Master Thesis in Engineering and Management

THE DETERMINANTS OF VENTURE CAPITAL INVESTMENTS IN ARTIFICIAL INTELLIGENCE START-UPS: LANDSCAPE, INVESTORS' AND INVESTEES' PROFILES

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Abstract

Given the important impact of the AI firms' development on the innovation and growth of economies, and the growing attention of VC funds in the AI sector, this thesis aims at investigating the landscape of VC investment in AI, analysing both the determinants of those investments and the profile of investors and investees. The dataset used for the analysis comes from the merge of two main data sources: *CrunchBase*, containing information regarding VC deals and *Market Inspection*, a panel containing macroeconomic variables used as control. In addition to investments and geographical analysis, the empirical method consists of a series of regression models and difference in means run on Stata software. Concerning investor profiles, VCs investing in AI start-ups tend to be smaller in size and less expert, confirming previous literature suggesting that inexperienced Venture Capital are more likely to heavily invest during boom periods without prior market cycle expertise. Moreover, the number of AI investors per deal is significantly higher if compared to non-AI counterparty, suggesting a syndication behaviour to share the intrinsic risk associated with the innovativeness of the industry and to reduce asymmetry of information / adverse selection bias. In addition, the analysis demonstrates that, despite receiving a higher round amount, due to the lack of VC expertise, AI-start-ups are less likely to result in a successful exit strategy, underlining VC expertise as a key success factor. Additional investigations demonstrate that AI industry has to be considered an investment driver especially during the early stages investment rounds, implying that investors are confident about the future growth and profits from AI expansion when other information are limited. Finally, the geographical distribution of AI start-ups tends to be concentrated in countries and cities perceived as innovation hubs, characterized by elevated technological levels, and developed economies. When analysing the impact of innovation hubs on investments, AI start-ups receive more funds than their non-AI counterparty, despite the geographical location. However, AI start-ups located in an innovation hub are less likely to receive heavy rounds, than those settled in other locations, suggesting that the over-proliferation of businesses operating in the same industry increases the competition among them, reducing the cluster beneficial effect.

Keywords: *Venture Capital, Artificial Intelligence, High-tech start-ups*

Résumé

Compte tenu de l'impact important du développement des entreprises d'IA sur l'innovation et la croissance des économies, ainsi que de l'attention croissante des Venture Capital dans le secteur de l'IA, cet article vise à étudier le paysage des investissements de capital-risque dans l'IA, en analysant à la fois les déterminants de ces investissements et le profil des investisseurs et des bénéficiaires. L'ensemble de données utilisées pour l'analyse provient de la fusion de deux sources de données principales: CrunchBase, contenant des informations relatives aux opérations de VC et Market Inspection, un panel contenant des variables macroéconomiques utilisées comme contrôle. Outre les investissements et l'analyse géographique, la méthode empirique consiste en une série de modèles de régression et de différences de moyennes exécutés sur le logiciel Stata. En ce qui concerne le profil des investisseurs, les sociétés de VC qui investissent dans des start-ups d'IA ont tendance à être de plus petite taille et moins expertes, ce qui confirme la littérature antérieure suggérant que les sociétés de VC inexpérimentées sont plus susceptibles d'investir massivement pendant les périodes d'essor sans expertise préalable du cycle du marché. De plus, le nombre d'investisseurs en IA par transaction est significativement plus élevé que celui des contreparties non IA, ce qui suggère un comportement de syndication pour partager le risque intrinsèque associé au caractère innovant de l'industrie et pour réduire l'asymétrie d'information / le biais de sélection adverse. En outre, l'analyse démontre que, bien que le montant du tour de table soit plus élevé, en raison du manque d'expertise en matière de capital-risque, les start-ups de l'IA sont moins susceptibles d'aboutir à une stratégie de sortie réussie, ce qui souligne l'expertise en matière de capital-risque comme un facteur clé de succès. Les enquêtes d'Addiction démontrent que l'industrie de l'IA doit être considérée comme un moteur d'investissement, en particulier au cours des premiers cycles d'investissement, ce qui implique que les investisseurs sont confiants dans la croissance et les bénéfices futurs de l'expansion de l'IA lorsque les autres informations sont limitées. Enfin, la répartition géographique des start-ups d'IA tend à se concentrer dans les pays et les villes perçus comme des pôles d'innovation, caractérisés par des niveaux technologiques élevés et des économies développées. Lorsqu'on analyse l'impact des pôles d'innovation sur les investissements, les start-ups d'IA reçoivent plus de fonds que leur homologue non IA, malgré la situation géographique. Cependant, les start-ups d'IA situées dans un pôle d'innovation sont moins susceptibles de recevoir des tours de table lourds que celles installées dans d'autres lieux, ce qui suggère que la surprolifération d'entreprises opérant dans le même secteur augmente la concurrence entre elles, réduisant l'effet bénéfique du cluster.

“There is no means of testing which decision is better,
because there is no basis for comparison.
We live everything as it comes, without warning,
like an actor going on cold.”

Milan Kundera

“Emotions are essential parts of human intelligence.
Without emotional intelligence,
Artificial Intelligence will remain incomplete.”

Amit Ray

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1.Introduction

Artificial intelligence's impact on society has been widely explored. Pwc (2008) studied the macroeconomic impact of artificial intelligence, forecasting that in 2030 Global GDP could increase by 14% ($15.7 trillion) due to AI. Venture Capital investments in AI firms have grown dramatically, from $3 billion in 2012, to $75 billion in 2020. 80% of the global VC funding has been absorbed by start-up firms based in the United States and China, followed by firms in the European Union and in the United Kingdom.

This thesis aims at investigating the VC Investments in Artificial Intelligence, studying the determinants of those investments, and both the profile of AI start-ups and Venture Capital companies investing in the field. Before starting the analysis and empirical methods, an introduction of the two key concepts of Artificial Intelligence and VC Investments is necessary. The following paragraphs present definitions and applications of AI technologies, as well as an introduction of Venture Capital Investment, showing key figures such as growth, size, and the related industries.

1.1. Artificial Intelligence

Artificial Intelligence (AI) is a general term that refers to any technology able to perceive the surrounding environment and take decisions to maximize its probability of success while achieving a predetermined goal (Russell & Norvig, 2020). An Artificial Intelligence technology is able to replicate human cognitive ability in problem-solving, decision-making and learning activities (Bellman, 1978), enabling perception, reasoning, and action (Winston, 1992).

AI is already infiltrating in everyday life; examples include deep question and answer systems, machine vision, and digital assistants such as Google's Assistant[1] or Apple's Siri[2]. Thanks to Artificial Intelligence, Machine and Humans are able to collaborate more closely, driving innovation and bringing high-tech solutions from lab to market.

[1] For more information visit: https://assistant.google.com/
[2] For further information visit: https://www.apple.com/siri/

Among key conclusions of PwC's Bot. Me6 report[3] is that AI is no longer primarily perceived as a business tool for increasing automation, but as an emerging technology that may be harnessed to address global concerns, resolving complicated issues plaguing modern society, such as bridging the educational gap, developing treatments for cancer and other diseases, and even addressing issues of gender inequality.

1.2. Classification

The landscape of Artificial Intelligence can be subject to different classifications. A first distinction is related to the approach, strong or weak:

Weak Artificial Intelligence is based on *"as if"*, that is, it acts and thinks *as if* it had a brain. The goal of weak AI is not to create machines that have human intelligence, but rather systems that can operate successfully in some complex human functions, such as the automatic translation of texts. The machine is able to make decisions by processing data without self-awareness and without understanding the real meaning, acting "as if" it were intelligent. Thus, Weak Artificial Intelligence systems are not intelligent themselves but are able to reproduce some complex functions performed by humans. For example, a chatbot conversing tool may seem intelligent, but it has no awareness of himself, nor of reasons why the conversation happens. Since these machines are not capable of thinking autonomously, but only imitates human activities, the presence of man is still fundamental for the correct functioning.

Strong Artificial Intelligence acts like a human mind, performing activities and making decisions with self-awareness. According to Searle's definition, in strong Artificial Intelligence, the machine is not just a tool, if properly programmed, it becomes a mind itself, with a cognitive capacity indistinguishable from the human one. The technology behind strong Artificial Intelligence is called Expert Systems and consists of a series of programs that want to reproduce the performance, and knowledge of expert people in a given field. This branch is much more complex, indeed, so far, the most evident advances have only been achieved in the weak paradigm.

[3] https://www.pwc.com/it/it/publications/assets/docs/PwC_botme-booklet.pdf

The second classification of AI concerns the width and maturity of the application, three categories can be distinguished:

Artificial Narrow Intelligence (ANI) consists of the use of AI for limited objectives, within a specific application domain. These systems are unable to apply in other contexts the knowledge they own. Nowadays, ANI systems are applied in many well-known technologies such as Apple's Siri.

Artificial General Intelligence (AGI) are systems capable of coping with generalized requests, applying the acquired knowledge to different contexts, just like a human being. This field is still very unexplored, as it is difficult to define the functioning processes of human intelligence itself.

Artificial Super Intelligence (ASI) consists of intelligence that equals and exceeds human intelligence in every field. ASI technologies are not just focusing on tasks execution but can have feelings emotions and relationships.

1.3. History & AI Development

The concept of Artificial Intelligence dates back to 20th century, when the famous English mathematician and computer engineer Alan Turning proposed in the article "Computing Machinery and Intelligence" a behavioural test, known as Turing's Test, used to answer the question "Can machines think?" (Turning, 1950).
The AI Discipline was officially created in 1956 during the Dartmouth College Conference in the United State. In this context, many research approached the topic of Artificial Intelligence, having as objective the development of a machine able to simulate human intelligence. Period from 1956 to 1974 was flourishing for Artificial Intelligence research, laying the foundation for Neural Networks and Machine Learning. In the "Golden Age", early investments in AI technology were mostly driven by government initiatives associated with the United States Department of Defence. At the time, economist Herbert Simon projected that, within twenty years, computers would be capable of doing any tasks a man performs.
This Golden Age of AI ended abruptly in 1974 when it became evident that AI expectations could not be met. First experimental results were not promising, the available algorithms were

not able to calculate accurate solutions, especially computer logic and computing power were not ready for AI technologies. During this period, the US Congress loses interest in AI research and significantly reduces its funding, thus shutting down the sector in the first "AI Winter" (Crevier, 1993).

During the 1980s, advances in knowledge-based expert systems enabled previous AI approaches to overcome their limitations, resulting in a rise in R&D and funding dedicated toward this new form of AI.

In 1987, with the failure of the Lisp Machine Market, the whole market collapsed again, owing to the decline of hardware and the expert system's limitations. Like the first one, the second "AI winter" was marked by a decline in government and investor financing, leading the sector to an apathetic period.

A second spring came in 1993, the increase in computing power and the shift towards data-driven AI increased the optimism about these technologies, driving investments again. Blue computer created by IBM to defeat the chess world champion Garry Kasparov, Amazon adopted artificial intelligence in its customer service department, Apple launched Siri, and IBM Watson defeated two of Jeopardy's greatest champions (Santos & Qin, 2019).

Today Artificial Intelligence's investment in research and development are continuously increasing, especially in machine learning and neural network. Investments reflect the positive market sentiment due to advances in computers 'computational power and the amount of data available. Big Data and Deep Learning techniques are driven the innovation process of the most used types of AI such as speech, text and image recognition.

Like all emerging technologies, Artificial intelligence has also been subject to fluctuating investment cycles, called "AI summers and winters (WIPO, 2019). While analysing the evolution of Artificial Intelligence, it would be interesting to refer to the Hype Cycle proposed by Gartner.

As shown in Figure 1.3-2, the Hype Cycle divide the development of a technology into five main phases: Starting from the entry of a new technology as a trigger event (technology trigger), an initial peak of euphoria follows (peak of inflated expectations). When these expectations fail to materialize, a phase of disillusionment occurs (trough of disillusionment); after dark period, a greater awareness of the real commercial applications of the technology follows (slope of enlightenment), the development is now stabilized, and the technology reaches the mass market (plateau of productivity) (Cantamessa & Montagna, 2015).

The development chart of Artificial Intelligence in Figure 1.3-1 follows the Gartner’s model, showing some differences from the theory. First, the presence of two peaks, reflecting the two “Summers” of artificial intelligence, characterized by an increase in euphoria and consequently of funding. These peaks are followed by two inflection points, the two “Winters”. Lastly, the final growth curve turns out to be much steeper than Gartner's forecasts.

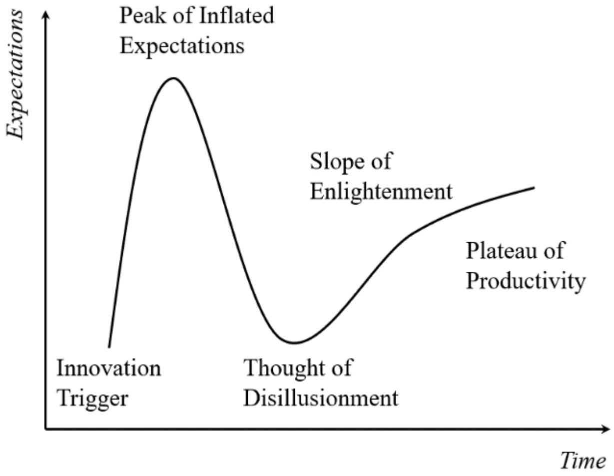

Figure 1.3-2: Hype Cycle; Gartner Model

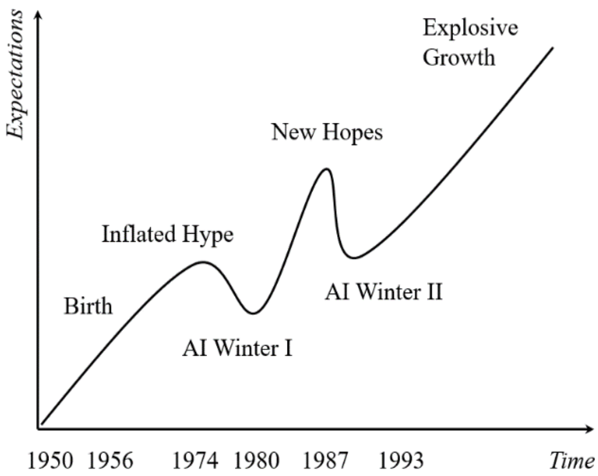

Figure 1.3-1: AI Hype Cycle; A. Stipic, T. Bronzin, B.Prole, Deep learning advancements: closing the gap

Compared to the dynamics of the past, characterized by initial peaks of euphoria then followed by periods of crisis, Artificial Intelligence is intrinsically riskier and depends heavily on investments, necessary to support long-term research activities. Artificial intelligence development curve appears different, “doubled”, if compared to other technologies, mainly because of the combinations of different driving factors (Corea, 2017)

- The exponential growth of the amount of data (big data) necessary to "feed" and improve algorithms.
- The technological progress and the scalability of computational power and computer memory.
- The reduction of technology’s cost, thanks to the democratization and more efficient allocation of resources, for instance through cloud services.

1.4. Research and Development

As underlined above, the development and investment cycle of Artificial intelligence has been subjected to different fluctuations. However, nowadays the opportunities opened by AI seems to be endless, and research's efforts are canalized to deliver new applications and technologies. The increasing popularity of Artificial Intelligence can be quantitatively measured analysing the number of AI papers realised per year. The Figure 1.4-1 shows the Number of AI papers published from 1990 to 2020. The increase in the period can be approximated as an exponential function, having an increase of almost 80% in the last 10 years.

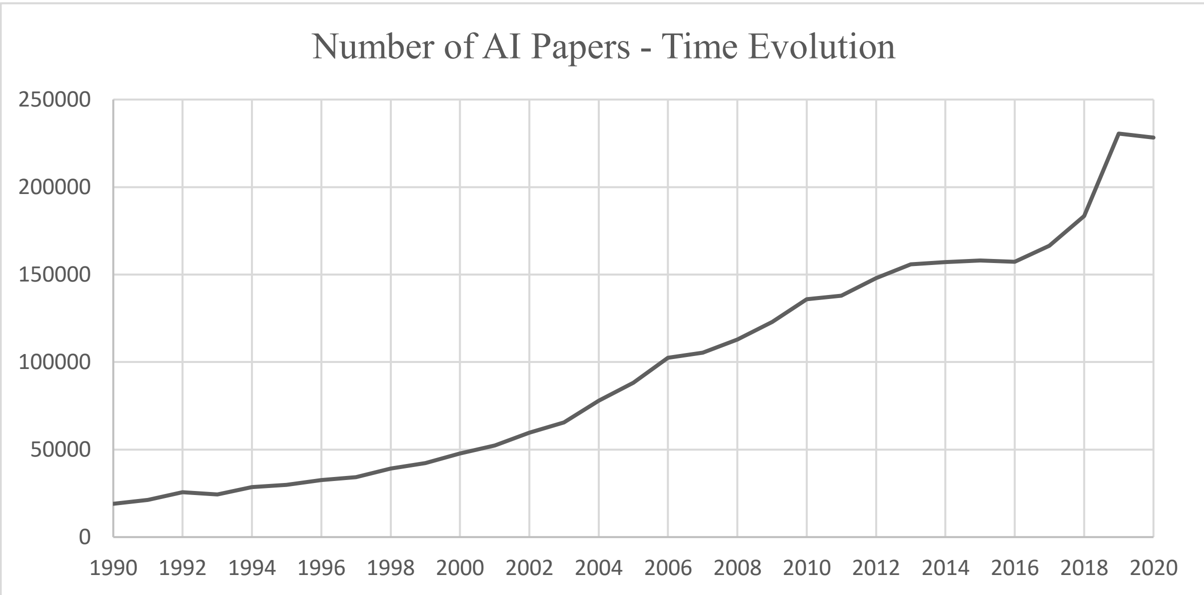

Figure 1.4-1: Evolution of Number of Artificial Intelligence Papers over time
(Artificial Intelligence Index Report , 2021)

The exponential growth can be partially due a general increase in the research effort in all different fields. This effect can be removed analysing the evolution of the percentage of AI papers on the total in Figure 1.4-2, confirming the increase in interest in time. The impact on total publications more than double in the analysed period, counting for 1,8% to 3,3% of total publications from 2000 to 2020.

