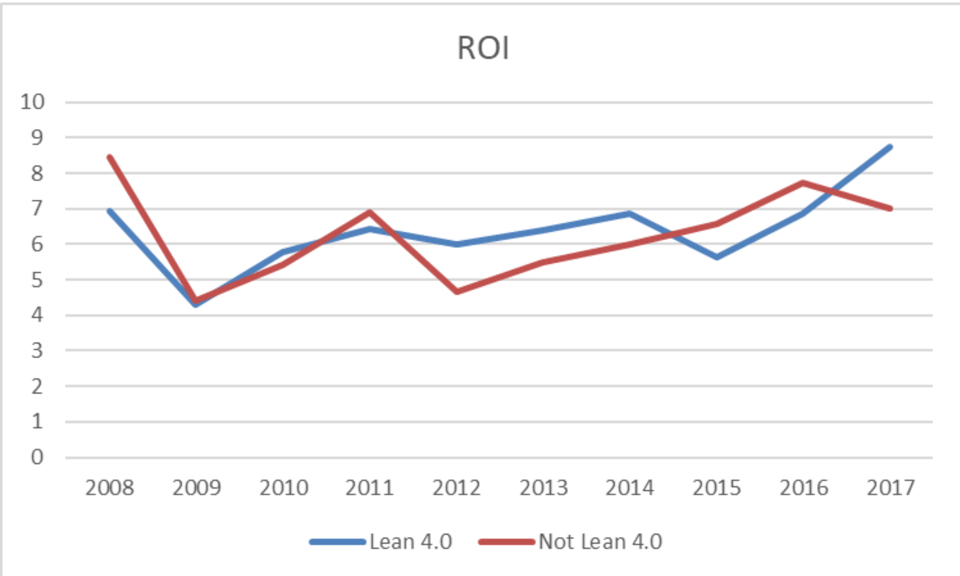

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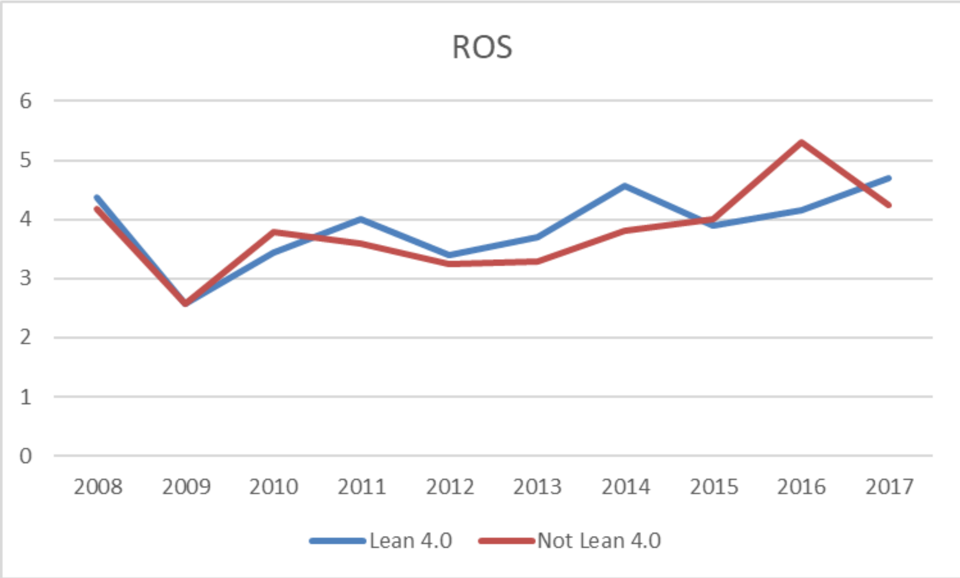

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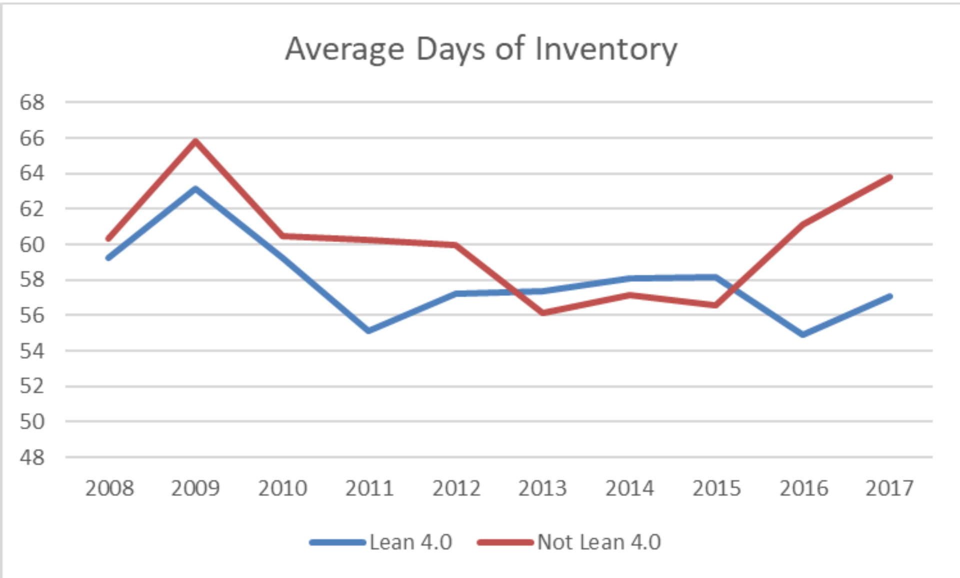

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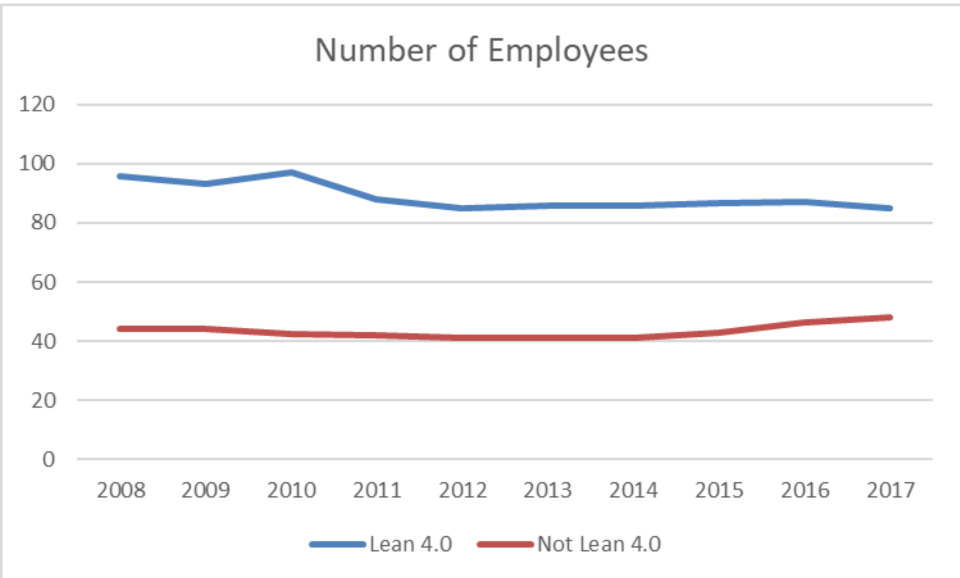