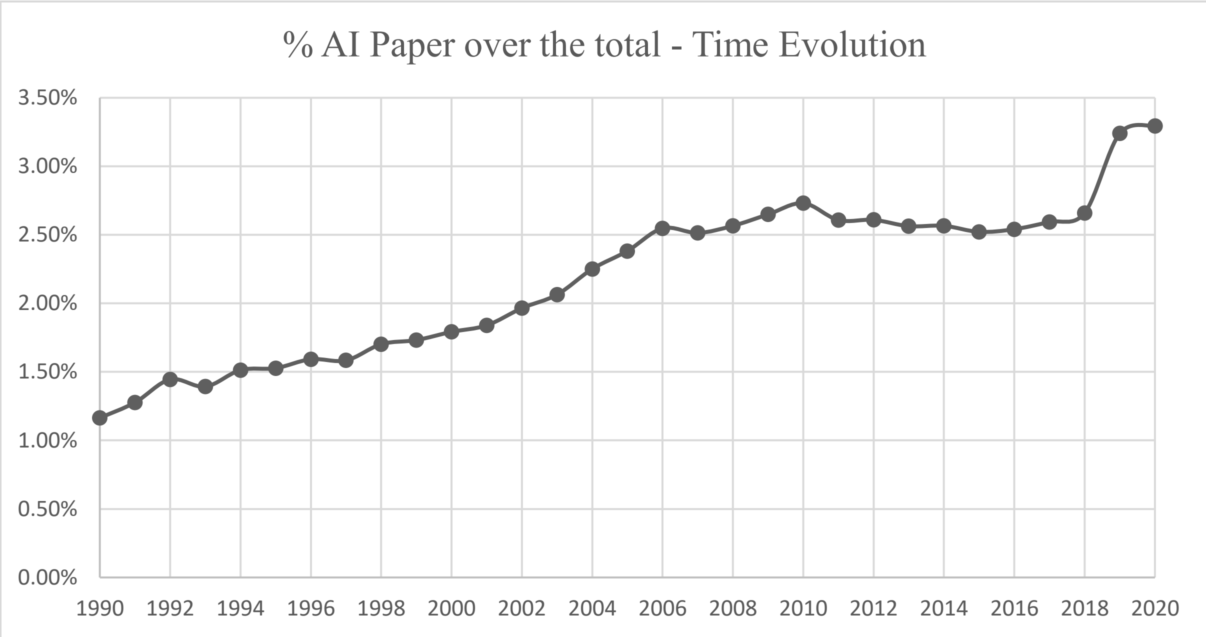

Figure 1.4-2: Percentage of Artificial Intelligence Paper over time
(Artificial Intelligence Index Report , 2021)

Clearly, from the analysis above, interest in Artificial Intelligence increases year after years. However, the growth per country is not homogeneous, and the research is enclosed in three main regions: the United States, China, and Europe, accounting for more than the 65% of the total. In Figure 1.4-3 is displayed the percentage of number of AI paper on the total publication, per year by China, the USA, and Europe. The US is leading the group, overtaking China in 2012. Noticeable is the growth rate of Chinese publication, that more than double in the last decade.

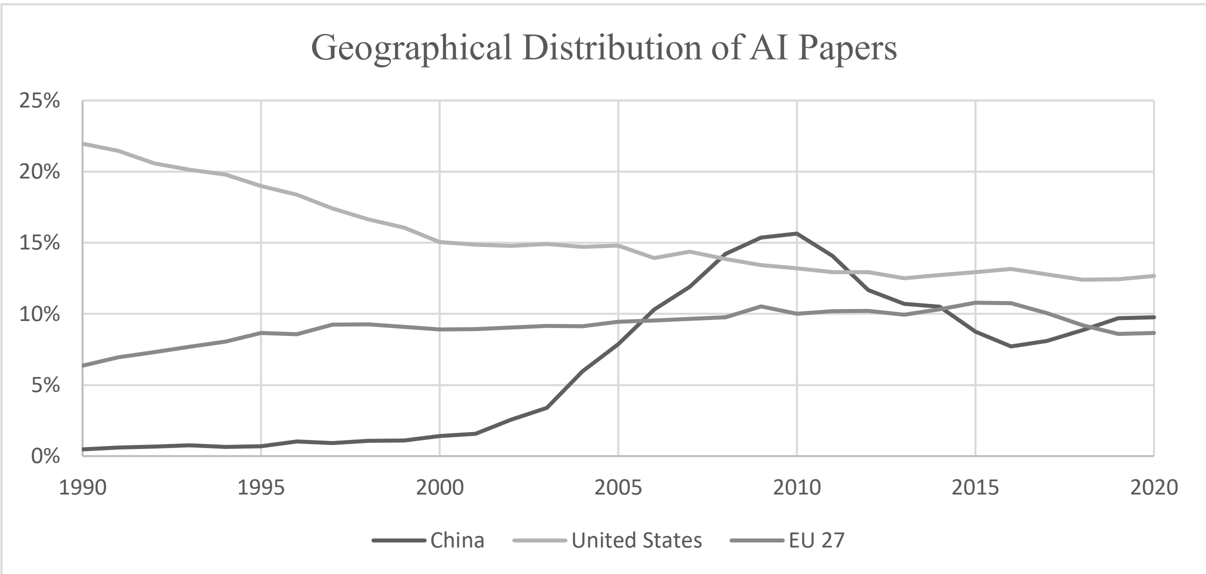

Figure 1.4-3: Top three countries AI Papers evolution over time
(Artificial Intelligence Index Report , 2021)

1.5. Demand and Supply Side

Nowadays Artificial Intelligence is already transforming the way we live and work, and the obvious question of how much these technologies will impact the business arises. The business application of these technologies impacts every level value chain, entirely renovating the business strategy. Moreover, Artificial Intelligence technologies impact both production and consumer side, increasing the throughput as well as the customer satisfaction.

According to PWC (2008), two primary strategies for introducing and implementing AI exist:

1. *"Human-in-the-loop" technologies*: software, systems, and robots that help or enhance the human actives, assisting them in performing their duties more effectively and efficiently and freeing up their time to pursue more exciting and value-adding tasks.
2. *"No-human-in-the-loop" technologies*: automating processes with robots or other technologies or developing autonomous agents that eliminate the need for human being entirely.

The effect on the production side is demonstrated in Table 1.5-1. Many businesses will likely implement a combination of the two strategies, resulting in benefits across the entire value chain, from generating insights in R&D to producing higher-quality outcomes with higher accuracy to increase consumer experience. The effect of Artificial Intelligence on business is an increase in the production efficiency, thus stimulating the overall economy with enhanced products and services.

On the other hand, AI drives also consumptions. The availability of Big Data and intelligent algorithms foster the customers analytics, enabling companies to deliver higher quality products and services. Thanks to AI technologies, customers benefit increase in terms of quality of the product, level of personalization and time required to search the right product, reducing the buying- effort. This results in an increase of customers' demand.

Value Chain	*AI Impact*	*Applications*
Strategy, business model, products, and services *The 'brains' of a company's operations, decision making about offerings, pricing, and go-to-market strategy.*	Reducing the risk, time and capital expended in the process of moving from strategy to execution.	• Simulating market conditions for production forecasts and pricing strategy. • Creating digital mock-ups of product features based on historically successful features/user preferences.
R&D and innovation *Discovery of new information and trends.*	Reducing the runway required before insights are generated.	• Drug repositioning, scanning scientific and clinical research data to identify other uses for drugs already approved.
Purchasing and production Sourcing raw materials and manufacturing	More output or better-quality output using fewer resources.	• Robotics automating assembly lines. • On-demand manufacturing: adjusting to produce goods based on order specifics or turning on/off autonomously
Supply chain and logistics *Getting production resources from A to B and getting the final product to the customer.*	Reducing the time and resources required in these processes.	• Auto-ordering raw materials based on sales patterns and known lead/production times. • Routing emergency vehicles to hospitals based on case criticality, staffing, expertise, traffic, and patient load
Marketing, sales, and customer service *Increasing customer engagement and conversion of customers*	Reducing the information asymmetry between producer and consumer and tailoring messaging accordingly.	• Personalized recommendations of products and services. • AI chatbot customer service agents. • Call center emotion detection and sales practice monitoring.
Enabling functions (finance, IT, risk) *Back-office supporting activities.*	Reducing costs and reducing risks with better planning and forecasting.	• Adverse event monitoring in pharmaceuticals (trends in doctor visits, social media reporting etc.).

Table 1.5-1: Artificial Intelligence impact on the value chain
(PWC , 2008)

1.6. AI's Economic Impact

Clearly Artificial Intelligence technologies are transforming our everyday life, a question about how these technologies will affect our business, consumptions and more in general the economy arises. Traditionally, many researchers attempted to quantify AI's impact on job market and productivity. This section presents some of the key finds according to the most relevant institutions and consulting companies.

According to a report released by Analysis Group (2016) and financed by Facebook, the effects on jobs and productivity are classified into two distinct streams: *direct effects* and *indirect effect* on GDP growth. The direct effect is due to an increase in revenue and employment of companies which develop of manufacture AI technology, while the indirect effect results from other industries implementing Artificial Intelligence in their business model, gaining process efficiency, and at the same time increasing their access to information. They find that a fair range of economic effect over the following decade would be between \$1.49tn and \$2.95tn.

Additionally, the United States' Executive Office report[4] focused on the economic impact of automation enabled by AI. The report acknowledges that generally, technology has increased productivity by reducing the amount of workforce required to produce the same amount of output, and that productivity increases typically result in salary increase, enhancing life's quality. According to this report, the economic impact would not be homogeneous, Artificial Intelligence will impact only certain tasks, in particular automation would replace less-skilled workforce in manual and repetitive activities.

Lately, McKinsey[5] described Artificial Intelligence as production engine, bridging the economic gap. According to the report, automation will boost economic growth by 0.8 to 1.4 percent over the next 50 years. However, in the short term, without an acceleration in productivity development, countries would be unable to reach their ambitions for GDP per capita growth.

[4] Artificial-Intelligence-Automation-Economy.PDF (archives.gov)
[5] https://www.mckinsey.com/global-themes/digital-disruption/harnessing-automation-for-a-future-that-works

According to Accenture[6], Artificial Intelligence will reinvent 'the new normal' as a phase of sustained economic expansion, having the potential to be a completely new factor of production, not merely another driver of Total Factor Productivity (TFP). Thanks to AI, by 2035 growth rates will have double and the US growth rate will be 4.6 percent, rather than 2.6 percent.

Finally, Pwc (2008) studied the overall marginal economic impact due to the implementation of Artificial Intelligence solutions, claiming effects both in the production and consumption side. In particular, Pwc forecast an increase in Global GDP by 14% by 2030, having impact on production and consumption respectively of 7% and 8%.

About the impact of AI in the labour market, there are both optimistic and pessimistic visions. On one side, the positive ones argues that the AI will mainly have an *"Augment"* function, that is, it will enhance the human capabilities, creating new opportunities. On the other hand, the pessimistic view sees AI in optics "*Replace*", foreseeing that it will replace human workforce, destroying jobs and tasks. Thus, AI has a double function of augment and replace depending on the contexts and type of jobs, certain tasks result more difficult for a machine to emulate, and the role of human will acquire the greatest value. In this context, literature defines different levels of intelligence, generating three labour economies (Huang & Rust, 2018):

1. *Mechanical Economy:* in which employment and wages are more attributable to physical, mechanical, and repetitive tasks.
2. *Thinking Economy*: where employment and wages are related to processing and interpreting information in order to solve a given task.
3. *Feeling Economy:* the set of jobs and salaries attributed to feeling tasks exceeds those attributable to mechanical or thought tasks. Feeling tasks consist of communication and coordination of people inside and outside the organization, empathy and the ability to establish and maintain interpersonal relationships.

In this regard, Feeling Intelligence is the most complex for AI to emulate, leading future workforce to be more people-oriented, rather than data-oriented. Thus, in the long term, some functions and occupations will become less useful, and eventually redundant. However, at the

[6] https://www.accenture.com/gb-en/insight-artificial-intelligence-future-growth

same time, AI will support human activities, enabling worker to better asses complex situations, which require judgements and creativity. Simultaneously, various new positions and roles centred on innovation and technology would emerge.
Looking at future strategies, education and training will be essential to hedge against the replacement side of Artificial Intelligence, enabling students and workers to develop the skills required by the new economy.

2.Venture Capital

Venture capital is an equity form of financing in which funds are invested in a firm, typically a start-up or a small corporation, in exchange for minority equity (generally less than 50%) of the company. VC is a sizable subset of a much bigger, more sophisticated segment of the financial landscape referred to as the Private Markets, which is capital invested in ownership shares in private companies. Venture capitals intervene at different stages of the company life cycle: in the development phase (*early stage or seed financing*), when the company need capital to start operations, or in more mature stages (*early growth and scale-up*), when the equity issuance is necessary to expand in the business and become profitable[7].

Venture Capitals play an important role in the challenging global innovation ecosystem. The last decade saw an incredible increase in capital deployed by VC and, at the same time, the number of innovative start-ups receiving these funds have grown significantly. Completely new financial intermediates appeared, for instance Crowd Founding Platforms, Accelerators and "Super-Angels". Nevertheless, financial institutions deployed massive investment into more mature Venture Capital Firms (Lerner & Nanda, 2020).

[7] https://pitchbook.com/blog/what-is-venture-capital

2.1. VC Investment in Artificial Intelligence

According to OECD (2021), despite the coronavirus pandemic in 2020, venture capital investments grew globally, reaching a total of $350 billion for the year.

AI start-ups received more than 20% of all venture capital investments in 2020 and accounted for about $75 billion. The percentage of venture capital invested in AI has risen year after year, over the past decade.
Annual venture capital investments in AI start-ups increased by 28 times from $2.6 billion in 2012 to $75 billion in 2020.
In 2020, US-based and Chinese start-ups account for more than 80% of the value of venture capital investments in AI start-ups, while Europe and UK show an increase in the amount invested but are positioned behind, which account respectively for 4% and 3%.

According to a Forbes article[8], overall financing and the average round size for AI have increased consistently over the last decade. In 2010, the average early-stage round for start-ups focused on artificial intelligence was around $5 million. In 2017, overall funding climbed by more than 200 times to $12 million for first-round early-stage round. In 2021, despite a decline in transaction volume, AI companies raised about $20 billion in investment.

"The venture capitalist (VC) sector tends to forerun general investment trends, indicating the AI industry is maturing. As the AI industry matures, the median amount per investment is growing, there are more very large investments and proportionately fewer investment deals at early stages of financing," (OECD, 2021)

[8]https://www.forbes.com/sites/cognitiveworld/2020/01/05/is-venture-capital-investment-for-ai-companies-getting-out-of-control/?sh=747ebffe7e05

2.2. VC Investment in Artificial Intelligence by Industry

Artificial Intelligence is a wide concept, applied in various sectors and technologies. Distinguishing Venture Capital investments in AI by industries is then necessary for the analysis.

According to OECD (Venture Capital Investments In Artificial Intelligence Report., 2021) firms operating in autonomous vehicles (AV) and mobility attracted the major portion of the AI investments, gathering \$19 billion in 2020 and having a total funding of \$95 billion in the period from 2012 to 2020. These results demonstrate that AI technologies are perceived as a promising solution to the future of mobility, confirming the growth prospect of 31.3% (CAGR 2021-2028) of autonomous vehicles' market.

The second segment by amount invested was healthcare, medicine, and biotechnology, accounting for 16% of the total in 2020. Investment in AI-healthcare sector doubled from \$6 billion in 2019 to \$12 billion in 2020. This remarkable increase can be as explained as a response to the pandemic where innovators in health technology played a significant role. Investment in AI were crucial to drive for faster drugs and vaccine discovery, but also to shift toward virtual care delivery, as well as to deep focus on mental health and well-being.

The third larger industry in 2020, accounting for 11% of total investment, was AI for business processes and support services. In this case, the pandemic drove digital transformation: companies required new solutions in term of automation to redesign processes in a more efficient and cost – saving manner.