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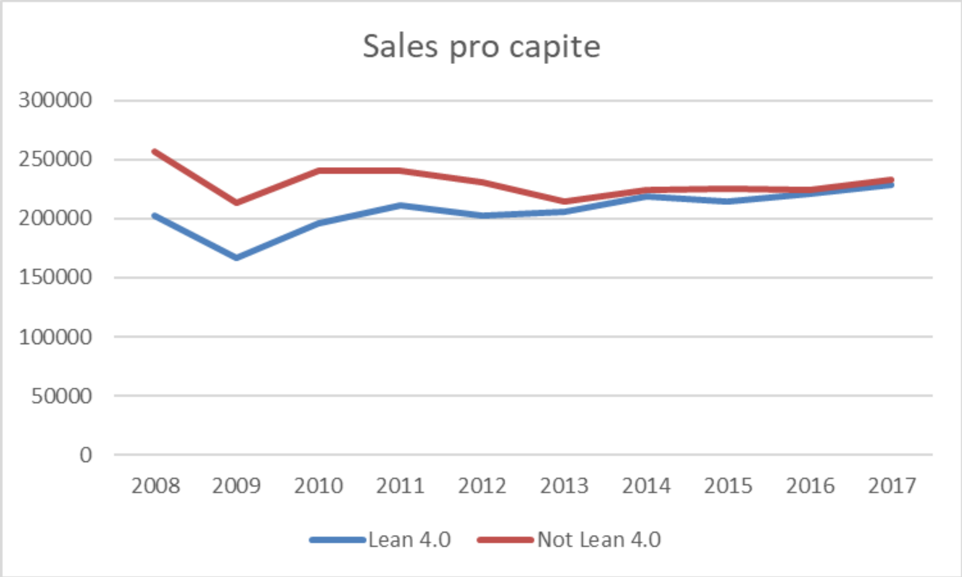

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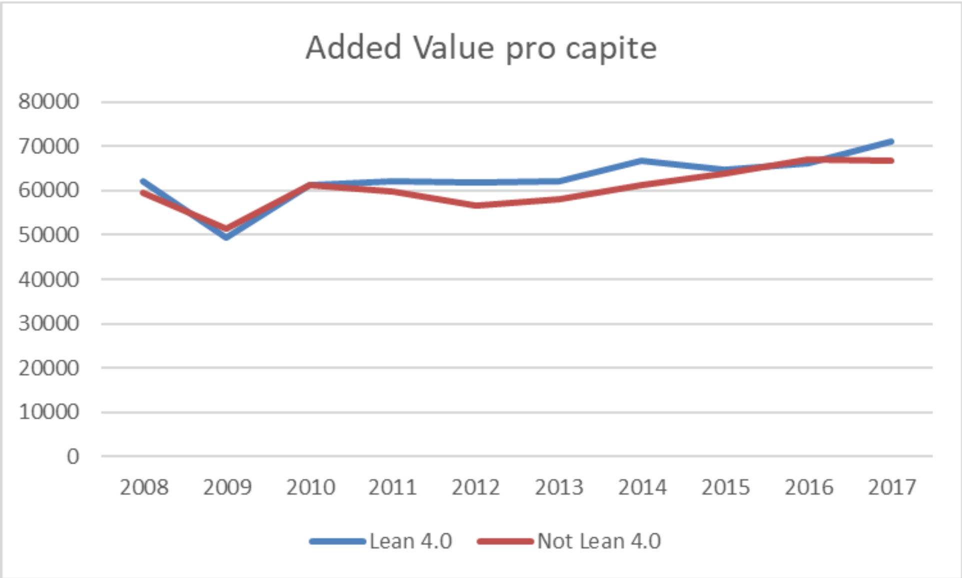

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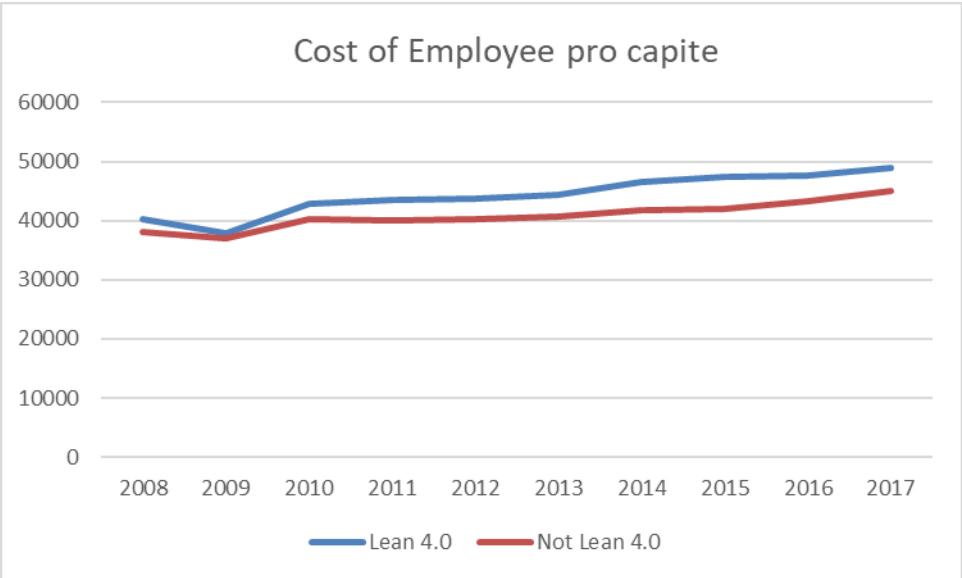

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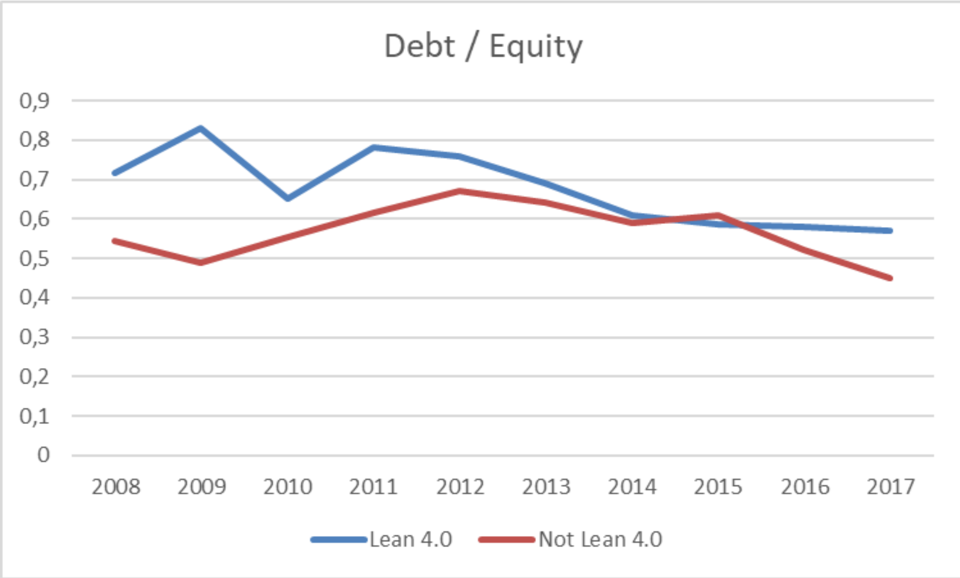

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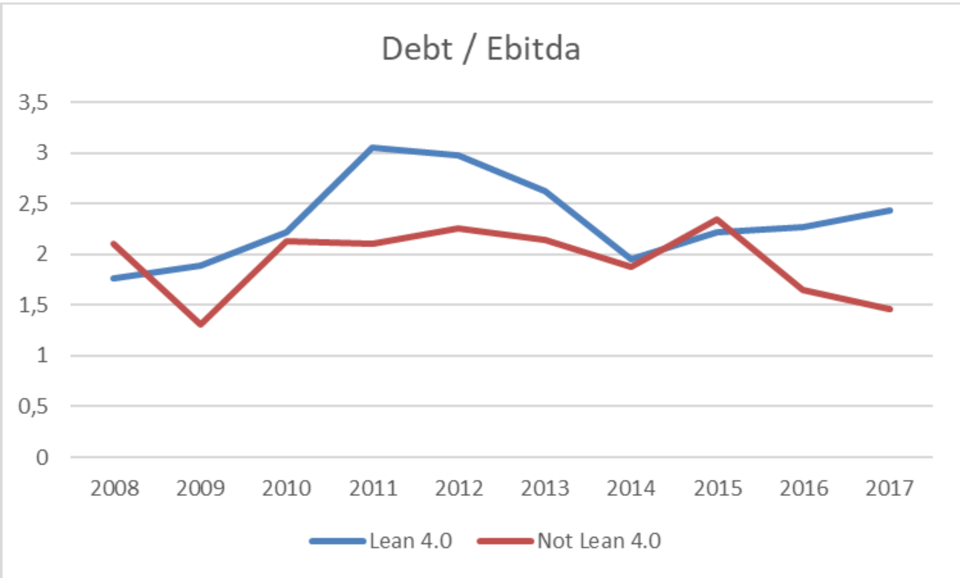

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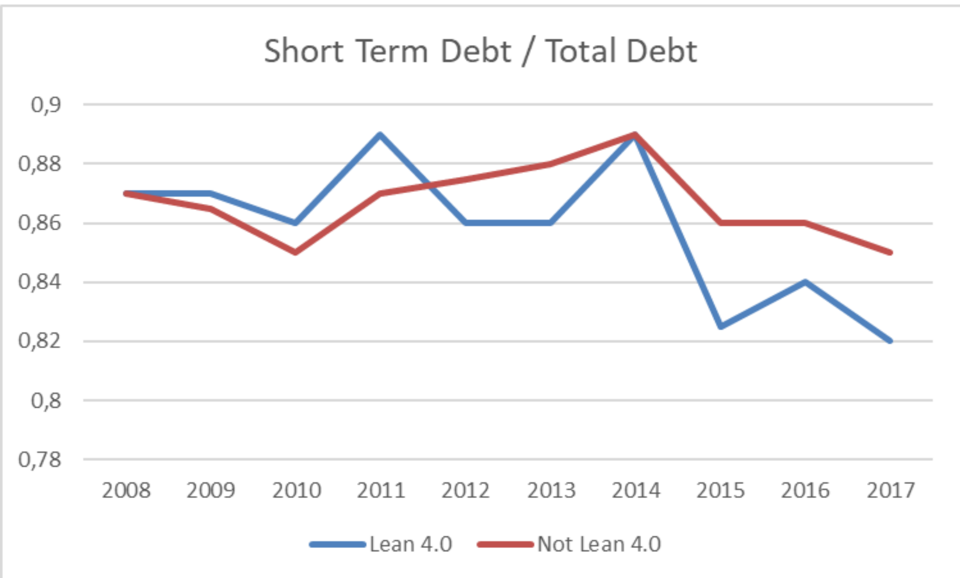

(Fig. 5.45)

Chapter 6: T-Test Analysis on dichotomous Sets and related Variables

This chapter focuses on developing and providing a first in-depth analysis on the variables presented in the previous section. Variables for each dichotomous set have been subject to t-test to prove correspondence with the hypothesis:

H0 → the true difference in means is equal to 0

Or

H1 → the true difference in means is not equal to 0

The purpose of the hypothesis testing is the one of validate statistically that the difference/effect is not caused by random variations and it is due to real statistical significance. P-value is the calculated probability of H0 being true. Therefore, it will be used for assessing results. More specifically, P-value is the probability of obtaining a result at least as extreme, given that H0 is true. If the P-value is lower than the predefined significant level, alpha significant level, then we reject H0 in favor of H1 because there is enough evidence to prove the H0 is wrong.

For those variables in which it will possible to reject H0 in favor of H1 it will be feasible to infer a statistical difference between the groups composing the single dichotomous set. In the other cases, not sound statements are viable as multiple reasoning could be made up upon the causes of such results.

The following assumptions before performing the t-test of each variable have been respected:

- Data are continuous numeric variables;
- Only two groups of data are compared;
- The two groups are independent;
- Data are normally distributed (Shapiro's Test);
- The groups have equal variance (Levene's Test);

According to each case by case variable have been performed transformation on the variables by squares or log functions and replaced by the same naming into the dataset in Rstudio.

In the next pages the results of singular t-test will be displayed. At the end of the 3 dichotomous sets there will be a table summarizing the results, considering the variables, means of each group and p-values.