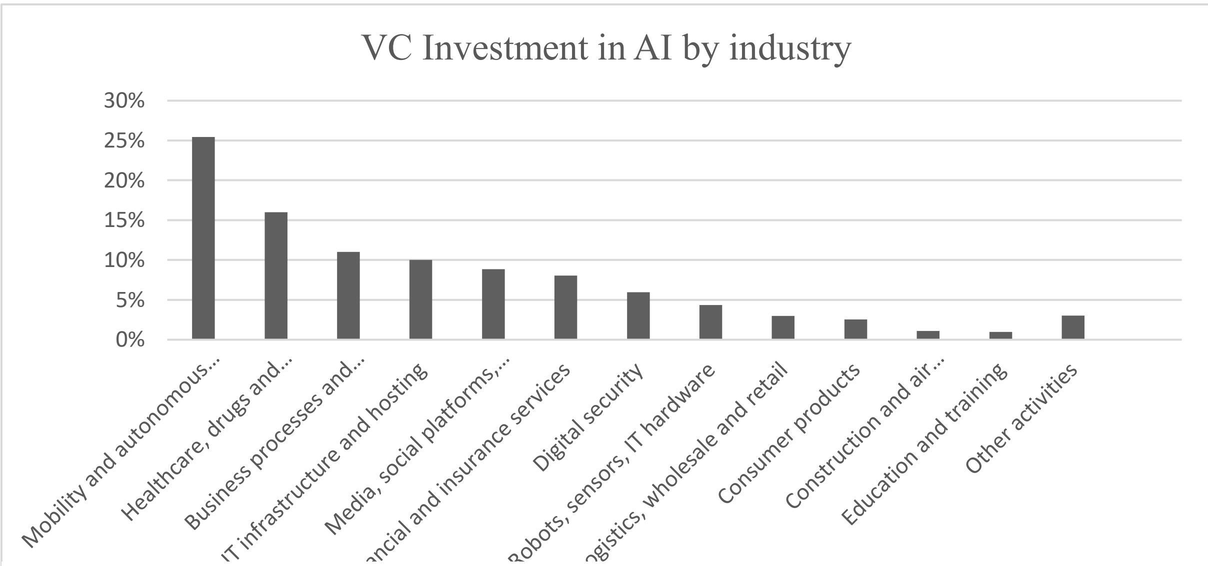

Figure 2.2-1: Venture Capital Investment in Artificial Intelligence by Industry
(OECD, 2021)

Except for mobility and driverless cars – both of which are a priority in the United States and China – Venture capital investments in AI start-ups in the United States, China, and the Europe targeted distinct sectors:

- Investments in the American AI-startups rely mainly in Mobility and Autonomous Vehicle (30%), followed by Health Care (13%), Business Process and Support Services (11%).
- Funds in AI-startups based in China are focused on Mobility and Autonomous Vehicle (41%), Media (13%), Robots, Sensors and Hardware (13%).
- While EU first target is Media (20%), followed by Business and Support Services (19%) and Financial Services (16%).

The "mobility and autonomous cars" industry, more than any other, has been dominated by AI start-ups located in the United States and China. They have raised a total of $ 92 billion during the last decade, accounting for 98 percent of the total. Chinese start-ups attracted 41% of funding, compared to 57% for American start-ups; more specifically, in the last two years, American start-ups raised nearly three times as much funds as Chinese start-ups.

Investment in Media, Social Platform and Marketing are mainly directed to the Chinese-based start-up ByteDance[9], owner of the social media "TikTok". The Chinese start-up raised more than $9 billion in the last eight years, accounting for the large majority of investments. Other start-ups invested in the industry account for a small percentage and are located mainly in China an in the USA.

Investments in Heal Care start-ups seem to be more distributed across start-ups in different countries, in 2020 thirty-three start-ups raised more than $100 million singularly, and are located in the USA, China, Canada, Germany and Israel. However, only four American Start-ups raised more than 300 million in 2020, namely *Tempus Labs*[10] ($550 million), *GRAIL*[11] ($390 million), *Olive AI*[12] ($383 million), *XtalPi*[13] ($319 million).

[9] For further information read https://www.bytedance.com/en/
[10] For further information read https://www.tempus.com/
[11] For further information read https://grail.com/
[12] For further information read https://oliveai.com/
[13]For further information read https://www.xtalpi.com/en/

3.Literature Review

Historically, start-ups relied mainly on bank financing. However, after the financial crisis, because of the structures and the rules of capital markets, venture capital became the main source of funding for new entrepreneurial activities. Start-ups, in fact, cannot afford the high interest rate banks ask nor are they able to provide the hard assets banks require to secure debt (Ziger, 1998).

Nowadays, Venture Capital is the main form of equity financing for early-stage companies, driving start-ups during innovation and development phase. Innovation and financing literature commonly argues that Venture Capital activities stimulate the development of new technology-based companies, such as Artificial Intelligence. Research demonstrated that just after the first financing round, VC activity positively impacted the growth of highly innovative and tech-based start-ups, improving the overall financials, especially increasing sales and number of employees (Bertoni, Colombo, & Grilli, 2011). Venture Capital support is extremely valuable for young high-tech companies for several reasons:

Firstly, this kind of business are the most likely to have founding constrains (Carpenter & Petersen, 2002). Indeed, small tech-based start-ups have restricted access to debt funding, and new equity form of financing are essential to cover soaring cost of capital and to increase in size (Hall, 2002). Given their ability in scouting businesses, Venture Capitals can identify the latent value of innovative companies and support them with the required capital and advice (Chang, 1983).

Secondly, apart from financing, Venture Capitalists provide start-ups with hands-on support in strategical and business development activities, providing helpful business advice (Sapienza, Manigart, & Vermeir, 1996). Literature claims that the first cause of venture failure is week administration, thus, VCs play an essential role in human resource management. Specifically, VCs-backed start-ups are likely to have a higher rate of turnover, since management is generally appointed by the Venture following the strategic interests of the company (Sapienza, 1992; Gorman & Sahlman, 1989).

Finally, companies supported by Venture Capital benefit from a positive signalling effect to other unfamiliar parties. Venture Capital supported start-ups have access to the VC network, hence, they are advantaged by competences and resources of external business partners (Stuart, Hoang, & Hybels, 1999; Colombo, Grilli, & Piva, 2006). This latter aspect is fundamental in the can grant access innovation field, where networking to the latest technologies, increase time to market and favour competences poll (Pittaway, Robertson, Munir, Denyer, & Neely, 2004).

Venture Capitalists have always been interested in risky investment, and research showed the close link between risk-taking and innovation (Hirukawa & Ueda, 2011; Arvanitis & Stucki, 2013; Rin & Penas, 2017; Davila, Foster, & Gupta, 2003). Artificial Intelligence is now considered at the core of the high-tech industry, representing the future of many businesses and sectors. Venture Capital Investment in Artificial Intelligence represents an opportunity risen in recent years, the pandemic acted as driver for digital innovation and automation and, companies and institutions understood its potential benefits. Given the important impact of the AI firms' development on the innovation and growth of economies, VC funds' attention in the AI sector has grown dramatically.

Despite the importance of the topic, the novelty of this investment opportunity causes shortage in the literature. Past research analysed the determinants of VC investments in highly innovative field such as Fintech. Concretely, investigations about the main economic and political determinants concluded that fintech start-ups are more likely to develop in well-developed countries having easy access to Venture Capital financing. Labour market played and essential role in the development, more liquid markets favourite the expansion of fintech start-ups as well as weaker regulation and the absence of a strong financial centre (Cumming & Schwienbacher, 2018; Haddad & Hornuf, 2018; Gazel & Schwienbacher, 2020).
All the previous investigations were conducted applying a regression model on a panel of data (databased divided by years and countries) considering the investment features and market variables to capture the most important factors using the marginal effect and the significancy level.

Following previous papers on Fintech investments, the ultimate purpose of this research is to investigate the landscape of VC investment in Artificial Intelligence start-ups, analysing both the determinants of those investments and the profile of investors and investee. The whole analysis aims to understand the differences between an investment in AI and non-AI start-ups, considering the unique approach of funding AI-related businesses by Venture Capitalists.

Research Questions:

What are the determinants of Venture Capital Investment in Artificial Intelligence start-ups?
Which is the profile of the Venture Capital investing in Artificial Intelligence?
Which is the profile of an Artificial Intelligence Start-up backed by a Venture Capital?

4.Hypotheses

The expertise of a Venture Capital is essential for its success. As underlined above, experienced VC support target start-ups with strategic and human resource management advice, enabling them the access to VC connections and network.
Venture Capitals collect crucial knowledge from previous investment experienced (Dimov & Martin de Holan, 2010; Gompers, Kovner, & Lerner, 2009). Domain-specific expertise is particularly important for the quality of their value-adding contributions, for instance the sectors understanding or phases of growth (Dimov & Martin de Holan, 2010; Gompers, Kovner, & Lerner, 2009).

Hedge et al. (2009) demonstrated that the services provided by more experienced Venture Capital are considerably more valuable if compared to non-experienced VC. In addition, start-ups backed by experienced Venture Capitals faced higher probability of a successful exit, both because the enhanced services received and because of the ability of skilled VCs in scouting market opportunity and targeting the right company to invest in (Sørensen, 2007).
The Venture Capital's reputation has been categorized as another key aspect of success, indeed, start-ups invested by more reputable Venture Capitals have higher likelihood of successful exit such as initial public offering (IPO), a faster access to public market and enhanced efficiency (Nahata, 2008).

Inexperienced Venture Capitals are more inclined to heavily invest during boom periods and invest without prior investment cycle expertise (Gompers & Lerner, 1999). According to conventional knowledge and well-known literature, boom periods in the investment cycle are associated with lower-quality target being funded (Gupta, 2000). Indeed, arguments concerning investor herd behaviour (Scharfstein & Stein, 1990), a loss of investment discipline, and the likelihood of lower discount rates in boom markets all support the idea that companies financed in “hot” markets are consistently weaker than those supported in less active periods. Evidences are shown in the stock market, researches shows that inexperienced investors, using fund manager age as a proxy, may play a role in the creation of tech bubble: around the peak of the tech bubble, investment funds run by young managers are more heavily financed by tech stocks if compared to their more experienced colleagues (Greenwood & Nagel, 2008).

Nanda & Rhodes-Kropf (2012) researched that probability of bankruptcy increases in start-up financed during more active funding period compared to those invested in periods when a smaller number of start-ups were financed. Authors explanation of their finding lies in the fact that less experienced investors are more likely to follow the market during boom period, while more experience Venture Capital would follow a more experimental scouting strategy.

In the last decade, Artificial Intelligence faced a substantial increase in investment. The market wave, as literature suggests, is more likely to be surfed by younger and less experienced Venture Capitals. Additionally, the following analysis will hypothesize that the increasing interest in AI-based start-up would lead VC to choose targets with lower accuracy, then the investment would be less likely to results in successful exit outcomes.

Hypothesis 1: *Venture Capital Investment in Artificial Intelligence has been more pronounced among less experienced Venture Capitals.*

Hypothesis 2: *Artificial Intelligence start-ups are less likely to result in successful exit outcomes.*

Given the high risk held by new-born businesses, Venture Capitals expect high returns, generally gained through capital gains, in the medium-long terms (Bovaird, 1990; Lerner J. , 1994). To address the high-risk level, Venture Capital companies have designed several risk management, target selection, and monitoring measures, first of all syndication strategy.
Syndication in Venture Capital investment is defined as the conjoint investment of two or more venture capital companies to obtain an equity share in a target company, sharing the decision-making process and profits (Wilson, 1968).

The reason behind syndication strategy is twofold: first, Venture Capital tends to co-invest to share the intrinsic / company risk associated to the target company, with the objective of diversify their investment portfolio; then, following the resource-based strategy, Venture Capital firms join an investment together to reduce asymmetry of information and adverse selection, gaining information access and enhancing the target selection and management strategy (Bygrave W. , 1987; Bygrave W. , 1988; Norton & Tenenbaum, 1993; Sahlman W. , 1990; Cumming D. , 2005; Brander, Amit, & Antwiler, 2004).
Another less tangible, but significant reason behind the syndication behaviour is the access to deal-flow. Being able to choose from a large pool of transactions makes Venture Capital in the position to compete for an elevated numbers of deals. This aspect seems to be beneficial for the quality of the deal, granting investment continuity when new Venture Capitals enter the transaction (Bovaird, 1990).
Bygrave (1988) demonstrated that innovation, technological level, stage of development and industry of the portfolio company positively influence the syndication behavior among Venture Capital Companies. When investing in innovative business, the Venture Capitals might not have a comprehensive knowledge of the field, the required actions, or the needed resources (Dimov & Milanov, 2010). In these cases, the Venture Capital own experience is not sufficient to accurately evaluate the deal, thus they seek for external business partners, syndicating (Casamatta & Haritchabalet, 2007)

Syndication behavior becomes crucial to properly fulfill the lag of competencies related to the novelty and innovativeness of investment, proving a disparate set of capabilities useful to properly evaluate the deal (Lerner J. , 1994). Moreover, the co-investment decision minimizes the single Venture Capital Company downsides (Lockett & Wright, 1999) and preserve a competitive edge when time is critical (Deeds & Hill, 1996).

Thus, because of the intrinsic risk associated to high technology investments like Artificial Intelligence and the novelty of the field, the following assessment will test the hypothesis that Venture Capital syndication behavior is more pronounces when investing in Artificial Intelligence startups.

Hypothesis 3: *Syndication behaviour is more pronounced in Venture Capital companies investing in Artificial Investment start-ups.*

Next, past research found that the venture capital activity aimed at supporting the development of young entrepreneurial start-ups may vary according to some country-related variables, ranging from political to legal to economic factors.

In particular, regulation, government incentives and labour market rigidities play an important role, as suggested by many academic papers. Specifically, both Sahlman (1990) and *Bozkaya & Kerr* (2014) found evidence in Europe that labour market rigidities prevent venture capital investing and Wang and Wang (2012) discover comparable findings in other countries, including Asia. The comprehensive analysis of the determinants of VC for 21 countries made by *Jeng & Wells* (2000) found out the critical role of IPOs, government policies, both at the regulatory and investment stage, and market labour regulation.

Numerous past research has shown a correlation between softer regulation and innovation and entrepreneurship. *Saxenian* (2000) linked weaker regulation with the development of innovative and entrepreneurial activities, arguing that the soft regulation and the liquidity of the California labour market were key determinants of the Silicon Valley development.

Moreover, firms in the United States that have recently gone public and are classified as "emerging growth companies" under the JOBS Acts' 2012 show a positive stock market reaction on the announcement date, due to the softer regulation guaranteed by the JOBS Act (Dharmapala & Khanna, 2016). Because opting for laxer regulation results in a favourable stock market reaction, the additional costs connected with laxer investor protection are less than the cost savings associated with the company's decreased need to disclose and comply with more severe legislation.

Levine et al. (2015) demonstrate the increase in costs associated with stringent regulation, proving that cross border acquisitions provide lower anormal returns in countries with tighter labour protection. Additionally, countries with a stronger labour protection counts less cross-border acquisitions.
Finally, Blind (2012) examines the impact of economic, social, and institutional regulations (OECD taxonomy) on innovation, finding that innovation is positively affected by regulation when the latter is able to create additional incentives.

Consequently, we can conclude that to set up and built new businesses, entrepreneurs require dedicated assets and a favourable environment: a skilled labour market and a flourishing business environment is essential for innovative business development (Berger & Udell, 1998; Carpenter & Petersen, 2002; Cosh, Cumming, & Hughes, 2009). Thus, since external resources are a key factor, businesses tend to concentrate in determinate geographic area, “clustering”. McCann & Folta (2008) investigate about the reason of businesses agglomeration, while many past investigation showed that concentration of business lead to many advantages such as cost reduction, labour force pooling and knowledge sharing (Ellison, Glaeser, & Kerr, 2007; Pe'er & Keil, 2013).

Literature stresses the fact that agglomeration favour the pooling of resources and knowledge (Wennberg & Lindqvist, 2010), this is extremely important for business in the high-tech sector, since they operate under different organizational structure, incorporating a more collaborative structure of activity development and knowledge sharing.

Hypothesis 4: *Venture Capital Investment in Artificial Intelligence start-ups has been more pronounced in countries having a major Technological Cluster.*

5. Empirical Method

This Chapter will present the empirical analysis modelled to test the hypothesis developed and based on the literary review.

The first Paragraph will present in detail the Dataset used for the model, the database is built merging two different data sources: Crunchbase for the deal information and a Market Conditions database which represent an aggregation of six families of macro and micro economic variables used as controls.

Then, in the Paragraph Variable Selection & Model Definition, the selected variables are presented and analysed, displaying the main dependent variable (Ln. Round Amount), the main independent (the binary variable Dummy AI), and the control variables selected from the Market Conditions database.

Before the description of the Empirical Methods, the Chapter will present a general overview of the Venture Capital Market investing in Artificial Intelligence, focusing on the geographical distribution and growth of the investment by single country and then by major investment poles in terms of cities.

After a description of the regression base model and the discussion of the descriptive statistics, a preliminary T-test has been performed on the regression sample using Stata Software, to capture differences between the AI and the non-AI investment groups.

Finally, the multivariate analysis will present several regression models used to determine the factors influencing venture capital investment in AI start-ups. The analysis consists in one general "base" model and four different sets of analysis, each broken down into different sub-analysis or models that will describe the landscape of AI investment, the characteristics of venture capital, the characteristics of start-ups, and the geographic determinants.

5.1. Dataset

The dataset used for the analysis comes from the merge of two main data sources: market-inspection and data from CrunchBase containing VC deals.

The Market Condition dataset counts 3,360 rows and assembles variables from the AI Index Report, OECD Database, and the World Bank. The result is a Panel of 168 OECD countries in a period ranging from 2000 to 2020: in this section the macroeconomic variables of an entity, a country, is observed across a 20 years' time period, analysing the evolution of a country's variable across different years.

The latter database has been extracted from CrunchBase and contains the information regarding Venture Capital deals, counting 437,747 rows. The dataset has already been used in previous research, for instance by Haddad, Hornuf (2018) and Cumming at al. (2016). Each row of the database represents a specific deal, pooling information regarding amount invested, industry, investor and investee.

The final dataset is a merge of the previous two, constructed using country code and year as the common key and containing both market and deal information. The deal code is the identifier of each row of the dataset, counting a total of 433,095 deals. For each deal, the dataset display information regarding year, country, investor, investee, and the market-inspection related variables. In order to display if the investee is in AI-industry, a dummy variable was added, having the value 1 if the deal is in AI or 0 otherwise.

In the following paragraphs a detailed description of the two datasets is presented, the final aim was to determine which variables were most appropriate for future investigations such as the t-test and the multivariate analysis.