6.1 Lean VS Not Lean Companies

> t-test (`Debt / EBITDA ratio Lean Companies', 'Debt / EBITDA ratio Not Lean Companies`)

Welch Two Sample t-test

data: Debt / EBITDA ratio Lean Companies and Debt / EBITDA ratio Not Lean Companies
t = -0.47474, df = 292.24, p-value = 0.6353
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-2.864696 1.751261
sample estimates:
mean of x mean of y
3.099408 3.656126

> t-test (`ROE Lean Companies', 'ROE Not Lean Companies`)

Welch Two Sample t-test

data: ROE Lean Companies and ROE Not Lean Companies
t = -0.85848, df = 391.47, p-value = 0.3912
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-4.769260 1.870137
sample estimates:
mean of x mean of y
10.01439 11.46395

```
> t-test (`ROA Lean Companies `, `ROA Not Lean Companies `)

        Welch Two Sample t-test

data:  ROA Lean Companies and ROA Not Lean Companies
t = -0.37316, df = 412.09, p-value = 0.7092
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -1.714913 1.167705
sample estimates:
mean of x mean of y
 6.616029 6.889633

> t-test (`ROI Lean Companies `, `ROI Not Lean Companies `)

        Welch Two Sample t-test

data:  ROI Lean Companies and ROI Not Lean Companies
t = 0.1178, df = 373.06, p-value = 0.9063
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -1.567087 1.766814
sample estimates:
mean of x mean of y
 9.727482 9.627619
```

```
> t-test (`ROS Lean Companies `, `ROS Not Lean Companies `)

            Welch Two Sample t-test

data:  ROS Lean Companies and ROS Not Lean Companies
t = -0.8132, df = 412.29, p-value = 0.4166
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -1.6377602 0.6792412
sample estimates:
mean of x mean of y
 5.621560 6.100819

> t-test (`Average Days of Inventory Lean Companies `, `Average Days of Inventory Not Lean Co
mpanies `)

            Welch Two Sample t-test

data:  Average Days of Inventory Lean Companies and Average Days of Inventory Not Lean Comp
anies
t = -0.84283, df = 399.63, p-value = 0.3998
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -15.336691 6.132459
sample estimates:
mean of x mean of y
 69.81694 74.41906
```

```
> t-test (`Employees Lean Companies `, `Employees Not Lean Companies `)

        Welch Two Sample t-test

data:  Employees Lean Companies and Employees Not Lean Companies
t = 5.9724, df = 225.63, p-value = 9.012e-09
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
  85.97707 170.64788
sample estimates:
mean of x mean of y
195.46324 67.15076

> t-test (`Sales pro capite Lean Companies `, `Sales pro capite Not Lean Companies `)

        Welch Two Sample t-test

data:  Sales pro capite Lean Companies and Sales pro capite Not Lean Companies
t = -0.9147, df = 439.4, p-value = 0.3609
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -76342.06 27850.42
sample estimates:
mean of x mean of y
 313415.0 337660.8
```

```
> t-test (`Added Value Lean Companies `, `Added Value Not Lean Companies `)

        Welch Two Sample t-test

data: Added Value Lean Companies and Added Value Not Lean Companies
t = 0.96614, df = 435.06, p-value = 0.3345
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -3625.509 10636.033
sample estimates:
mean of x mean of y
 80204.68  76699.42

> t-test (`Cost of Employee pro capite Lean Companies `,`Cost of Employee pro capite Not Lean C
ompanies `)

        Welch Two Sample t-test

data:  Cost of Employee pro capite Lean Companies and Cost of Employee pro capite Not Lean Co
mpanies
t = 4.1561, df = 436.26, p-value = 3.898e-05
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 2222.969 6211.766
sample estimates:
mean of x mean of y
 48634.07 44416.70
```

Industry 4.0 VS Not Industry 4.0 Companies

> t-test (`Debt / EBITDA ratio Industry 4.0 Companies`, `Debt / EBITDA ratio Not Industry 4.0 Co
mpanies `)

Welch Two Sample t-test

data: Debt / EBITDA ratio Industry 4.0 Companies and Debt / EBITDA ratio Not Industry 4.0 Co
mpanies
t = -1.0018, df = 126.35, p-value = 0.3183
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-5.500579 1.803083
sample estimates:
mean of x mean of y
2.946582 4.795331

> t-test (`ROE Industry 4.0 Companies `, `ROE Not Industry 4.0 Companies `)

Welch Two Sample t-test

data: ROE Industry 4.0 Companies and ROE Not Industry 4.0 Companies
t = 0.76622, df = 216.95, p-value = 0.4444
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-2.605858 5.920532
sample estimates:
mean of x mean of y
10.547815 8.890478

```
> t-test (`ROA Industry 4.0 Companies `, `ROA Not Industry 4.0 Companies `)

        Welch Two Sample t-test

data:  ROA Industry 4.0 Companies and ROA Not Industry 4.0 Companies
t = 0.4565, df = 229.08, p-value = 0.6485
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -1.359893 2.180034
sample estimates:
mean of x mean of y
 6.312835 5.902765

> t-test (`ROI Industry 4.0 Companies `, `ROI Not Industry 4.0 Companies `)

        Welch Two Sample t-test

data:  ROI Industry 4.0 Companies and ROI Not Industry 4.0 Companies
t = -0.46872, df = 225.88, p-value = 0.6397
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -2.629726 1.619079
sample estimates:
mean of x mean of y
 8.963958 9.469282
```

```
> t-test (`ROS Industry 4.0 Companies`, `ROS Industry 4.0 Companies `)

        Welch Two Sample t-test

data:  ROS Industry 4.0 Companies and ROS Industry 4.0 Companies
t = 1.0512, df = 238.19, p-value = 0.2942
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -0.6850849 2.2528849
sample estimates:
mean of x mean of y
 5.842832 5.058932

> t-test (`Average Days of Inventory Industry 4.0 Companies `, `Average Days of Inventory Not Ind
ustry 4.0 Companies `)

        Welch Two Sample t-test

data:  Average Days of Inventory Industry 4.0 Companies and Average Days of Inventory Not Indu
stry 4.0 Companies
t = -1.6111, df = 210.71, p-value = 0.1087
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -27.033367 2.718226
sample estimates:
mean of x mean of y
 70.40850 82.56607
```

```
> t-test (`Employees Industry 4.0 Companies `, `Employees Not Industry 4.0 Companies `)

        Welch Two Sample t-test

data:  Employees Industry 4.0 Companies and Employees Not Industry 4.0 Companies
t = 2.7816, df = 284.46, p-value = 0.00577
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 16.06466 93.82385
sample estimates:
mean of x mean of y
131.99593 77.05168

> t-test (`Sales pro capite Industry 4.0 Companies `, `Sales pro capite Not Industry 4.0 Companies `)

        Welch Two Sample t-test

data:  Sales pro capite Industry 4.0 Companies and Sales pro capite Not Industry 4.0 Companies
t = -0.53339, df = 227.1, p-value = 0.5943
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -67514.37 38749.41
sample estimates:
mean of x mean of y
 280332.0 294714.5
```

```
> t-test (`Added Value Industry 4.0 Companies`, `Added Value Not Industry 4.0 Companies`)

        Welch Two Sample t-test

data:  Added Value Industry 4.0 Companies and Added Value Not Industry 4.0 Companies
t = 1.25, df = 237.91, p-value = 0.2125
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -3254.873 14557.376
sample estimates:
mean of x mean of y
 77124.20 71472.95

> t-test (`Cost of Employee pro capite Industry 4.0 Companies', 'Cost of Employee pro capite Not I
ndustry 4.0 Companies`)

        Welch Two Sample t-test

data:  Cost of Employee pro capite Industry 4.0 Companies and Cost of Employee pro capite Not In
dustry 4.0 Companies
t = 2.4171, df = 263.34, p-value = 0.01632
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
  571.3193 5592.1443
sample estimates:
mean of x mean of y
 46883.00 43801.27
```

6.2 Lean 4.0 VS Not Lean 4.0 Companies

```
> t-test (`Debt / EBITDA ratio Lean 4.0 `, `Debt / EBITDA ratio Not Lean 4.0 `)

        Welch Two Sample t-test

data:  Debt / EBITDA ratio Lean 4.0 and Debt / EBITDA ratio Not Lean 4.0
t = -0.90694, df = 235.17, p-value = 0.3654
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -3.542911 1.309225
sample estimates:
mean of x mean of y
 2.979789 4.096632

> t-test (`ROE Lean 4.0 `, `ROE Not Lean 4.0 `)

        Welch Two Sample t-test

data:  ROE Lean 4.0 and ROE Not Lean 4.0
t = 0.21345, df = 225.44, p-value = 0.8312
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -3.504405 4.355808
sample estimates:
mean of x mean of y
10.113074 9.687373
```

> t-test (`ROA Lean 4.0 `, `ROA Not Lean 4.0 `)

Welch Two Sample t-test

data: ROA Lean 4.0 and ROA Not Lean 4.0

t = -0.14793, df = 222.86, p-value = 0.8825

alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:

-1.776523 1.528439

sample estimates:

mean of x mean of y

6.046352 6.170394

> t-test (`ROI Lean 4.0 `, `ROI Not Lean 4.0 `)

Welch Two Sample t-test

data: ROI Lean 4.0 and ROI Not Lean 4.0

t = 0.059339, df = 175.28, p-value = 0.9527

alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:

-2.086361 2.215709

sample estimates:

mean of x mean of y

9.227083 9.162409

```
> t-test (`ROS Lean 4.0 `, `ROS Not Lean 4.0 `)

        Welch Two Sample t-test

data:  ROS Lean 4.0 and ROS Not Lean 4.0
t = -0.16289, df = 214.2, p-value = 0.8708
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -1.515643 1.284259
sample estimates:
mean of x mean of y
 5.417715 5.533408
```

```
> t-test (`Average Days of Inventory Lean 4.0 `, `Average Days of Inventory Not Lean 4.0 `)

        Welch Two Sample t-test

data:  Average Days of Inventory Lean 4.0 and Average Days of Inventory Not Lean 4.0
t = -0.86332, df = 204.55, p-value = 0.389
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -20.190232 7.893228
sample estimates:
mean of x mean of y
 71.30137 77.44987
```

```
> t-test (`Employee Lean 4.0 `, `Employee Not Lean 4.0 `)

        Welch Two Sample t-test

data:  Employee Lean 4.0 and Employee Not Lean 4.0
t = 3.866, df = 106.24, p-value = 0.0001909
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
  52.5807 163.2752
sample estimates:
mean of x mean of y
182.58148 74.65353

> t-test (`Sales pro capite Lean 4.0 `, `Sales pro capite Not Lean 4.0 `)

        Welch Two Sample t-test

data:  Sales pro capite Lean 4.0 and Sales pro capite Not Lean 4.0
t = -0.69144, df = 237.75, p-value = 0.49
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -65137.49 31292.16
sample estimates:
mean of x mean of y
 274939.7 291862.3
```

```
> t-test (`Added value pro capite Lean 4.0 `, `Added Value pro capite Not Lean 4.0 `)

        Welch Two Sample t-test

data:  Added value pro capite Lean 4.0 and Added Value pro capite Not Lean 4.0
t = 1.047, df = 182.95, p-value = 0.2965
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -4256.913 13882.527
sample estimates:
mean of x mean of y
 77970.57 73157.77

> t-test (`Cost of Employee pro capite Lean 4.0 `, `Cost of Employee pro capite Not Lean 4.0 `)

        Welch Two Sample t-test

data:  Cost of Employee pro capite Lean 4.0 and Cost of Employee pro capite Not Lean 4.0
t = 3.021, df = 172.1, p-value = 0.002904
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 1409.727 6724.485
sample estimates:
mean of x mean of y
 48344.02 44276.91
```

6.3 Tables summarizing T-Test Results of each Dichotomous Set

Lean VS Not Lean Companies				
Variable	P-Value	Mean Lean	Mean Not Lean	Means ≠ 0
Debt / Ebitda	0,635	3,10	3,66	no
ROE	0,391	10,01	11,46	no
ROA	0,71	6,62	6,89	no
ROI	0,906	9,73	9,63	no
ROS	0,417	5,62	6,10	no
Average Days of Inventory	0,400	69,82	74,42	no
Employees	0,000	195,46	67,15	yes
Sales pro capite	0,361	313.415,00	337.660,80	no
Added Value pro capite	0,335	80.204,68	76.699,42	no
Cost of Employee pro capit	0,000	48.634,07	44.416,70	yes

(Fig 6.1)

Industry 4.0 VS Not Industry 4.0 Companies				
Variable	P-Value	Mean Industry 4.0	Mean Not Industry 4.0	Means ≠ 0
Debt / Ebitda	0,318	2,95	4,80	no
ROE	0,444	10,55	8,89	no
ROA	0,649	6,31	5,90	no
ROI	0,640	8,96	9,47	no
ROS	0,294	5,84	5,06	no
Average Days of Inventory	0,109	70,41	82,57	no
Employees	0,006	132,00	77,05	yes
Sales pro capite	0,594	280.332,00	294.714,50	no
Added Value pro capite	0,213	77.124,20	71.472,95	no
Cost of Employee pro capit	0,016	46.883,00	43.801,27	yes

(Fig. 6.2)

Lean 4.0 VS Not Lean 4.0 Companies				
Variable	P-Value	Mean Lean 4.0	Mean Not Lean 4.0	Means ≠ 0
Debt / Ebitda	0,365	2,98	4,10	no
ROE	0,831	10,11	9,69	no
ROA	0,883	6,05	6,17	no
ROI	0,953	9,23	9,16	no
ROS	0,871	5,42	5,53	no
Average Days of Inventory	0,389	71,30	77,45	no
Employees	0,000	182,58	74,65	yes
Sales pro capite	0,490	274.939,70	291.862,30	no
Added Value pro capite	0,297	77.970,57	73.157,77	no
Cost of Employee pro capit	0,003	48.344,02	44.276,91	yes

(Fig. 6.3)

These tables report the results obtained by applying t-test to the variables utilized for analyzing the performance of each group composing the dichotomous sets. The 3 dichotomies report similar results. A significative difference between the means, such as that it is different from 0, can be found solely in a couple of variables. These are respectively "Employees" and "Cost of Employees pro capite".