5.1.1. Dataset: Market Conditions

This first database was entirely constructed in house, merging various data sources from AI Index Report, OECD Database, and the World Bank. The aim of these data is to capture the impact of some macroeconomic variables in the analysis, presented in the form of panel, meaning that the observation of a variable is displayed by every OECD country and repeated for 20 years, from 2000 to 2020.

The market-inspection dataset contains forty-six macroeconomic variables clustered into six families: *Artificial Intelligence Related*, *Business*, *Education*, *Labour*, *General Variables* and *Technological Development*.

In order to define the best control variables for the future regression model, every market variable was analysed in terms of number of observations, mean, standard deviation, minimum and maximum value. Then, the variables with a great (>30%) number of missing were excluded from the analysis to not bias future analysis. Among variables of the same family, correlation was performed to investigate the relationship between market-variables, analysing which variables can be interchangeable in the analysis (correlation near to 1) and which are negatively correlated.

Below a detailed description of the six families composing the Market Conditions Dataset:

1. Artificial Intelligence Related Variables

The AI-family contains indicators describing the development of Artificial Intelligence Technology in different countries. The aim is to investigate the technological dynamism and research status using variables in Table 5.1.1-1

Indicator (Label)	***Description***	***Missing***
Number of AI Patents (NrAIPatents)	Number of patents per year and country *Microsoft Academic Graph, 2020 | Chart: 2021 AI Index Report*	33%

Number of AI Papers (NrAIPapers)	Number of Artificial Intelligence publications, journals, conference publications, and patent. *Microsoft Academic Graph, 2020 | Chart: 2021 AI Index Report*	33%
AI hiring Index (AIHiringInd)	The number of LinkedIn users who have AI skills or work in AI-related fields, divided by the total number of LinkedIn members in the nation. This rate is then indexed to the 2016 average; the index for a year is the average of the indexes for all months in that year. *LinkedIn, 2020 | 2021 AI Index Report*	96%
Number of AI Citations (NrAICitations)	Number of Artificial Intelligence citations of journals, conference publications, and patents. *Microsoft Academic Graph, 2020 | Chart: 2021 AI Index Report*	77%

Table 5.1.1-1: AI Related Variable Description

Then, the correlation between variable was performed in Table 5.1.1-2. The Number of AI Papers has an acceptable level of missing and, as expected, is strongly correlated with Number of AI Citation and Number of AI patents. Thus, the variable is a good proxy for the development of AI, reflecting the technological dynamism of a given country in a given year.

	NrAIPapers	*NrAICitations*	*AIHiringInd*	*NrAIPatents*
NrAIPapers	1			
NrAICitations	0.7394	1		
AIHiringInd	-0.0388	-0.1333	1	
NrAIPatents	0.6894	0.7922	0.0425	1

Table 5.1.1-2: Correlation AI Related Variables

2. *Business Related Variables*

The business-related family is a set of variables introduced to understand the presence of constrains or incentives in opening a new business, a start-up, in a given country. This family account for regulatory effects such as taxation or cost to start a new business, as well as for other determinants, for instance Venture Capital Availability or Number of Listed companies. Table 5.1.1-3 shows the full description of the indicators present in the family, as well as sources and the related percentage of missing in the dataset.

Indicator (Label)	***Description***	***Missing***
Cost of business (CostOpen)	Cost to open a new business divided the gross national income per capita *World Bank, Doing Business Project*	30%
Ease of doing business (EaseBusiness)	Benchmark country's regulatory effect on running business. [0 = worst regulatory effect; 100 =best regulatory effect] *World Bank, Doing Business Project*	78%
Listed domestic companies (ListedComp)	Number of listed domestic companies, excluding Investments Funds, Unit Trusts, Investment Companies. *World Federation of Exchanges database*	53%
New business density (NewBusiness)	New businesses registered each year scaled over 1000 people *World Bank's Entrepreneurship Survey & Database*	59%
Time required to start a business (Timetostart)	Days required to complete the practices to legally run a business *OECD Statistics*	30%
Corporate Tax Rate (CorpTax)	Corporate Tax Rate *World Economic Forum*	9%
VC investments (VCInvest)	Sum of all early stages (including pre-seed, seed, start-up and other early stage) and later stages VC fundings *OECD Statistics*	87%
VC Availability (VCAvail)	"In your country, how easy is it for entrepreneurs with innovative but risky projects to find venture capital? [1 = extremely difficult; 7 = extremely easy]" *World Economic Forum*	90%

Table 5.1.1-3:Business Related Variable Description

Table 5.1.1-4 below presents the correlation between variables in the Business family. Cost of Start-up is negatively correlated with Easy of Doing Business, the Number of Listed Companies and New Business Density and all the other variables those increase would represent a positive impact. The same reasoning can be applied for the variable Corporate Tax Rate, that represents a barrier while creating and developing a business.

	[1]	[2]	[3]	[4]	[5]	[6]	[7]
CostOpen	1						
EaseBusiness	-0.5497	1					
ListedComp	-0.142	0.2451	1				
NewBusiness	-0.1788	0.5279	0.0184	1			
Timetostart	0.3424	-0.4034	-0.137	-0.2234	1		
CorpTax	0.2205	-0.3628	0.2317	-0.1999	0.1903	1	
VCInvest	-0.0778	0.2299	0.5066	-0.1283	-0.1018	0.2427	1
VCAvail	-0.3927	0.4225	0.3122	0.3301	-0.2195	0.0529	0.3134

Table 5.1.1-4: Correlation Business Related Variables

3. *Education Related Variables*

The education family counts variable used to detect the education attainment of a given country. Artificial intelligence technologies necessitate advanced mathematical and programming skills. Creating a business in AI industry imposes not just a strong concept and a solid business strategy, but also technical abilities, which are often provided by engineers, mathematicians, or computer scientists, resulting in a global scarcity of artificial intelligence professionals. For this reason, the education level is an essential factor to be considered while analysing AI-start-ups development. The education family contains variables described in Table 5.1.1-5 extracted from *UNESCO Institute for Statistics*.

Indicator (Label)	*Description*	*Missing*
Compulsory Education Duration (DuraEdu)	Years required to complete compulsory education	11%
Current education expenditure (EduExpen)	Percentage of education expenditure over the total expenditure in public institutions	63%
Bachelor Total (Bach)	The percentage of population ages 25 and over that completed bachelor's or equivalent.	86%
Bachelor Female (BachF)	The percentage of female population ages 25 and over that completed bachelor's or equivalent.	86%
Master Total (Mast)	The percentage of population ages 25 and over that achieved master's or equivalent.	89%
Master Female (MastF)	The percentage of female population ages 25 and over that achieved master's or equivalent.	89%
Expenditure primary education (ExpPrim)	Percentage of total governmental expenditure on primary education	63%
Expenditure secondary education (ExpSeco)	Percentage of total governmental expenditure on secondary education	63%
Expenditure tertiary education (ExpTert)	Percentage of total governmental expenditure on tertiary education	59%

Table 5.1.1-5: Education Related Variable Description

Analysing the correlation between variables of the same family in Table 5.1.1-6 no significant results have been discovered. Moreover, all the variables display a non-conforming level of missing: the percentage of missing observation is so high that would not add significative insides in a regression model. Thus, for further analysis the education family has been discarded, using all the other families as a control.

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
DuraEdu	1.0								
EduExpen	0.1	1.0							
Bach	0.1	0.0	1.0						
BachF	0.1	0.0	1.0	1.0					
Mast	0.0	0.1	0.6	0.6	1.0				
MastF	0.0	0.1	0.6	0.6	1.0	1.0			
ExpPrim	-0.2	-0.1	-0.6	-0.6	-0.5	-0.4	1.0		
ExpSeco	0.0	0.1	0.2	0.1	0.3	0.3	-0.6	1.0	
ExpTert	0.0	-0.2	0.1	0.1	0.1	0.1	-0.4	-0.1	1.0

Table 5.1.1-6: Correlation Education Related Variable

4. General Variables

General variables have been added in the dataset to control for macroeconomic aspects and for the regulatory effect displayed by different countries and years. The economic advancement of an entity may conceivably interfere with the business development, as well as with investment behaviour of a Venture Capital. A detail description of the variables included in this family can be found in Table 5.1.1-7.

***Indicator* (Label)**	***Description***	***Missing***
Adjusted net national income (ANI)	Gross National Income minus Consumption of fixed capital and natural resources depletion *World Bank*	16%
General government debt (GovDebt)	General Government Debt as a percentage of GDP *OECDC (2021)*	76%
CPIA (CPIA)	Transparency, accountability, and corruption in the public sector ranging from 1 (low) to 6 (high) *World Bank*	77%

GDP per capita (GDPcap)	Gross Domestic Production per capita *World Bank national accounts data, and OECD National*	4%
GDP per capita growth (GDPgro)	Annual growth of GPD per capita *World Bank national accounts data, and OECD National*	3%
Population growth (PopGro)	Annual population growth *World Bank national accounts data, and OECD National*	0%
Population, total (Pop)	Total population *World Bank national accounts data, and OECD National*	0%
Time dealing requirements regulations (TimeReq)	Percentage of weekly management time spent dealing with required governmental regulation *World Bank enterprise survey*	91%
R&D tax incentives (RDTaxInc)	Government tax incentive support for business R&D as percentage of GDP *OECD (2020). OECD R&D tax incentives database Report, 2020*	76%
Government budget allocations for R&D (GovRD)	Governmental budget allocation on research and development activities *OECD (2020). OECD R&D tax incentives database Report, 2020*	78%

Table 5.1.1-7: General Variables Description

As pointed out in Table 5.1.1-8, the variables are not related with strong correlation. The intrinsic nature of the variable and the high percentage of missing of regulatory indicator may interfere. Thus, the variables selected as control for the following analysis were those with the lowest level of missing and more correlated with other variables: GDP per capita has 4% missing and it is the one more correlated with government incentives and regulation, and GDP Growth can be another control for the stage of development of a given country, emerging countries would have an higher increase.

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
ANI	1.0									
GovDebt	0.3	1.0								
CPIA	0.1	.	1.0							
GDPcap	0.3	0.1	0.4	1.0						
GDPgrow	0.0	-0.3	0.1	-0.1	1.0					
Pop	0.4	0.0	0.1	-0.1	0.1	1.0				
PopGro	-0.1	-0.2	-0.2	-0.1	-0.1	0.0	1.0			
TimeReq	0.0	0.1	0.0	0.0	-0.1	-0.1	0.0	1.0		
RDTaxInc	0.2	0.4	0.0	0.2	-0.1	0.1	0.0	0.0	1.0	
GovRD	0.2	0.1	0.0	0.5	-0.2	0.1	0.1	-0.2	0.1	1.0

Table 5.1.1-8: Correlation General Variables

5. *Labour Variables*

As underlined in the literary review, the characteristics of labour market is fundamental for both business development and fund allocation. More Liquid markets provide incentives to start-up development and found raising, population has more job opportunities and entrepreneurial spirit. Thus, a labour control should be introduced in a regression model. The variables present in the Labour Family are described in Table 5.1.1-9.

Indicator (Label)	***Description***	***Missing***
Employers (Employers)	Percentage of entrepreneur over the total employment, estimate the entrepreneurial dynamism *International Labour Organization, ILOSTAT database. Data retrieved on January 29, 2021.*	12%
Employers, female (EmployersF)	Percentage of female entrepreneur over the total employment, estimate the entrepreneurial dynamism *International Labour Organization, ILOSTAT database. Data retrieved on January 29, 2021.*	12%
Labour force	Percentage of working people over the total	12%

(LabForce)	International Labour Organization, ILOSTAT database. Data retrieved on January 29, 2021.	
Labor tax and contributions (LaborTax)	Amount of taxes and mandatory contributions on labour paid by the business expressed as a percentage of commercial profits *World Bank, Doing Business project*	37%
Unemployment, total (Unemployment)	Unemployment refers to the percentage of the labour force that is without work but available for and seeking employment. *International Labour Organization, ILOSTAT database. Data retrieved on June 15, 2021.*	10%

Table 5.1.1-9: Labour Related Variables Description

Given the correlation in Table 5.1.1-10, and the percentage of missing, two variables seem incorporate the Labour effect: Unemployment and Labour Tax. The first is correlated with the other Labour variables and can be used as a proxy for all of them, while the latter, even with a higher level of missing, can capture the job market regulation effect.

	[1]	[2]	[3]	[4]	[5]
Employers	1				
EmployersF	0.8442	1			
LabForce	0.0904	0.3556	1		
LaborTax	0.2864	0.1209	-0.0878	1	
Unemployment	0.3756	0.3661	0.044	0.3146	1

Table 5.1.1-10: Correlation Labour Related Variables

6. *Technological Development Variables*

The Technological development family contains variables used to detect the technological vivacity of a given country in a given year. The level of technological advancement is key for growth and expansion of Artificial Intelligence. This technology, indeed, required high level of research, and a large amount of R&D investment. The high-tech import and export are another essential factor to gather the last technology available in the market and to profits on technological spread. Table 5.1.1-11 shows the variables present in the Technological Development family.

Indicator	***Description***	***Missing***
Individuals using the Internet (UseInternet)	Percentage of total population that has actively used internet in the past three months *International Telecommunication Union (ITU) World Telecommunication/ICT Indicators Database*	10%
Patent applications, residents (PatentRes)	Patent applications of residents *World Intellectual Property Organization (WIPO), WIPO Patent Report: Statistics on Worldwide Patent Activity*	44%
Patent applications, nonresidents (PatentNonR)	Patent applications of non-residents *World Intellectual Property Organization (WIPO), WIPO Patent Report: Statistics on Worldwide Patent Activity*	42%
High-technology exports (HightechExp)	Percentage of high-technology exports over total exports *United Nations, Comtrade database through the WITS platform*.	49%
ICT goods exports (ICTExp)	Percentage of ICT export over the total United Nations Conference on Trade and Development's UNCTADstat	21%
ICT goods imports (ICTImp)	Percentage of ICT imports over the total United Nations Conference on Trade and Development's UNCTADstat	19%
Investment in ICT (InvICT)	Yearly expenditure in USD in ICT investment World Bank, Private Participation in Infrastructure Project Database	21%
Medium and high-tech exports (TechExp)	Percentage of medium and high-tech manufactured exports over the total manufactured exports. United Nations Industrial Development Organization (UNIDO), Competitive Industrial Performance (CIP) database	15%
Scientific and technical	Number of articles published in the following fields: physics, biology, chemistry, mathematics, clinical medicine, biomedical	93%

journal articles (ScientArticl)	research, engineering and technology, and earth and space sciences. National Science Foundation, Science and Engineering Indicators.	
Percent of firms that spend on R&D (SpendingRD)	Percent of firms that spend on research and development. World Bank, Enterprise Surveys	97%

Table 5.1.1-11: Technological Development Related Variables Description

After performing the correlation among the family variables in Table 5.1.1-12, ICT export seems to be those that better capture the technological development. Indeed, it shows positive and relatively high correlation with all the other variable, demonstrating to be the most suitable to use in the following models.

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
UseInternet	1.00									
PatentRes	0.10	1.00								
PatentNonR	0.14	0.64	1.00							
HightechExp	0.39	0.20	0.21	1.00						
ICTExport	0.23	0.21	0.19	0.69	1.00					
ICTImpor	0.22	0.18	0.20	0.61	0.87	1.00				
TechExport	0.52	0.23	0.25	0.59	0.55	0.48	1.00			
ScientArticl	0.24	0.76	0.91	0.25	0.22	0.25	0.33	1.00		
SpendingRD	0.07	0.14	0.15	0.02	0.00	0.20	-0.03	0.12	1.00	
InvICT	0.02	0.24	0.30	0.21	0.32	0.28	0.34	0.37	0.51	1.00

Table 5.1.1-12: Correlation Tech Development Variable

5.1.2. Dataset: Deal Information

The Deal Information Database has been extracted from CrunchBase and contains the information regarding Venture Capital deals, counting 437,747 rows. The deal unique identifier has been used as the unique identifier, meaning that each row of the dataset represents a specific deal between a specific start-up and an investor. In an investment round, is one start-up is invested by N investors, the dataset would present N different rows.

The Deal Dataset contains general information regarding the deal, the start-up invested and the investor:

- Regarding the deal, the dataset displays, among other, the fund round name, the year, the type of investment (seed, pre seed, series a, ect…), the amount invested in USD$ and the number of investors in a round.
- Then, the most important information regarding the investors is the Name, the type, the geographic location in terms of Region, Country and City, the total funding of that investor and the funding year. The dataset then presents all the contacts of an investor, such as email or website.
- Finally, among others, companies' information accounts for start-up name, the status (operating, acquired, IPO or closed), the number of funding round received, the total amount of funds received in USD$, the funding year and the industries in which it operates.

In order to capture differences in between Artificial Intelligence related start-ups and non-AI start-ups, a dummy variable called *d_AI* has been added in the database. This variable displays a value of 1 if the start-up operates in Artificial Intelligence business, and a value of 0 otherwise. Considering the total number of deals, deals in Artificial Intelligence related start-ups are the 5.29% of the total, accounting for 22,931 deals.

5.2. Investment & Start-ups Geographical Distribution

The following paragraph will present some descriptive statistics of the variables used in the analysis, starting from a general overview of VC market in terms of growth, funds, and geographical distribution, and then focusing on Artificial Intelligence investment.

Starting from a general overview of the VC market, Figure 5.2-1 represents the geographical distribution of Venture Capitals investment during 2019. As expected, the investment flow is not homogeneous and mainly around most developed country, having a flourishing entrepreneurial activity and favourable regulation: the United States, the European Union and China alone counts more than 80% of the total investment, with the USA leading the group counting alone more 50% of total funding.

When analysis the single country distribution, start-ups located in the *USA, China, Great Britain, India, Israel, Germany, France, Canada, Singapore and Japan* has received the majority of the funds, forming the Top 10 investment group.

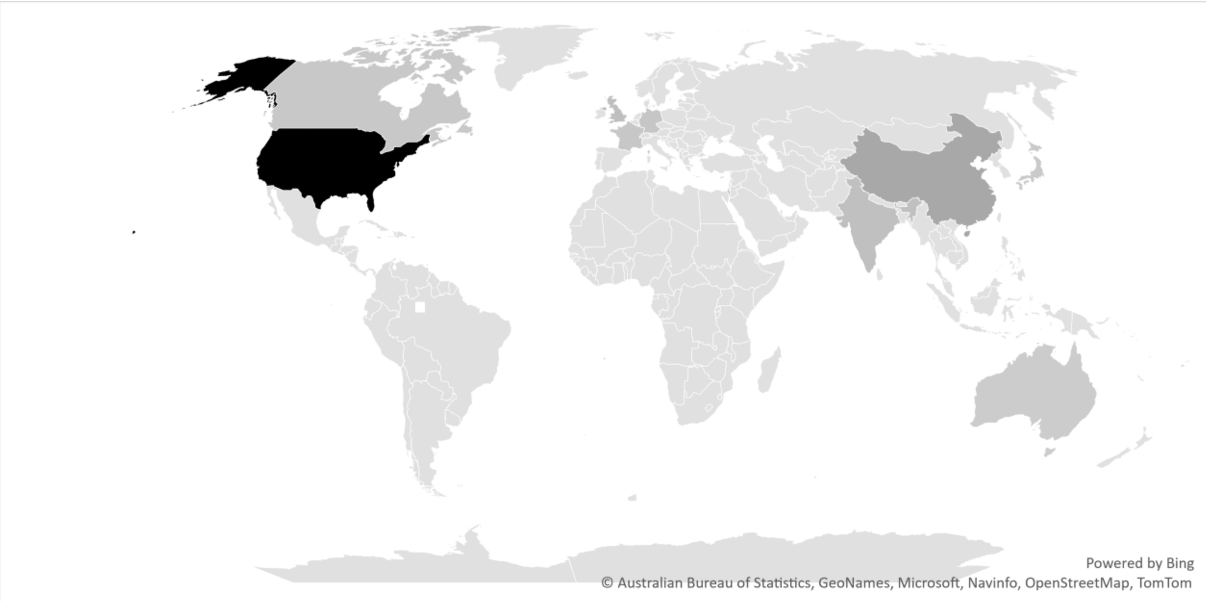

Figure 5.2-1: Geographical Distribution of VC investment

Table 5.2-1 describes the cumulated amount received by start-ups per year and country. Please note that data are displayed in Billions of USD$. The analysis was performed considering the first seven countries by amount invested (*United State, China, Great Britain, India, Israel Germany d and France*). Results are coherent with expectations, USA is leading the investment group (194B$ in 2019), followed by China (36B$ in 2019) and Great Britain (15$ in 2019). In general, the amount invested has significantly increased in all the countries during the period, with the exception of 2019, where covid-19 pandemic slowed down the investment growth.

When considering the growth percentage in the period, USA almost triple the amount invested (x3.9 from 2012 to 2019), while growth in China outperformed other countries: investment increased by a multiple of 18x. Indian and Israeli relative growth during the period is remarkable, VC investments has grown by a multiple of 14x and 12x respectively.
The Compounded Average Growth Rate (CAGR) is 17% for the USA, compared to 50% of China, 27% for Great Britain, 46% for India, 42% for Israel and 32% for Germany and France. Thus, the USA has the primacy in terms of amount invested, but the lower growth rate of the group for the year.

Year	USA	CHN	GBR	IND	ISR	DEU	FRA
2012	65	2	3	1	1	1	1
2013	81	3	3	1	2	3	2
2014	129	12	7	2	2	3	2
2015	172	19	8	8	3	5	3
2016	143	19	8	6	4	6	3
2017	172	30	13	6	6	6	5
2018	215	57	14	10	8	7	8
2019	194	36	15	14	9	8	8
Total	1171	177	71	47	35	40	32

Table 5.2-1: Total Funding Round by Year and County in Billion USD$

The logical continuation of the analysis is that of investigating the amount invested in Artificial Intelligence start-ups. This section will present a geographical distribution of Venture Capital Investment in Artificial Intelligence, the investment amount and relative growth.
Analysing Artificial Intelligence investment only, the geographical distribution of funding is even more concentrate embracing specific countries with an elevated technological level and

developed economies. Figure 5.2-2 displays top 10 countries receiving founds, in order the *United States, China, Great Britain, Canada, France, Israel, Singapore, Switzerland, Germany, and Japan.*

Comparing Artificial Intelligence funding allocation with the whole VC market, the podium remains stable, seeing the USA, China and Great Britain as major beneficiaries. India, the fourth country in the entire VC analysis, exit from the top 10 list, substituted by Canada, receiving about 5B$. France is scaling the ranking receiving about 4B$, absorbing about 5% of funding. Interesting to notice is the presence of Switzerland in the group. Notoriously, besides the extremely attractive taxation system and fiscal advantages for start-ups, in the past years the federation implemented an ambitus Digitalization Strategy comprehensive of a guiding framework on Artificial Intelligence.

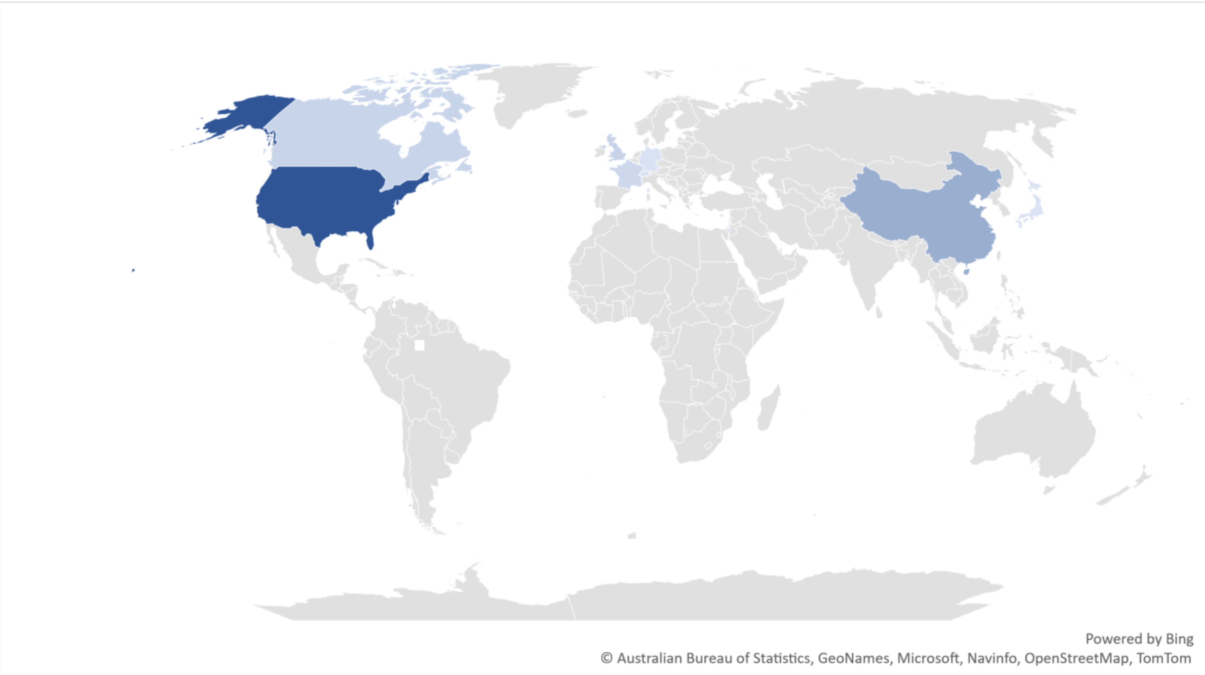

Figure 5.2-2: Geographical Distribution of VC investment in AI firms

Table 5.2-2 describes the cumulated amount received by Artificial Intelligence related start-ups per year and country. As in the previous Table, results are reported in Billions of USD$ invested. Even in this case, United States, China and Great Britain are the greater investors. However, the investment distribution change significantly, Canada and France are rising thought the ranks, gaining the fourth and fifth place. Moreover, when considering Artificial Intelligence start-up, Singapore is becoming a key player, obtaining the seventh position.

Then, analysing the investment growth over the period, China has massively increased its funding in Artificial Intelligence start-ups, scaling from 35,200,000$ in 2012 to about 17,000,000,000$ in 2019, with a percentage increase of almost 50000%. Additionally, the relative growth of Israel is significantly high, increasing its investment by a multiple of x152. These results are surprisingly significant if compared to the relative growth of Artificial intelligence investment of USA, which have growth by a multiple of x31 if compared 2012 and 2019.

Year	**USA**	**CHN**	**GBR**	**CAN**	**FRA**	**ISR**	**SGP**
2012	1.42	0.04	0.05	0.10	0.04	0.02	0.02
2013	3.19	0.01	0.22	0.02	0.16	1.27	0.01
2014	9.12	0.13	0.23	0.11	0.53	0.14	0.10
2015	13.34	0.74	0.93	0.35	1.35	0.30	0.10
2016	14.14	2.39	1.51	0.09	0.45	0.79	0.15
2017	26.90	15.99	3.40	1.31	0.58	1.41	0.17
2018	36.56	24.09	4.61	1.17	1.54	1.31	0.72
2019	45.16	17.20	5.63	5.01	3.77	2.45	1.16
Total	149.84	60.58	16.58	8.16	8.42	7.69	2.45

Table 5.2-2: AI start-ups total Funding Round by Year and County in Billion USD$

Additional growth analysis has been performed in
Figure 5.2-3 to assess the relative change in investment received by relevant countries during the period 2012 – 2019. The Venture Capital investment in Artificial Intelligence start-ups has grown significantly during the period, staring from about 2B$ in 2012 and reaching a peak of almost 80B$ in 2019, with a CAGR of 59%.

The geographical distribution has considerably changed during the period. Indeed, in 2012 the United States absorbed almost the entire investment flow, attracting about 1,4B$ and largely predominating all the other players.

Because of the maturity of the AI technologies, the market hype and the consequent positive investment sentiment, other players started investing in AI start-ups and the market stated soaring in 2017, seeing Chinese start-ups increasing their funding and competing with Americans for supremacy.

From 2017 onwards new countries entered in the rank, absorbing a marginal portion of the investment flow but with a significant growth potential (e.g., Great Britain, Canada, France); however, both China and the USA continue attracting the majority of funds, dividing the market.

In 2019, China was the first country impacted by Covid-19, investors fear triggered by economic concerns and uncertainty caused a slows down in investment of about 7B$. During the year American start-ups attract about the 50% of the funds, while other countries such as Canada multiplied the amount received (5x).

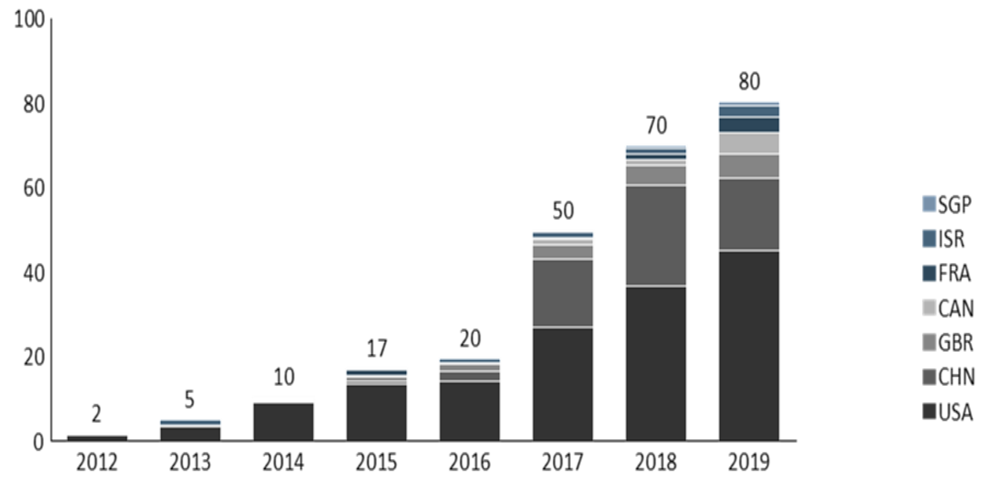

Figure 5.2-3: VC Investment in AI growth

Figure 5.2-4 analysis in more detail the geographical cluster, focusing the investment among cities. The top ten cities by Venture Capital Investment are Beijing, San Francisco, New York, London, Paris, Boston, Austin, Pittsburgh, San Jose and Tel Aviv.

1. ***Beijing, China***

   Zhongguancun, province located in the north-west part of Beijing, also known as the "Chinese Silicon Valley", is China's flagship innovation hub, in 2019 the city attracted about 14B$ Venture Capital Investment in Artificial Intelligence start-ups. Established to promote the domestic high-tech industry, it has grown to become a hub of international influence in the field of start-ups incubation. Funded by Beijing's leadership, it represents one of the focal points for the modernization strategy of the Chinese economy. Alibaba, DiDi, TikTok and JD.com are counted among the most successful domestic and international applications born in the city. Moreover, Beijing is the regional headquarters of many tech giants such as Google, Intel, Sony and many others. The city is also a global distinguished AI educational pole, counting many prestigious technical universities and headquarter of Google's Artificial Intelligence Research centre (2017).

2. **San Francisco, California, USA**

   Proximity to Silicon Valley, tax relief, presence of tech giants and the population demographic make San Francisco a promising environment for the growth and development of tech start-ups. Indeed, AI start-ups located in San Francisco attracted about 11B$ in 2019. Since 2011, the city implemented different initiatives to attract tech-companies starting from a temporary tax relief, that opportunistically exempted firms to pay 1,5% payroll taxes when moving to San Francisco. These initiatives attracted many tech-giant, among other Twitter, Apple, Uber, Salesforce, Airbnb. A part of major companies, San Francisco is the headquarter of numerous start-ups, attracted by the vibrant environment, and technological education. Indeed, the city hosts relevant universities in the tech / AI field such as Stanford, California Institute of Technology, Harvey Mudd, and UCLA. Analysing the demographics, San Francisco population is particularly young (about 40% less than 44 years old) and highly educated, moreover, the genuine interest in technology, made San Francisco professionals early adopter of the latest technological development.

3. **New York, USA**

   NYC tech-industry has largely expanded in the last decade, positioning the city among the top tech-hubs. New Yorkers Artificial Intelligence start-ups has received more than

8M$ during 2019, almost reaching West Coast investment level. Tech-giants as Google, Facebook, Apple, Amazon and TikTok are expanding their offices sqm in the city, with the objective of massively increase the workforce in the next 5 years. Both giants and innovative start-ups can draw talent from prestigious universities focusing on Artificial Intelligence such as Cornel University, New York University and Columbia University. Moreover, in order to fill the competence gap and train thousands of citizens at every expert level, the city organizes different initiatives such as Union Square Tech Training Centre, Tech Talent Pipeline, Fullstack Cyber Bootcamp, etc.

4. ***London, UK***

London is the most important European technology hub, Londoners start-ups attracted about 5B$ of the whole investment flow. The British city shows a favourable technological environment in terms of AI education, technological development, and regulatory polity. Indeed, English government is more than conscious of the potential of AI, a new Artificial Intelligence implementation strategy has been published with the objective of further stimulate the technological growth, maintaining and developing London as a world key technological pole. London AI policy fits into a County context which provides strong initiatives and investments based on three main axes:

a. *resources availability*: to facilitate access to competent people, data, computational capacity and investments in the sector. It follows the need to invest heavily in education in the AI sector (train 50,000 - 100,000 experts in AI to implement the strategy);
b. *social justice*: to ensuring the homogeneous AI development in all sectors and regions of the United Kingdom, so as to maximise the return on investment in the whole country;
c. *management and regulation*: to improve regulatory policy, enabling an effective and efficient management of the adoption of AI systems, ensuring the safety and rights to all citizens.

5. **Paris, France**

Paris boats an extremely attractive Venture Capital environment, gathering the second place in the European panorama: Parisian AI start-ups attracted more than 3B$ investment during 2019. French government put in place an ambitious Artificial Intelligence strategy, covering AI education and training plan and research programs, with the objective of fostering the technological development and getting over future challenges such as employment gap. A part of counting on very prestigious and cutting-edge universities – first of all the École Polytechnique de Paris – the city has a dynamic VC landscape, that favour the development of high-tech start-ups. In 2017 the President Macron unveiled Station F the biggest European incubator, counting more than 34 thousand square meters, hosting about 1.000 start-ups with more than 10 accelerator programs.

6. **Boston, Massachusetts, USA**

   Boston is one of the most important innovation ecosystems, many factors have decreed the success of the Bostonian environment: the location of renowned research centres and universities, such as MIT or Harvard, the elevated concentration of VC and Business Angels and a very dynamic and active financial community. In the last decade, Boston is raising importance in Artificial Intelligence research field, to fuel innovation in bio-tech, manufacturing and robotic industry and continue to be the a worldwide spearheads of these industries. In 2019 start-ups operating in Artificial Intelligence field attracted about 3B$.

7. ***Austin, Texas, USA***

   American well known technology hub, also known as the American capital "Artificial Intelligence". The city boats more then 3B$ invested in Artificial Intelligence start-ups, driven by a flourishing innovation and research environment. Indeed, Austin counts distinguished research hubs and universities in AI field, first of all the University of Texas in the global fifth position for AI education. The university has been selected by the National Science Foundation to lead the "NSF AI Institute for Foundations of Machine Learning and the Machine Learning Laboratory".