Most of the p-values stand far from being close to be accepted by the confidence interval of 95%. The related variables belonging to this group may provide high p-value because of truly similarity between the data or because data collected are not enough to capture the real distribution of the samples.

Chapter 7: Linear Regressions on Performance Variables

7.1 Introduction

In this chapter numerous multiple linear regressions will be employed for modeling a relationship between a scalar response and more explanatory variables.

Each regression is set with a different dependent variable chosen among those already examined with the T-Test in the previous chapter. The independent variables are instead selected by the database originated by the questionnaire, the AIDA online source and individual newly created variables:

- Export (yes=1 ; no=0) ;
- Age;
- Employees;
- Family Business (yes=1 ; no=0) ;
- One Tech Companies (yes=1 ; no=0) ;
- Two Tech Companies (yes=1 ; no=0) ;
- Three or more Tech Companies (yes=1 ; no=0) ;
- Lean Companies (yes=1 ; no=0) ;
- Industry 4.0 Companies (yes=1 ; no=0) ;

Values concerning the independent variables have been re-managed in the database, differently from what done in the previous two chapters. Dependent variables data have been purified by outliers according to 10% levels. Moreover, all values for both independent and dependent variables have been recalculated for being normalized according to sector-performance 3-year median values.

The goal of this analysis is the one of explaining variation in the response variable that can be attributed to variation in the explanatory variables, quantify the strength of the relationship between the response and the explanatory variables, and in particular to determine whether some explanatory variables may have no linear relationship with the response.

In the following pages the results are shown as output of the analysis carried out by Rstudio. Results are discussed at the end of the chapter. A particular focus will be dedicated to the discussion of the dummies variables related to the dichotomous sets of Lean and Industry 4.0, in order to understand if there are similarities with was has been stated in Chapter 6.

More or less all regressions are characterized by low levels of Adjusted R-squared which means that regression do not work effectively in predicting the dependent variables according to the independent variables presented. But these models still have some point of interest if considered for explaining relatively small variations, which was the concern of this section.

Intercepts' coefficients can be interpreted as the value the dependent variable would have if all others independent variables were equal to 0. They anchor the starting point from which values get modified by further conditions. In these regression lines intercepts results to be always significant.

The continuous numeric variables such as Age and Employees represents the difference in value of Y for each one-unit difference in the variables, keeping others variables constant. This means that if Age differed by one-unit while other variables did not Y will differ by Age's coefficients on average.

Similarly, categorical predictors variables such as dummy variables like Export, Family Business, Lean, Industry 4.0, One Tech, Two Tech, Three or more Tech show the difference in value of Y for each one-unit difference in the variable if others stay constant. However, since they are categorical variable coded as 0 or 1, a one-unit difference represents switching from one category to the other.

By running multiple linear regression model during the research, it is possible to state that small level of correlation exists between variables and therefore it is important not to forget that each coefficient is influenced by the other variables in a regression model. Because predictor variables are nearly always associated, two or more variables may explain some of the same variation in Y. Therefore, each coefficient does not measure the total effect on Y of its corresponding variable, as it would if it were the only variable in the model. Rather, each coefficient represents the additional effect of adding that variable to the model, if the effects of all other variables in the model are already accounted for.

Coefficient makes reference to normalized variables by each sector performance. A thing to keep in mind when considering the magnitude of the effect.

7.2 Lean Companies' Linear Regressions Normalized

Ebitda / Sales

```
Coefficients:
                     Estimate Std. Error t value Pr(>|t|)    
(Intercept)          1.053009   0.131985   7.978 1.74e-14 ***
Age                  0.001307   0.002516   0.520  0.60369    
Export1              0.308025   0.105102   2.931  0.00358 ** 
`Family Business`1 -0.002950   0.083921  -0.035  0.97198    
Lean1                0.116997   0.078081   1.498  0.13485    
Employees            0.005486   0.004863   1.128  0.25991    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.744 on 383 degrees of freedom
Multiple R-squared:  0.03687, Adjusted R-squared:  0.0243 
F-statistic: 2.933 on 5 and 383 DF,  p-value: 0.01301
```

ROE

```
Coefficients:
                     Estimate Std. Error t value Pr(>|t|)    
(Intercept)          2.662584   0.379176   7.022    1e-11 ***
Age                 -0.027600   0.007098  -3.888 0.000119 ***
Export1             -0.166080   0.294241  -0.564 0.572787    
`Family Business`1   0.083446   0.237130   0.352 0.725106    
Lean1                0.278836   0.217785   1.280 0.201205    
Employees            0.029846   0.013349   2.236 0.025941 *  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.084 on 383 degrees of freedom
Multiple R-squared:  0.05499, Adjusted R-squared:  0.04265 
F-statistic: 4.457 on 5 and 383 DF,  p-value: 0.0005854
```

ROA

```
Coefficients:
                     Estimate Std. Error t value Pr(>|t|)    
(Intercept)          1.580553   0.255247   6.192 1.53e-09 ***
Age                 -0.006957   0.004907  -1.418   0.1571    
Export1              0.229034   0.203803   1.124   0.2618    
`Family Business`1   0.095092   0.163360   0.582   0.5608    
Lean                 0.325854   0.150991   2.158   0.0315 *  
Employees            0.001167   0.006385   0.183   0.8551    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.449 on 383 degrees of freedom
Multiple R-squared:  0.02131, Adjusted R-squared:  0.008535 
F-statistic: 1.668 on 5 and 383 DF,  p-value: 0.1413
```

ROI

```
Coefficients:
                     Estimate Std. Error t value Pr(>|t|)    
(Intercept)          1.088654   0.170527   6.384 5.46e-10 ***
Age                 -0.004072   0.003017  -1.350   0.1780    
Export1              0.281474   0.133087   2.115   0.0351 *  
`Family Business`1 -0.014693   0.101434  -0.145   0.8849    
Lean1                0.188357   0.092700   2.032   0.0429 *  
Employees           -0.006582   0.003975  -1.656   0.0986 .  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.8565 on 351 degrees of freedom
Multiple R-squared:  0.03552,	Adjusted R-squared:  0.02178 
F-statistic: 2.585 on 5 and 351 DF,  p-value: 0.02586
```

ROS

```
Coefficients:
                      Estimate Std. Error t value Pr(>|t|)    
(Intercept)          1.152e+00  2.088e-01   5.517 6.37e-08 ***
Age                 -8.509e-05  4.035e-03  -0.021   0.9832    
Export1              2.874e-01  1.667e-01   1.724   0.0855 .  
`Family Business`1  1.592e-01  1.329e-01   1.198   0.2317    
Lean1                2.057e-01  1.232e-01   1.669   0.0958 .  
Employees            4.138e-04  4.904e-03   0.084   0.9328    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.177 on 381 degrees of freedom
Multiple R-squared:  0.02076,	Adjusted R-squared:  0.007907 
F-statistic: 1.615 on 5 and 381 DF,  p-value: 0.1549
```