8. **Pittsburgh, Pennsylvania, USA**

   Hometown of the concept of Artificial Intelligence, Pittsburgh is putting in place its transition from the "Steal City" into the "AI City", in 2019 Artificial Intelligence start-ups received about 2B$, among the most important Duolingo and Aurora. Pittsburgh offers a dynamic and innovative environment, having an average population age of 33 years old and counting of Carnegie Melon University, graduating the most brilliant computer scientist and software engineers in the USA. Moreover, the city emerges as leader in the "Smart Mobility": Pittsburgh is collaborating closely with the Department of Innovation and Performance to foster the development of AI for intelligent mobility and vehicle-to-vehicle / vehicle-to-infrastructure communication (Mobility as a Service, Autonomous Vehicles, Electric Vehicle, IoT connected devices, etc.).

9. San Jose, California, USA

San Jose is the county seat of Santa Clara in Silicon Valley, the cradle of technology par excellence, at least the first example of a science park in the world and among the most important technology investment poles. Artificial Intelligence start-ups located in the San Jose alone attracted more than 2$ in 2019.

Starting a technology business in a similar environment with a well-established business infrastructure, a pool of talented resources, and a thriving market provides a clear competitive advantage over other locations, among others:

a. *Networking*: many start-ups are founded by employees and partners of established technology giants, facilitating networking and mentorship activities among experts in the same filed and boosting the development of innovative initiatives;
b. *Information Flow*: Silicon Valley provides easy access to the free flow of critical information and is a unique destination to attend seminars, events, product fairs and workshops on technical developments, breakthroughs and next-generation technologies;
c. *Regulation:* Local regulation play an important role in supporting businesses. Silicon Valley has efficient laws and policies to safeguard business interests, trade secrets, and the intellectual properties. Such conditions act as a shield for technology companies, especially for new-born innovative start-ups. The State of California has been feeding this massive ecosystem of technology innovation for over 20 years, programmatically and structurally, granting funds, grants, and the institutions' medium-long-term vision able to create one of the most influential start-ups ecosystems in the world.

10. Tel Aviv, Israel

The investment in children's technological education and public incentives to stimulate entrepreneurial spirit are the main reasons why Israel became the "Start-up Nation", with $2 billion raised only by Artificial Intelligence start-ups in 2019.

In 2020 alone, 15 Israeli companies achieved the Unicorn status, and with 30 already in existence, making up 10% of global unicorns. Cybersecurity, solutions for remote work, big data, med-tech are the main sectors that have attracted large investments in the past years. The entrepreneurial spirit is strongly supported by incentives of the Innovation Authority, which manages investments by the Ministry of Economy in R&D (4.95% of GDP according to the World Economic Forum). In order to increase seed capital investments, the Authority has established a 40% co-financing of the first round, and the Venture Capital can decide whether to return the sum in exchange for shares within three years. Another initiative was to encourage more traditional investors, such as insurance and pension funds, and to act as guarantors of 40% of the investment in the event of bankruptcy.

Figure 5.2-4: AI Investment Breackdown by Top 10 cities

5.3. Investors Geographical Distribution

After having discuss the investment flow geographical destination of Venture Capital investment in Artificial Intelligence start-ups, the following paragraph will focus on the evolution and geographies of AI investors, analysing the absolute number of investors evolution over years and the related geographies.

Figure 5.3-1 shows the evolution of the number of VC investors over the time period 2013 – 2019, focusing on non-AI and AI investor.
The overall VC investors number increases significantly over the period, ranging from about 4.000 in 2013 to more than 7.000 investors in 2019. Venture Capitals involved in non-AI deals have grown from about 3.900 in 2013 to about 6.000 in 2019, showing a CAGR of +7% over the period analysed. On the other hand, AI investors have grown at a higher pace, more than three times non-AI investors, passing from 400 in 2013 to about 1500 in 2019, with a CAGR of +25%. When investigating the percentage of AI investor over the total, the rate of investors choosing to fund the technologies always increases in the period of analysis: in year 2013, AI investors accounted for 9% of the total, while in 2019 for the 20%, doubling their incidence.

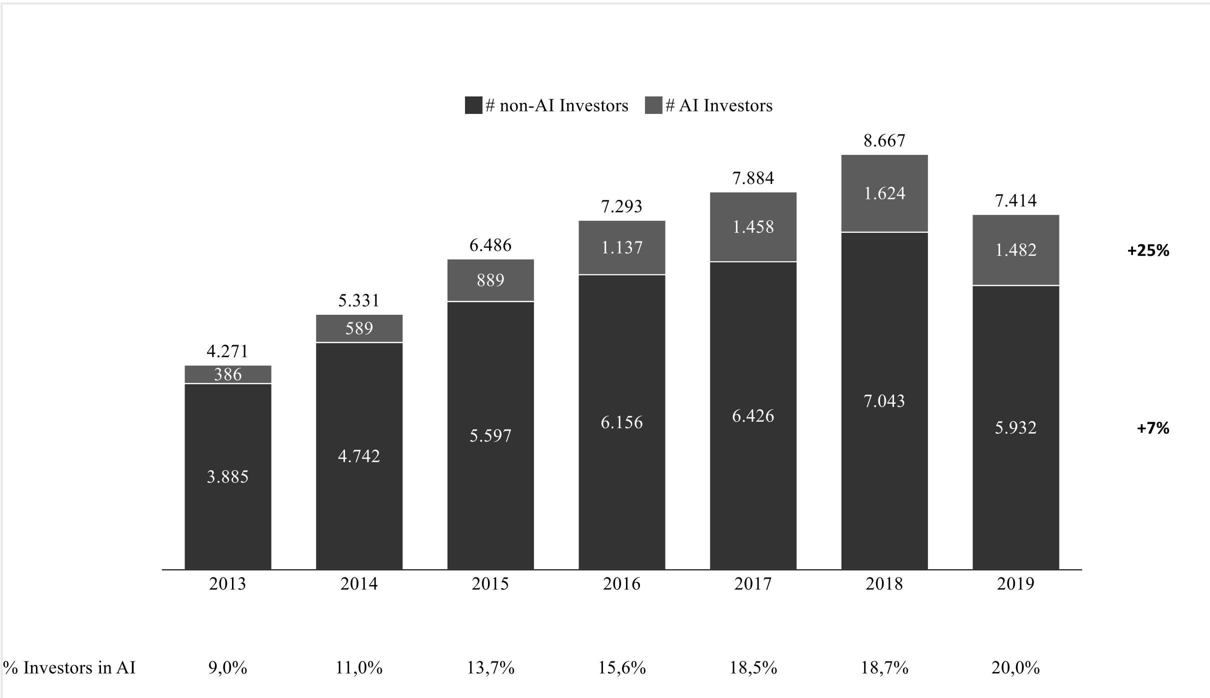

Figure 5.3-1: Evolution of AI and non-AI Investors over time

Figure 5.3-2 is a logical continuation of the above analysis, focusing on the AI-investors only and the related investors geographies.

Locations having the higher number of Artificial Intelligence investors in 2019 are respectively the *United States, China, Great Britain, Canada, Germany, France, Japan, India, and Netherlands.* The top ten countries per number of AI investors accounted together for the 75% of the total, being alone more than 1.100.

In 2013, the investors panorama was dominated by American Venture Capital, counting for about the 75% of the total, leaving little room for other nationality investors. During the period, the percentage of American investors start decreasing, dropping to 58% in 2019, seeing Chinese and English Investors increasing to 11% and 9% respectively. Moreover, during the period of analysis, the nationality diversification of investors investing in Artificial Intelligence technologies increases significantly, indeed, if the USA was predominating in 2013, in 2019 investors origins are more various, including Canada, Germany, France, Japan, India and Nederland.

The growth rate of investors changes significantly in different countries, American AI investors accounts for the majority of the total, always predominating among other geographies, however, display the lower CAGR in the sample (+19%). Chinese AI investors are those risen the most during the period with a CAGR of 85%, demonstrating an increasing interest in the field. Japanese and German AI investors are positioned in the second and third place by growth rate, displaying respectively +51% and + 38% growth rate over the period 2013 – 2019.

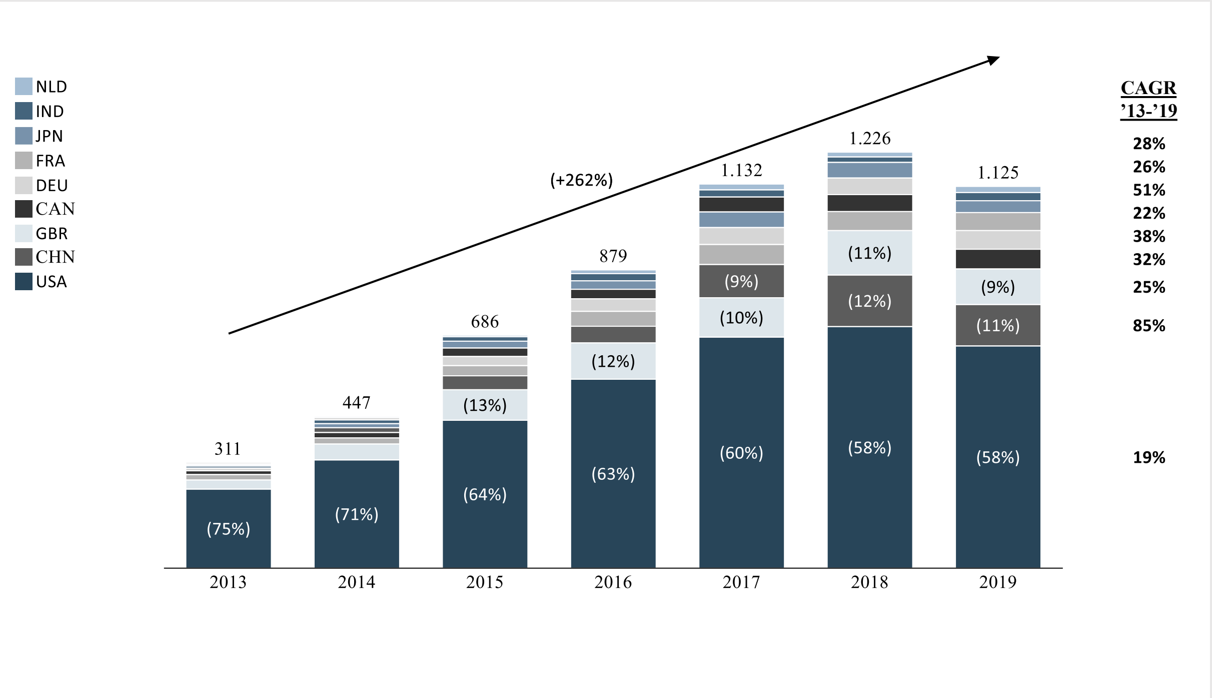

Figure 5.3-2: AI Investors Geographies over time

Finally, Figure 5.3-3 represents a deep dive in 2019, analysing the number of AI and non-AI investors by top-ten countries.

The percentage of investors which have chosen to invest in Artificial Intelligence start-ups over the total number of investors varies from country to country. In particular, the number of American AI investors is the greatest in absolute terms (655 investors), with a rate investing in Artificial Intelligence of 24.3%. The rate increases in other countries, counting less absolute number of AI investors. In particular, 32.4% of German investors, 31.2% of Canadian, 26.9% of French, are investing in Artificial Intelligence field.

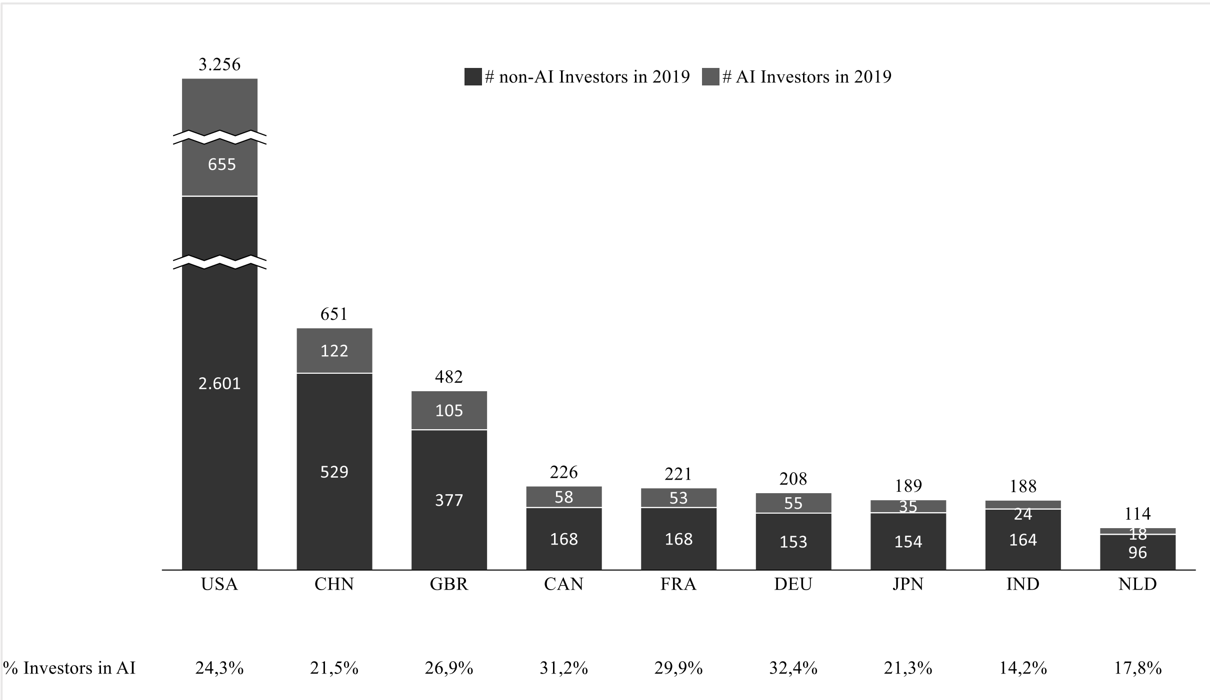

Figure 5.3-3: AI and non-AI investors per country in 2019

5.4. Variable Selection & Model Specification

The following paragraph deeply analyses the variables used in multivariate analysis and that would define the sample used in the descriptive statistics and difference in mean investigation. In particular, this paragraph will present the dependent, the main independent, the control variables and the fixed effects. In the last section the sample used in the "Base" model will be identified. The latter model is particularly important since represents the foundations of all the different regression models used in the multivariate analysis.

The *dependent variable* chosen is *"Log Round Amount"*. It represents the amount in USD$ a start-up received in a given round by a given investor. For each deal in the dataset, the round amount is displayed. A natural logarithm has been applied in order to distribute the variable under a normal distribution, indeed, in an OLS model we assume a linear relationship between variables, and the Round Amount magnitude was expressed in millions.

The *main independent variable* is the dummy *"d_AI"*. This dummy takes the value of 1 if the start-up involved in the deal main field of operation is Artificial Intelligence, and 0 otherwise. The underlined hypothesis is that the amount a start-up received depends on the field of operation of the latter, implying that the investment is driven by the fact that the company is in the Artificial Intelligence field or not.

The model counts ten different *control variables*, used to check if the amount invested is effectively due to the fact that a start-up is in AI or due to other determinants.

- A first control is the *Company Age*, assuming that the amount invested may change according to the development of the start-ups, younger and less developed start-ups are expected to be less likely financed with large amount.
- The *Investor Age* is inserted as a control. As underlined in the literary review, the expertise of a VC is an essential factor to be confided in deal, and we assume that the age can be a good proxy for capturing the expertise of an investor.
- The analysis control for the *Number of Artificial Intelligence Papers*. This variable is the one representative of the Family "Artificial Intelligence Related Variables", and it was used to capture the impact of the development of this technology in the model. The flourishing

of AI research environment may dive the investment decision and the related amount invested.

- Then moving into the "Business Related Family", the *Cost to Open a New Business* has been added to check if the investment decision may depend on the capital required to fund a startup. As expressed, before in the literature, generally VC investment are driven by a relaxed policy, and we can expect that they would invest more in startups located in countries with a lower required cost. This variable is divided by the gross national income per capita, in order to have an acceptable magnitude level.
- Always among the "Business Related Family" the analysis control for the *Corporate Tax Rate*. Indeed, as literature suggests, the tax environment of a given country play an essential role as a diver of Venture Capital investment, they generally tend to invest in start-ups located in countries with less stringent tax burdens.
- Then, moving to the "General Variables", the *GDP per capita* has been taken into account. The variable truck the wealth of a country economy, and the capital allocation may depend on the economic development the country in which the start-up is located. In general, start-ups established in countries with a more developed economy enjoy higher funds.
- Another "General Variable" considered is the *GPD growth.* The variable measures the speed in which an economy grows. The fasted and economy develops, the fasted technological development comes. As literature suggests, Venture Capital investment would be driven by the rate of economic growth of a country, meaning that biggest investment would be expected in companies founded in countries with a higher GDP growth.
- *Unemployment* has been added as a control variable related to the "Labour Family". A More Liquid markets provide incentives to start-up development and found raising, thus an high unemployment level would result in less fund allocated.
- Always among the "Labour Family" the analysis control for the *Labour Tax Rate*. Labour tax may be an important constrain to attract and retain talents needed for the success of an Artificial Intelligence start-up. Regulatory environment plays a crucial role in the fund allocation, thus an high level of labour tax would prevent VC to highly invest in a given country, worried about the subsequent development of the company.
- The last variable belonging to the "Technological Development Family" is *ICT Exports*, measured as a percentage of total exports. The variable captures the level of technological advancement, that is a key features for growth and expansion of Artificial Intelligence

technology. Moreover, export possibilities are a fundamental aspect a Venture Capital should consider when investing in a company, in order to investigate the probability of success and future exit opportunities.