7.3 Industry 4.0 Companies' Linear Regressions Normalized

Ebitda / Sales

```
Coefficients:
                    Estimate Std. Error t value Pr(>|t|)    
(Intercept)         0.944555   0.176353   5.356 1.93e-07 ***
Age                -0.001281   0.003533  -0.363  0.71714    
Export1             0.363099   0.134079   2.708  0.00723 ** 
`Family Business`1  0.065956   0.115434   0.571  0.56826    
`Industry 4.0`1     0.220915   0.104679   2.110  0.03582 *  
Employees           0.012972   0.006327   2.050  0.04139 *  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.8165 on 250 degrees of freedom
Multiple R-squared:  0.07232,	Adjusted R-squared:  0.05377 
F-statistic: 3.898 on 5 and 250 DF,  p-value: 0.002024
```

ROE

```
Coefficients:
                    Estimate Std. Error t value Pr(>|t|)    
(Intercept)         2.316370   0.491409   4.714 4.04e-06 ***
Age                -0.040851   0.009862  -4.142 4.71e-05 ***
Export1             0.116485   0.366440   0.318   0.7508    
`Family Business`1  0.394982   0.319706   1.235   0.2178    
`Industry 4.0`1     0.671289   0.285034   2.355   0.0193 *  
Employees          -0.005469   0.023181  -0.236   0.8137    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.226 on 250 degrees of freedom
Multiple R-squared:  0.08522,	Adjusted R-squared:  0.06693 
F-statistic: 4.658 on 5 and 250 DF,  p-value: 0.0004392
```

ROA

```
Coefficients:
                     Estimate Std. Error t value Pr(>|t|)    
(Intercept)         1.3240614  0.3017048   4.389 1.68e-05 ***
Age                -0.0127044  0.0061890  -2.053   0.0411 *  
Export1             0.4545644  0.2264646   2.007   0.0458 *  
`Family Business`1  0.1416112  0.1988255   0.712   0.4770    
`Industry 4.0`1     0.3707296  0.1795011   2.065   0.0399 *  
Employees          -0.0002665  0.0145983  -0.018   0.9855    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.402 on 250 degrees of freedom
Multiple R-squared:  0.04982,	Adjusted R-squared:  0.03082 
F-statistic: 2.622 on 5 and 250 DF,  p-value: 0.0248
```

ROI

```
Coefficients:
                    Estimate Std. Error t value Pr(>|t|)    
(Intercept)         1.361215   0.212272   6.413 8.15e-10 ***
Age                -0.011343   0.004067  -2.789  0.00573 ** 
Export1             0.240028   0.157363   1.525  0.12857    
`Family Business`1  0.019941   0.132138   0.151  0.88018    
`Industry 4.0`1    -0.002981   0.118682  -0.025  0.97999    
Employees          -0.006712   0.009303  -0.721  0.47135    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.8849 on 228 degrees of freedom
Multiple R-squared:  0.04853,	Adjusted R-squared:  0.02767 
F-statistic: 2.326 on 5 and 228 DF,  p-value: 0.04372
```

ROS

```
Coefficients:
                    Estimate Std. Error t value Pr(>|t|)    
(Intercept)         0.993356   0.297196   3.342 0.000959 ***
Age                -0.007013   0.005939  -1.181 0.238754    
Export1             0.349938   0.230068   1.521 0.129529    
`Family Business`1  0.315855   0.188360   1.677 0.094829 .  
`Industry 4.0`1     0.202097   0.174262   1.160 0.247274    
Employees           0.010242   0.010414   0.984 0.326318    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.346 on 248 degrees of freedom
Multiple R-squared:  0.03742,	Adjusted R-squared:  0.01801 
F-statistic: 1.928 on 5 and 248 DF,  p-value: 0.09024
```

7.4 Number of Technologies Companies' Linear Regressions Normalized

Ebitda / Sales

```
Coefficients:
                         Estimate Std. Error t value Pr(>|t|)    
(Intercept)              0.930929   0.177254   5.252 3.24e-07 ***
Age                     -0.001053   0.003547  -0.297  0.76679    
Export1                  0.376012   0.134940   2.787  0.00574 ** 
`Family Business`1      0.063720   0.115750   0.550  0.58247    
`One Tech`1             0.160507   0.126214   1.272  0.20467    
`Two tech`1             0.242026   0.142811   1.695  0.09138 .  
`Three or more Tech`1   0.355750   0.185258   1.920  0.05597 .  
Employees                0.012193   0.006441   1.893  0.05950 .  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.8181 on 248 degrees of freedom
Multiple R-squared:  0.07617,	Adjusted R-squared:  0.0501 
F-statistic: 2.921 on 7 and 248 DF,  p-value: 0.005913
```

ROE

```
Coefficients:
                         Estimate Std. Error t value Pr(>|t|)    
(Intercept)              2.345925   0.493801   4.751 3.43e-06 ***
Age                     -0.041150   0.009894  -4.159 4.40e-05 ***
Export1                  0.092905   0.369717   0.251   0.8018    
`Family Business`1      0.392015   0.321097   1.221   0.2233    
`One Tech`1             0.662109   0.340964   1.942   0.0533 .  
`Two tech`1             0.863304   0.397466   2.172   0.0308 *  
`Three or more Tech`1   0.367359   0.491367   0.748   0.4554    
Employees               -0.005295   0.023413  -0.226   0.8213    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.231 on 248 degrees of freedom
Multiple R-squared:  0.08823,	Adjusted R-squared:  0.0625 
F-statistic: 3.428 on 7 and 248 DF,  p-value: 0.001614
```

ROA

```
Coefficients:
                         Estimate Std. Error t value Pr(>|t|)    
(Intercept)              1.314737   0.303232   4.336 2.11e-05 ***
Age                     -0.012547   0.006212  -2.020   0.0445 *  
Export1                  0.470962   0.228306   2.063   0.0402 *  
`Family Business`1      0.134592   0.199671   0.674   0.5009    
`One Tech`1             0.279943   0.216960   1.290   0.1981    
`Two tech`1             0.440485   0.248166   1.775   0.0771 .  
`Three or more Tech`1   0.488865   0.304521   1.605   0.1097    
Employees               -0.001585   0.014742  -0.107   0.9145    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.406 on 248 degrees of freedom
Multiple R-squared:  0.05204,	Adjusted R-squared:  0.02528 
F-statistic: 1.945 on 7 and 248 DF,  p-value: 0.06326
```

ROI

```
Coefficients:
                        Estimate Std. Error t value Pr(>|t|)    
(Intercept)             1.347754   0.212080   6.355 1.14e-09 ***
Age                    -0.011042   0.004060  -2.719  0.00705 ** 
Export1                 0.263864   0.157717   1.673  0.09571 .  
`Family Business`1      0.005595   0.132241   0.042  0.96629    
`One Tech`1            -0.135723   0.142097  -0.955  0.34053    
`Two tech`1             0.080484   0.162268   0.496  0.62038    
`Three or more Tech`1   0.205170   0.199615   1.028  0.30513    
Employees              -0.008672   0.009347  -0.928  0.35450    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.8827 on 226 degrees of freedom
Multiple R-squared:  0.06161,	Adjusted R-squared:  0.03254 
F-statistic:  2.12 on 7 and 226 DF,  p-value: 0.04255
```