The “Base Model” also include organizations’ country, stage of development and year f*ixed effect*, in order to control for effects not captured by the other variables. The inclusion of these fixed effect, among other things, is used to detect probable disparities in economies of scale and scope between countries, as well as differences in time-invariant business regulations, levels of corruption, and different reporting methods.
Among other things, it is meant to capture possible differences in economies of scale and scope across countries, and differences in time-invariant business laws, level of corruption, and misreporting practices across countries (Djankov, La Porta, Lopez-de-Silanes, & Shleifer, 2002; Johan & Zhang, 2016).

In the formula below is reported the “Base” Regression model used for the estimation of the coefficients. The model used in the following investigation also includes stage of development country and age, fixed effect.

$$\begin{aligned} LogRoundAmount &= \beta_0 + \beta_1 d\_AI + \beta_2 CompanyAge + \beta_3 InvestorAge + \beta_4\, NrAIPapers \\ &+ \beta_5 CostOpenBusiness + \beta_6 CorpTaxRate + \beta_7 GDPperCapita \\ &+ \beta_8 GDPgrowth + \beta_9 Unemployment + \beta_{10} LabourTax \\ &+ \beta_{11} ICTExport + \epsilon \end{aligned}$$

The base model counts 179,629 observations and it is used as a baseline to develop the further multivariate analysis and to investigate the hypothesis developed and based on the literature review.

5.5. Descriptive Statistics

Finally, Table 5.5-1 represents the descriptive statistics of the variables used in the following models. The number of observations ("Obs") used in the analysis is 179,629. Clearly the number is minor if compared to the initial dataset, this is the effect of the regression on Stata, which generate a sample of data, eliminating the missing and considering only the useful observations.

Variable	Obs	Mean	Std.Dev	Min	Max
Log Round Amount	179,629	15.2	1.9	11.3	18.1
Deal Information					
Dummy AI	179,629	0.1	0.3	0.0	1.0
Company Age	179,629	3.9	3.4	0.0	13.0
Investor Age	179,629	12.3	11.7	1.0	42.0
AI Related					
Log n.r AI Patents	179,629	7.7	1.5	0.0	9.1
Business					
Cost Start-up	179,629	2.6	4.5	0.0	141.9
Corporate Tax Rate	179,629	30.8	7.6	0.0	39.1
Market Variable					
GDP per Capita	179,629	46,033.5	17,944.6	379.6	105,454.7
GDP Growth	179,629	2.0	1.8	-14.5	24.0
Labour					
Unemployment	179,629	5.8	2.8	0.1	29.1
Labour Tax	179,629	16.6	12.6	0.0	54.0
Tech. Development					
ICT Exports	179,629	8.6	6.7	0.0	56.6

Table 5.5-1: Summary of Descriptive Statistics

5.6. Difference in Means

In a preliminary analysis, t-tests were performed to capture the difference between AI and non-AI deals. T-test, or difference in means, is an interferential statistic tool used to verify if the mean value of two groups is significantly different. This statistical tool is used in the Hypothesis Testing analysis, and in the following analysis it is performed to capture the difference between AI and non-AI deals. The analysis aimed at spotting differences in the profile of start-ups, the country distribution of the deal, and investors characteristics.

To be coherent and not bias the analysis, the difference in means has been perform using the same sample of the original regression model, having 179,629 total observations and results are shown in

Table 5.6-1.

	Non-AI Start-ups		AI-Start-ups		Diff. Mean Test
Variable	**Obs**	**Mean**	**Obs**	**Mean**	**t-value**
Raised Amount USD	167,074	28,000,000	12,555	17,100,000	6.20
Total Funding	167,074	110,000,000	12,555	54,400,000	8.40
Number of Funding Round	167,074	3.99	12,555	3.87	4.40
Number of Investors	167,074	4.28	12,555	4.66	-11.0
Company Age	167,074	4.50	12,555	2.89	28.15
Investor Age	167,074	13.71	12,555	12.71	6.44

Table 5.6-1: T-test Analysis Results

Firstly, analysing the investment characteristic, the average round amount in Artificial Intelligence start-ups is significantly smaller ($17,000,000) compared to non-AI ($28,000,000). Similar conclusions can be drawn while considering the total raised amount by different organizations: on average the total amount raised by a non-AI start-up ($110,000,000) is significantly larger than the amount raised by AI ($54,400,000). Moreover, non-AI start-ups seem to receive a higher number of founding rounds, that results significant at 1% level.

A larger proportion of AI deals are in the development stage (66.4%) versus non-AI (49.1%). Relatively more AI deals are in the pre-seed, seed and series A stages (3.6%, 39.3%, and 19.9%, respectively) than their non-AI counterparty (1.2%, 27.7 %, and 17.0%, respectively).
When considering organizations, AI companies are significantly younger (average year 2.89) than their non-AI counterparts (average year 4.50).

Analysing investors characteristics, Venture Capital that invested in AI start-ups (year 12.71) are relatively younger than those investing in non-AI (year 13.71), and the difference is significant at 1% level. The number of investors per round is 1% significant level higher (4.3) when investing in AI start-ups compared to non-AI start-ups (4.7).
Moreover, AI companies are more likely to be financed by smaller investors ($370,000,000) if compared to non-AI companies ($460,000,000). While considering the investor type, AI start-ups are often financed by private investors (15.6%), then non-AI companies (12.9%).

In conclusion, key findings of this first analysis highlight that Artificial Intelligence related start-ups are on average younger than their non-AI counterparty, also, due to the novelty of AI investment opportunity, they generally are in an earlier stage of financing.

In addition, Venture Capitals investing in Artificial Intelligence are likely to be younger, less experiences, and generally smaller in size. An interesting finding regards the number of investors per round, indeed the number Venture Capital per round investing in AI tends to be higher if compared to investment in non-AI start-ups, Venture Capitals tend to show a syndication behaviour. Syndication refers to a group of investors pooling their funds to participate in a deal rather than making the full investment alone. This behaviour occurs for three specific reasons: first, the size of the Venture Capital is not sufficiently high to cover the whole investment alone; second, Artificial Intelligence start-ups generally carries an high risk and investors prefer to diversificate their investment and share the risk with other Venture

Capitals; lastly, syndication means that more investors would gather information and analyse the target company, resulting in a more accurate due diligence process.

Even if the difference in means assessment seems confirming Hypothesis 1 and Hypothesis 2 and Hypothesis 3, additional analysis is required. T-test is only used to check if the two groups (AI-start-ups and non-AI start-ups) show a different behaviour, evaluating if a variable mean changes in one group if compared to the other. However, the analysis does not control for other factors, and do explain the reason behind a given phenomenon. A multivariate analysis will explain a functional relationship between a dependent and an independent variable, understanding the determinants of the given phenomenon, also controlling for the effects of other factors (control variables).

5.7. Multivariate Analysis

This paragraph will present the multivariate analysis, in which different regression models were run in in order to capture which are the determinants of VC investment is AI start-ups. In order to properly confirm or reject the Hypothesis, the paragraph will present describes one general of "base" model and four different set of analysis, each divided into different sub-analysis or models that will describes the AI investment panorama, the Venture Capital characteristics, the start-ups characteristics and the geographical determinants. Below a brief summary of the three sets:

- **Base Model:** the base model was run to generally capture the determinants of AI investment, running a full sample OLS model having a dummy as main dependent variable indicating if the start-up operates in the Artificial Intelligence field and control variables controlling for external factors, already described in the variables analysis.

- **Analysis 1 – VC Profile:** the first set of analysis will explain Hypothesis 1 "*Venture Capital Investment in Artificial Intelligence has been more pronounced among less experienced Venture Capitals*". In this section is divided into two regression models, run using different samples to test the hypothesis in first place and to capture the profile of a VC investing in AI start-ups.

- **Analysis 2 – AI start-ups Profile:** this set will test the Hypothesis 2 "*Artificial Intelligence start-ups are less likely to result in successful exit outcomes*". Analysis 2 has been divided into three different models comprehending OLS and Dprobit regressions to capture the overall characteristics of an Artificial Intelligence start-up invested by a Venture Capital.

- **Analysis 3 – Syndication:** the third analysis will test Hypothesis 3 "*Syndication behaviour is more pronounced in Venture Capital companies investing in Artificial Investment start-ups*". The model consists in an OLS regression model, departing from the "Base model" in terms of dependent and control variables. A precise description of the model will be presented in the dedicated chapter.

- **Analysis 4 – Geographical Development:** this sets of analysis have been performed to challenge Hypothesis 4 "*Venture Capital Investment in Artificial Intelligence start-ups has been more pronounced in countries having a major Technological Cluster"*. This hypothesis has been partially confirmed in the geographical overview, however, three addiction models (OLS regressions and the study of marginal effects) has been run to further understand the regional development and the investment flow.

5.7.1. Base Model

Output of the Base Model are displayed in 5.7.1, in terms of variables used, coefficient and significance level. This first analysis consists in a OLS multivariate analysis studying the relative changes of a the Ln.Round Amount (dependent variable) based on the main independent (binary variable called Dummy AI) and control variables. The model also consider country, stage of development and year fixed effect.

Analysing more in-depth factors influencing the investment, binary variable Dummy AI is significant at 1% level, with a positive coefficient, this results can be interpreted as if the start-ups operates in Artificial Intelligence field the Ln.Round Amount would increase by 0,091. Among other factors influencing the investment, the more aged are companies and the Venture Capitals, the more investment a start-up would receive. These results are coherent with expectation, since more mature venture capital probably has most disposable investment capacity to invest and more mature start-ups would be perceived as less risky and attract more funds.
With respect to labour market, the unemployment rate negatively affects the investment flow, meaning that start-ups located in countries with a more liquid labour market, and thus a lowers unemployment rate, would receive higher financing.
Finally, the investment amount depends on the technological development of the country, start-ups born in more technologically advance country would receive higher investment.

The results obtained considering the variable Corporate Tax Rate and Labour Tax may be misleading since can be interpreted as the higher the rate the higher the investment, meaning than start-ups located in countries with a stringent taxation collect higher investment. The reason may be found analysing the regression sample, indeed countries with the higher tax rate are those with the higher number of observations. For example, the average corporate tax rate in the period of analysis is about 35%, considerably higher than the average of the other countries (about 30%), however the USA observation accounts for about the 50% of the total. Another reason may be found in the nature of the index, many countries grant tax relieve to new-born businesses, so that start-ups can benefit for a fiscal incentive for the first years of operations, paying just a percentage of the tax rate.

Variable	Coefficient	Significance Level
Main Independent		
Dummy AI	0.091	0.0%
Start-up & VC Fund		
Company Age	0.020	0.0%
Investor Age	0.010	0.0%
AI development		
Ln. Nr AI Patents	0.018	53.1%
Business Development		
Cost of Starting a Business	0.000	79.9%
Corporate Tax Rate	0.003	0.5%
Market Conditions		
GDP per Capita	0.000	94.2%
GDP Growth	0.005	13.6%
Labour Related		
Unemployment Rate	-0.022	0.0%
Labour Tax	0.010	0.3%
Tech Development		
Percentage of ICT Exports	0.009	0.8%

Table 5.7.1-1: OLS Base Model Output

5.7.2. Analysis 1 – VC Profile

The fist analysis is used to test the first hypothesis, assuming that Venture Capitals investing in AI start-ups are on average less experienced. The hypothesis was based on Literary Review, demonstrating that less experienced Venture Capital are more likely to surf “hot market” opportunities like Artificial Intelligence. Indeed, the industry demonstrate an incredible hype in the last decade, followed by a consistent investment amount growth.

Two OLS models were used to test the hypothesis: the first model was run on sub-sample made by more experienced venture capital, considering investment deals financed by Venture Capital having more than eight years old; the second model considers investments made by less experienced Venture Capital with less than eight years of experience. The threshold of eight years old represent the median age of the entire sample of Venture Capitals.

In Table 5.7.2-1 display model 1 and 2 results. In the first model, those only considering experienced Venture Capital, the binary variable Dummy AI is significant at 5% with a positive coefficient of 0,036. When considering less experienced VC, the dummy variable is significant at 1%, displaying a positive coefficient of 0,13. Thus, the round amount would increase when investing in an Artificial Intelligence start-up, both for less and more experienced Venture. However, the significancy and the marginal effect are quite different, the Ln. Round Around would increase more in case of younger and less knowledgeable Venture Capital.

Thus, the OLS output partially confirm the first hypothesis, considering that less experienced venture capital are keener to invest heavy amount in Artificial Intelligence start-ups that their more experienced counterparty, embracing the thesis of Gompers & Lerner (1999), assuming less expected Venture Capital to be more active during boom periods and investing without a prior cycle expertise.

	Model 1 Experienced VC			Model 2 Inexperienced VC		
Variable	**Coefficient**	**Std. Error**	**P>t**	**Coefficient**	**Std. Error**	**P>t**
Dummy AI	0.036	0.017	3.7%	0.132	0.017	0.0%
Company Age	0.017	0.001	0.0%	0.021	0.001	0.0%
Investor Age	0.007	0.000	0.0%	0.000	0.002	88.8%
Ln. Nr AI Patents	0.004	0.040	91.5%	-0.036	0.041	38.5%
Cost of Starting a Business	0.004	0.003	16.1%	-0.002	0.003	47.8%
Corporate Tax Rate	-0.007	0.002	0.0%	0.009	0.002	0.0%
GDP per Capita	0.000	0.000	6.5%	0.000	0.000	0.0%
GDP Growth	0.003	0.005	58.4%	0.005	0.005	25.6%
Unemployment Rate	-0.043	0.006	0.0%	0.003	0.005	53.2%
Labour Tax	0.002	0.006	76.9%	0.011	0.004	1.7%
Percentage of ICT Exports	-0.002	0.004	66.4%	0.012	0.005	1.5%

Table 5.7.2-1: Analysis 1 – VC start-ups Profile: OLS Model 1 & 2

5.7.3. Analysis 2 – AI start-ups Profile

The flowing section will present three different model used to capture whether the investment is driven by the fact that the start-ups operate in the Artificial Intelligence field or by other exogenous factors.

A first analysis has been performed dividing the overall sample into two sub-samples one having start-ups in early stages and the other with late stages using a dummy variable equal to 1 if the start-ups is in early stage.

Analysing the OLS regressions output on Table 5.7.3-1 of the model run on early-stage start-ups, the main independent variable is significant at 1% having a positive coefficient, meaning that the investment amount is driven by the industry: the Ln. Round Amount increases if the start-ups operate in the Artificial Intelligence field.

On the other hand, the variable dummy AI in not significant when considering start-ups in later stages, and the investment is driven by other macroeconomic factors such as the country development, the labour market, and the technological development.

A possible explanation is that in early stages, the investment decision is more based on trust, and in particular Venture Capitals seek for companies operating in industries with high growth and earning potential (Bachher & Guild, 1996). Thus, industry characteristic plays a fundamental role in investment decision in particular during early stages, in which investors may be biases by start-ups operating in promising industries, that they believe will boost in the medium – long term. Investment decision changes during the development phase, more mature start-ups developed a more consistent business model, solutions portfolio, customers base so that investors can take more informed decisions basing their analysis merging intrinsic business characteristics and industry growth potential.

	Model 1 Early Stage Only			*Model 2 Early Stage Excluded*		
Variable	**Coefficient**	**Std. Error**	**P>t**	**Coefficient**	**Std. Error**	**P>t**
Dummy AI	0.173	0.021	0.0%	0.024	0.015	10.1%
Company Age	0.011	0.002	0.0%	0.021	0.001	0.0%
Investor Age	0.011	0.001	0.0%	0.009	0.000	0.0%
Ln. Nr AI Patents	0.140	0.057	1.3%	0.008	0.032	81.3%
Cost of Starting a Business	-0.014	0.004	0.0%	0.006	0.002	1.2%
Corporate Tax Rate	0.023	0.002	0.0%	-0.007	0.001	0.0%
GDP per Capita	0.000	0.000	35.4%	0.000	0.000	87.9%
GDP Growth	-0.009	0.006	11.4%	0.010	0.004	1.0%
Unemployment Rate	-0.036	0.008	0.0%	-0.014	0.004	0.1%
Labour Tax	0.008	0.006	19.9%	0.002	0.004	69.9%
Percentage of ICT Exports	-0.003	0.009	76.2%	0.006	0.003	8.5%

Table 5.7.3-1: Analysis 2 – AI start-ups Profile: OLS Model 1 & 2

Third model was performed to properly test the second hypothesis regarding the successful exit, running a dprobit regression. In statistics and econometrics, the dprobit model is a nonlinear regression model used when the dependent variable is binary. The objective of the model is to establish the probability with which an observation can generate one or the other value of the dependent variable, directly reading the marginal effects dF/dx.

The objective of the dprobit model is to analyse the impact of the Artificial Intelligence industry on the successful exit probability of a start-up. Thus, the main dependent variable used in the model is a binary, taking the value of 1 if the exit was successful. According to literature, the analysis considers as successful IPO and M&A exits.

In the regression output in Table 5.7.3-2 the main independent variable Dummy AI is significant at 1% level with a negative marginal effect, this result can be interpreted as – the probability of a successful exit decrease if the start-up operates in AI field, thus we cannot reject Hypothesis 2. According to the output successful exits depends on many factors. Firstly, the Ln. Amount is significant at 1% and with a positive contribution, meaning that highly financed start-ups have more probability of an IPO or an M&A exit. Then both start-ups stage of development (company age) and investor expertise (investor age), play a significant role in the exit of a start-ups. The assumption behind these results is that start-ups backed by more experienced Venture Capital can benefit from a wider network of skills and resources, better strategic advice, and investment power. Among exogenous factors, the Cost to Open a new business and labour tax are significant at 1% and 10% level respectively, and demonstrate a negative marginal effect, meaning that start-ups located in countries with a more benevolent regulation on new business formation have more probability of success.

Interesting to notice, comparing Analysis 2 with the Base Model, is that the Ln. Round amount increases when a Venture Capital Invests in Artificial Intelligence amount, however AI start-ups has a lower successful exit probability. The logical consequence may be that the investment provided by Venture Capital is a necessary but not sufficient ingredient of start-ups success. Experience of venture capital in seeking investment opportunity, selecting the target, and accompanying the start-up during its development phase with strategic advice and filling the competence gap is crucial for the success of the business.

Variable	dF/dx	Robust std. Err.	P>|x|
Dummy AI	-0.012	0.003	0.0%
Ln. Round Amount	0.026	0.001	0.0%
Company Age	0.002	0.000	0.0%
Investor Age	0.001	0.000	0.0%
Ln. Nr AI Patents	0.011	0.008	14.8%
Cost of Starting a Business	-0.001	0.000	0.3%
Corporate Tax Rate	0.002	0.000	0.0%
GDP per Capita	0.000	0.000	19.9%
GDP Growth	-0.001	0.001	15.9%
Unemplyment Rate	0.001	0.001	57.5%
Labour Tax	-0.002	0.001	5.3%
Percentage of ICT Exports	-0.001	0.001	26.3%

Table 5.7.3-2: Analysis 2 – AI start-ups Profile: Dprobit Model 3

5.7.4. Analysis 3 – Syndication

In order to test the third hypothesis a different multivariate model has been run, changing the dependent and the controls variables. Before, analysing the regression output, a deep dive of the variables is considered necessary:

- *Investor Count* has been included as the main dependent, the variable counts the number of investors per deal and can be considered as the most precise proxy of syndication.
- Dummy AI, as in the previous model, is the main independent variable. The assumption based on the Literary review is that the innovative and high companies risk intrinsic to the nature of the AI industry may potentially impact the Venture Capital companies' behaviour, which syndicating to reduce information asymmetry, sharing resources.

Then, the model includes six control variables, briefly described below:

- *Ln Raised Amount*, which accounts for the size of the deal, assuming that the higher the funding round the higher the number of investors participating the deal.
- *Company Age* may be considered as a proxy of risk associated to the start-up. Previous literary demonstrate that the stage of start-ups is an essential factor impacting the syndication behaviour, assuming that younger start-ups are in less mature stages of development, thus bearing higher risk. The assumption behind the selected variable is that the more aged are the company, the less the risk, the less the number of investors participating in the deal.
- *Investor Age* has been included since the variable is a proxy of the maturity of the Venture Capital. More mature, thus more expert Venture Capitals, gained Industries and scouting expertise, reducing their need to seek to pool the investment.
- *Ln Investor Total Funding* variable control for the size of the investor. The variable has been included assuming that the Venture Capitals having higher investment power, are those having more resources to properly assess the deal, thus do not requiring other investors resources.
- *GDP per Capita* and *GDP growth* has been included to control for macroeconomic factors influencing the syndication behaviour, considering that in developing countries the information asymmetry may lead investors to cooperate, displaying a syndication behaviour to reduce and share the information risk.

The OLS model is shown below and also accounts for Country, Stage of Development and Year fixed effect.

$$
\begin{aligned}
Investor\ Count \\
&= \beta_0 + \beta_1 d_{AI} + \beta_2 LnRaiseAmount + \beta_3 CompnayAge \\
&+ \beta_4\, InvestorAge + \beta_5 LnInvestorTotalFunding + \beta_6 GDPperCapita \\
&+ \beta_7 GDPgrowth + \epsilon
\end{aligned}
$$

In the regression output presented in Table 5.7.4-1, the main independent variable Dummy AI is significant at 5% level with a positive contribution of 0,21. The results can be interpreted as "the number of investors per deal increases when Venture Capital companies invest in AI start-ups". This result is coherent both with the difference in means analysis and with previous literature indicating that Venture Capitals tend to syndicate when investing in risky and innovative businesses, diversifying their portfolio to reduce potential downsides, and sharing knowledge and resource to better assess the target company. Indeed, Artificial Intelligence investment bear both the market and the technological risk, leading investors to seek other parties with which co-invest, polling their industry and technological knowledge and together fulfil the competences and information gap needed to properly assess and accompany the start-up.

Analysing the impact of controls variables, the syndication behaviour increases significantly with the deal size, the relationships between the two variables is significant at 1% with a positive coefficient of 0,88.

Moreover, as expected, the maturity of the start-ups and the Venture Capital expertise also impact the syndication. The significant level of the two control variables is 1% for both, and the coefficient is negative, meaning that VC investing in more mature start-ups and more expert Venture Capital Companies have less probability to syndicate. Indeed, the information asymmetry is reduced in more mature start-ups which have already been invested in previous rounds and display more detail historical information and already passed through a due diligence phases. In addition, more expert Venture Capital companies may have gained in previous investment cycle the required technological and industry knowledge, do not requiring additional parties to properly assess and finance the target.

The same reasoning may be applied analysing the impact of the size of the Venture Capital firms, the coefficient is negative (-0,06) and significant at 1% level. This result demonstrate that size negatively influence the syndication behaviour, the more the financial resources held by a VC, the less the need of risk and profit sharing, the less the number of investors required for a deal.

Finally, moving to macroeconomic variable, syndication behaviour is less pronounced in countries with an elevated GDP per capita (5% level of significancy). Indeed, investors located in more developed countries tend to have more financial resources, and less asymmetry of information, reducing the adverse selection bias.

Variable	**Coefficient**	**Standard Error**	**Significance Level**
Dummy AI	0.210	0.089	1.8%
Ln Raised Amount	0.884	0.015	0.0%
Company Age	-0.055	0.004	0.0%
Investor Age	-0.017	0.001	0.0%
Ln Investor Total Funding	-0.060	0.010	0.0%
GDP per Capita	0.000	0.000	2.7%
GDP Growth	0.009	0.022	67.8%

Table 5.7.4-1: Analysis 3 – Syndication: OLS Regression Model

5.7.5. Analysis 4 – Geographical Development

The following section analyses the geographical development of Venture Capital investment in Artificial Intelligence start-ups, specifying the benefits arising from clustering and testing the fourth hypothesis. As detailed in the Literary Review, business tend to agglomerate in "clusters" to gain economy of scale and scope, for resource pooling and knowledge sharing. This evidence seems particularly true for small high-tech businesses, that require capital and knowledge intensive operations.

The hypothesis has been partially confirmed in a preliminary analysis performed in the geographical distribution chapter, demonstrating that the investment flow in AI start-ups is highly concentrated on countries and cities with a flourishing and dynamic technological environment, known as technological hubs.

To further investigate the hypothesis, a binary variable called "Tech – Centre" has been created, taking the value of 1 if the Venture Capital invested in a start-up located in a technology hub, and the value of 0 otherwise. United Stated, China, Great Britain, Japan, Germany, France and Korea are considered as tech centre according to the definition of World Intellectual Property Report. Then, a margins pairwise comparison - .margins i.d_AI#i.d_techcentre , pwcompare(pveffects) – has been performed on the fit "Base Model". This model compares all the possible combinations between the two dummy variables, Dummy AI and Tech – Centre, on the regression model obtaining in total six effects.

The margins pairwise comparison results are displayed in Table 5.7.5-1, and they may be interpreted as following:

- *Non-AI start-up in a Tech-Centre vs. non-AI start-up not in a Tech-Centre:* the effect is significant at 1% with a negative contrast of -0,119. Thus, start-ups non-operating in the Artificial Intelligence field are disadvantages if located in a tech-hub, receiving less investment amount. This result is coherent with expectation since the concept of Artificial Intelligences embraces most of the products or services considered as high-tech; a start-up having a different core business may not enjoy the benefits specific for high-tech environment, the business development requires different knowledges, capabilities and network.

- *AI-start-up not in a Tech-Centre vs. non-AI start-up not in a Tech-Centre:* the effect is significant at 1% and with a positive contribution of 0,068. Stripping out the effect of a tech-hub, on equal footing, AI start-ups receive more investment than their counterparty not operating in the Artificial Intelligence field.
- *AI-start-up in a Tech-Centre vs. non-AI start-up not in a Tech-Centre:* in this pairwise comparison the effect is not significant, thus not impacting the analysis.
- *AI-start-up not in a Tech-Centre vs. non-AI start-up in a Tech-Centre:* the effect is significant at 1% level, showing a positive contrast of 0,186. AI start-ups not located in a tech centre receives higher fund amount than a non-AI start-up located in technology hub. As underlined above, non-AI start-ups do not directly benefit from a tech-centre, and the investments those business is generally poorer than those in Artificial Intelligence.
- *AI-start-up in a Tech-Centre vs. AI start-up not in a Tech-Centre:* the effect is significant at 1% level with a negative contrast of -0,072. The interpretation is that artificial intelligence start-ups located in tech-centre received less funds. This result may seem contradictory since previous chapters underline the importance of resource pooling and knowledge sharing gathered into a cluster of businesses. However, we can conclude that the majority VC investments flows in regions known to be innovation hubs, where an incredible number of start-ups born and develop. The over-proliferation of businesses causes a competition increase, and the consequent fragmentation of the investment received. Thus, also according to literature, businesses tend to cluster in region with a high resources' availability, favouring economies of scale and networking activities, however an elevated amount of start-ups operating in the same field increases the competitions, reducing the cluster beneficial effect (Wennberg & Lindqvist, 2010).

d_AI#d_TechCentre	**Contrast**	**Standard Error**	**t**	**P> |t|**
(0 1) vs (0 0)	-0.119	0.012	-9.79	0.0%
(1 0) vs (0 0)	0.068	0.025	2.67	0.8%
(1 1) vs (0 0)	-0.005	0.018	-0.27	78.5%
(1 0) vs (0 1)	0.186	0.027	7.02	0.0%
(1 1) vs (0 1)	0.114	0.014	8.25	0.0%
(1 1) vs (1 0)	-0.072	0.029	-2.47	1.0%

Table 5.7.5-1: Analysis 4 - Geographical Development - Pairwise Margins Comparison

6. Conclusions

Investors, governments, and companies are increasingly interested in the Artificial Intelligence field, perceiving the technology as a key enabler for a paradigm shift and digitalization objectives. The Venture Capital investment in Artificial Intelligence start-ups has grown significantly during the period, staring from about 2B$ in 2012 and reaching a peak of almost 80B$ in 2019, with a CAGR of 59%.

A preliminary analysis phase consisted in analysing the investment round amount received by start-ups operating in AI field. When analysing the difference in means between AI and non-AI start-ups through a t-test, results show that on average the investment received by Artificial Intelligence business is smaller than the non-AI start-ups. T-test is only used to check if the two groups (AI-start-ups and non-AI start-ups) show a different behaviour, evaluating if a variable mean changes in one group if compared to the other. However, the analysis does not control for other factors, and do explain the reason behind a given phenomenon. A multivariate analysis has been performed using control variables described in Paragraph 5.4 considering the effect of different countries, stage of development and years, demonstrating that on equal footing, the round amount increases significantly if the start-up invested operates in the Artificial Intelligence field, confirming the industry as a key investment driver.

The objective of the first hypothesis was to investigate the intrinsic nature of Venture Capital investing in Artificial Intelligence, surfing the market wave. The key assumption from Literary Review is that inexperienced Venture Capital are more likely to heavily invest during booms periods without prior market cycle expertise, convicted to make profits from industry expansion.

The results gained in the t-test analysis tend to confirm this hypothesis, underling that Venture Capitals investing in Artificial Intelligence start-ups are more likely to be smaller in size and younger. Moreover, the number of investors per round is significantly higher compared to non-AI deals, suggesting a syndication behaviour. Smaller and less experienced Venture Capitals syndicate to be able to cover the investment despite their size, to diversificate the risk associated to a high-tech investment like Artificial Intelligence and to gain more market information, reducing asymmetry during a target due diligence phase. The multivariate analysis confirms the hypothesis, underling that less experienced Venture Capital, tend to invest more in artificial intelligence start-ups than their more experienced counterparty.

As underlined in the Literary Review, Venture Capital experience is a key factor for the success of start-up. Past literature proved that services provided by more experience Venture Capitals have to be considered as more valuable and, because of their enhanced services and their ability in scouting market opportunities and targets, start-ups backed by experienced VC have more probability of success.

Thus, a reasonable consequence was to test the effects of less expertise in the success of a small business. The dprobit outcome confirmed the second hypothesis assuming Artificial Intelligent start-ups are less likely to results in successful exit. Indeed, despite the pure financial benefits, Venture Capitals provide strategic and human resource management advice, connections, and network, able to accompany small business during their development phases.

Moreover, analysing the investment in early stages Artificial Intelligence start-ups versus those in more mature start-ups, results demonstrate that industry specific characteristics impacted the investment amount only when considering less mature business. This result is consistent with previous literature, stating that investment decisions on early stages are more based on trust, in this case the potential growth and expansion of the AI industry may be considered as a key driver for investors decisions.

Finally, the fourth hypothesis investigate the geographical distribution of the investment flow, both in terms of absolute value and assimilated by individual start-ups. A preliminary analysis performed in Descriptive Statistics chapter examines the difference among the Venture Capital funds destinated to Artificial Intelligence start-ups and the overall investment. Analysing Artificial Intelligence investment only, the geographical distribution of funding is even more concentrate embracing specific countries with an elevated technological level and developed economies: top 3 country per overall investment remains stable in the rank (USA, China, and Great Britain), followed by Canada, France, Israel and Singapore which are gradually absorbing the investment flow, growing at rapid pace.

Further investigation has been performed dividing the investment by regions, discovering that a great percentage of funds received by a country flow into specific areas, creating a cluster of start-ups. Artificial Intelligence start-ups invested by a venture capital are generally located in innovation hubs, and the majority of investment focuses on Beijing and California, known as technology centres par excellence. With respect to policy implication, the variable Unemployment is significant at 1% showing a negative coefficient in the majority of the models presented, meaning that start-ups receiving higher fund amount are located in countries with a more liquid labour market. This result is consistent with previous literature, in particular Sahlman (1990) and Bozkaya & Kerr (2014) found evidence in Europe that Venture Capital companies are less keen to invest in start-ups located in countries with a more rigid labour market, while Wang & Wang (2012) found similar evidences in Asian markets. Following the same logic, *Saxenian* (2000) argued that the liquidity of Californian labour market was a key factor for the development of innovative and entrepreneurial activities. When considering the Technological Development, the variable ICT Export play a crucial role, demonstrating that the investment flow is canalised towards countries having a flourishing technological environment and favourable trade policies. The previous output is in line with past literature, suggesting that innovative and digitalized environment is essential for the development of tech businesses (Saxenian, 2000; Cumming & Schwienbacher, 2018).

The logical consequence of the analysis is to understand the role an innovation hub plays in the development of a business. In the Chapter Multivariate Analysis, a pairwise margins comparison has been performed to capture the impact of location into the investment decision. The results demonstrate that stripping out the effect of a tech-hub, AI start-ups receive more investment than their non-AI counterparty. Moreover, start-ups non-operating in the Artificial Intelligence industry are disadvantaged if located in an innovation hub, they require different competences and network to develop their capabilities. Finally, AI start-ups located in an innovation hub are less likely to receive heavy round amount, than those settled in other locations. Thus, the over proliferation of businesses operating in the same industry increase the competition among them and the wide investment possibilities fragmented the fund allocation across an increasing number of start-ups.

To conclude, innovation hubs may be beneficial for Artificial Intelligence small businesses, in terms of economy of scale, scope, network expansion and competence sharing, however the elevated number of start-ups increase the competition, reducing the fund received by businesses and thus the beneficial effect of being in a dynamic and innovative environment.

7.Limitations and Future Research

Crunchbase dataset is very accurate and complete, however, another source would be useful to capture discrepancy, verify consistency of the analysis and update results to a more recent date. Indeed, Crunchbase dataset at disposal contain a series variable describing start-ups, investors, and deals characteristics until 2019. It would be interesting to analyse a more updated database also to capture the impact on AI Venture Capital investments of exogenous events such as Covid-19 pandemic, inflation increase, energetic and raw material crisis. A difference in difference analysis would compare investment behaviour before and after the critical event, better explaining the resilience and shifts of the market.

With respect to the Market characteristic database, variables having a lower missing level should be integrated both on the Artificial Intelligence and to the Business-related family. In particular, variables describing the tax relief or other forms of regulatory or governmental concession that would favour the born and development of start-ups in a given country. For instance, the variable R&D tax incentives describes government tax incentive support for business R&D as percentage of GDP, the higher R&D spending drives innovation and leads to formation of new business and further the inflow of funds from VCs. This variable was inserted in the Market Conditions database, however, the elevated number of missing would have negatively impacted further analysis, thus it has been excluded from the regressions model.

Moreover, additional variable could be useful to evaluate the quality of the investment. As underlined above, apart from the financial support, Venture Capitals accompany start-ups during all their maturity phases, proving strategic support, expanding their capabilities and network. An aggregated indictor which captures the adding value provided by investor, thus the quality of the support received by a start-ups, should be used to evaluate the overall support provided and the impact on Artificial Intelligence start-ups exit.

Finally, Artificial Intelligence is a wide concept, embracing multiple sectors. Another possible analysis could classify AI start-ups by sectors of application of the technology and replicating the paper of Haddad & Hornuf (2018) about fintech start-ups, transposed into Artificial Intelligence field.

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