ROS

```
Coefficients:
                        Estimate Std. Error t value Pr(>|t|)   
(Intercept)             0.960169   0.298938   3.212  0.00149 **
Age                    -0.006548   0.005955  -1.100  0.27258   
Export1                 0.389821   0.232852   1.674  0.09538 . 
`Family Business`1      0.303168   0.188793   1.606  0.10960   
`One Tech`1             0.076698   0.209370   0.366  0.71444   
`Two tech`1             0.241908   0.240759   1.005  0.31599   
`Three or more Tech`1   0.470881   0.300597   1.566  0.11852   
Employees               0.008772   0.010610   0.827  0.40913   
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.347 on 246 degrees of freedom
Multiple R-squared:  0.04356,	Adjusted R-squared:  0.01634 
F-statistic:   1.6 on 7 and 246 DF,  p-value: 0.1358
```

7.5 Resume Tables of Linear Regression Results according to Independent Variables

Independent Var.	Dependent Var.	Estimate	P-value	Significance
Lean	Ebitda / Sales	0,1169	0,1348	
Lean	ROE	0,2788	0,2012	
Lean	ROA	0,3258	0,0315	*
Lean	ROI	0,1883	0,0429	*
Lean	ROS	0,2057	0,0958	.

(Table 7.1)

Independent Var.	Dependent Var.	Estimate	P-value	Significance
Industry 4.0	Ebitda / Sales	0,2209	0,0358	*
Industry 4.0	ROE	0,6712	0,0193	*
Industry 4.0	ROA	0,3707	0,0399	*
Industry 4.0	ROI	-0,0029	0,9800	
Industry 4.0	ROS	0,2021	0,2473	

(Table 7.2)

Independent Var.	Dependent Var.	Estimate	P-value	Significance
One Tech	Ebitda / Sales	0,1605	0,2047	
Two Tech	Ebitda / Sales	0,2420	0,0914	.
Three or more Tec	Ebitda / Sales	0,3558	0,0560	.
One Tech	ROE	0,6621	0,0533	.
Two Tech	ROE	0,8633	0,0308	*
Three or more Tec	ROE	0,3674	0,4554	
One Tech	ROA	0,2799	0,1981	
Two Tech	ROA	0,4405	0,0771	.
Three or more Tec	ROA	0,4889	0,1097	
One Tech	ROI	-0,1357	0,3405	
Two Tech	ROI	0,0805	0,6204	
Three or more Tec	ROI	0,2052	0,3051	
One Tech	ROS	0,0767	0,7144	
Two Tech	ROS	0,2419	0,3160	
Three or more Tec	ROS	0,4709	0,1185	

(Table 7.3)

Tables for 7.1 to 7.3 shows how the independent variables matter of focus of this chapter result to be in relation with the dependent variables researched. Not all independent variables manage to reach a significant level due to their p-values but it is still possible to notice some interesting inference. All estimate agrees in sign (+ ; -) according to what the theory expected.

Lean variable is significant for ROA, ROI and ROS. Being a lean company, considering all the other variables constant and for the model developed, can lead to a major improvement of the sector-normalized values of the dependent variables by respectively 32%, 18% and 20%.

Industry 4.0 variable is significant for Ebitda / Sales, ROE and ROA. Being an industry 4.0 company, considering all the other variables constant and for the model developed, can lead to a major improvement of the sector-normalized values of the dependent variables by respectively 22%, 67% and 37%.

The third table represent which amount of technologies provide beneficial result for the dependent variables. All result arises in exact correspondence with the results provided by industry 4.0. Ebitda / Sales benefit form industry 4.0 technologies when two, three or more of these are undertaken, considering all the other variables constant and for the model developed. Three or more Tech variables set the base of a higher improvement in the performance compared to only Two Tech variable. Same reasoning follows for ROE with One Tech and Two Tech variables and ROA with Two Tech variable.

Chapter 8: Conclusions

This work wanted to discuss lean, industry 4.0 and lean 4.0 application from a theoretical point of view and further verify if northern Italian companies are already benefitting from past investments into the first two of these. Two different statistical approaches were undertaken for study singularly the effects: t-tests and linear regression were carried out on important dependent variables of financial and operative performance.

The two statistical approached differs from each other because of the data management system. T-tests elaborate data close to those that were gather by the questionnaire and AIDA database without particular data-management, while linear regressions are set on the basis of adaptation because of a sector-based normalization and elimination of outliers.

At first glance t-test do not highlight in fact any considerable difference between the dichotomous sets, suggesting that a more pragmatical approach was necessary to be undertaken if there was the will to find out possible significant result through the subsequent linear regression method.

Linear regression provides instead interesting results in financial performance indicators. Being a lean or industry 4.0 company can lead to improvements in specific financial results.

Lean variable is significant for ROA, ROI and ROS. Being a lean company, considering all the other variables constant and for the model developed, can lead to a major improvement of the sector-normalized values of the dependent variables by respectively 32%, 18% and 20%.

Industry 4.0 variable is significant for Ebitda / Sales, ROE and ROA. Being an industry 4.0 company, considering all the other variables constant and for the model developed, can lead to a major improvement of the sector-normalized values of the dependent variables by respectively 22%, 67% and 37%.

By running multiple linear regression model during the research, it is possible to state that small level of correlation exists between variables and therefore it is important not to forget that each coefficient is influenced by the other variables in a regression model. Because predictor variables are nearly always associated, two or more variables may explain some of the same variation in Y. Therefore, each coefficient does not measure the total effect on Y of its corresponding variable, as it would if it were the only variable in the model. Rather, each coefficient represents the additional effect of adding that variable to the model, if the effects of all other variables in the model are already accounted for.

The research ends up suggesting investing into lean and industry 4.0 application. In the first chapters theory and practical examples provide guidelines for managing these two concepts that despite the different acknowledgment are not that much diffuse among all companies properly.

There have been proven statistical results, nevertheless, the research presents some point that could be improved by similar future researches. First of all, companies seem to inflate the number of those that declare using specific 4.0 robotics. Second, a small database has prevented the research from improving focus by ultra-segmenting the dichotomous sets into specific groups. Third, companies have been considered performing lean or industry 4.0 on the base of self-provided answers in the questionnaire. A problem of profiling may arise due to the fact that no international standards have been clearly applied for defining the belonging to a group. This limit also the comparability of the research through researchers around different universities and entities. Shortly, most of the research's validity stands on data-creation and data-management, which being conveniently self-filled by companies may lack on certain elements of soundness.

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