The role of Corporate Venture Capital and of geographical location on startups' successful Exit: the case of artificial intelligence and information technology startups

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ABSTRACT

English

Corporate Venture Capital (CVC) is a diffused practice among incumbents, funding startups to exploit synergies. CVC is increasingly oriented towards funding new emerging disruptive technologies: the current Digital Era calls for innovating and keeping up with the contextual evolution. Among the new Information Technology (IT) solutions, Artificial Intelligence (AI) is catalyzing the new disruptive context. AI can indeed find a broad scope of application across business functions and industries. Previous literature has analyzed the emergence of CVC practice within the IT and AI context. However, this study aims to add new elements to previous research, deeply exploring the relationship between CVC and AI startups and measuring the extent to which this relationship impacts on startups' successful exit, while accounting for the degree of innovation of startups' locations, also expected to contribute to startups' success. Indeed, startups' success also depends on their qualities and on the ecosystem in which are located; more active ecosystems may offer more innovation opportunities. The Hypotheses are tested on a sample of 108,441 investments allocated on 39,502 AI startups, founded between 2000 and 2019; the startups are located among 183 Countries, assigned with innovation indices, according to the Global Innovation Index by the World Intellectual Property Organization. We find that the degree of innovation of AI startups' location significantly and positively impacts the startups' probability to succeed, moving from less to more innovative areas. Moreover, CVC's presence significantly and positively impacts AI startups' probability of successful exit too. CVC investments contemporarily positively moderate the location effect.

Portuguese

O Corporate Venture Capital (CVC) é uma estratégia adotada por grandes empresas para financiar startups com o objetivo de explorar sinergias. Atualmente, o CVC tem-se focado em novas tecnologias disruptivas, uma exigência da Era Digital que impulsiona a inovação. Entre as Tecnologias da Informação (TI), a Inteligência Artificial (IA) destaca-se como um catalisador fundamental deste contexto disruptivo. A IA apresenta um vasto leque de aplicações nas funções empresariais e industriais. A literatura existente aborda o surgimento do CVC no contexto das TI e IA. Este estudo aprofunda essa investigação, explorando a relação entre o CVC e a IA e o impacto de CVC no sucesso das startups. Paralelamente, é analisado o papel do grau de inovação das localizações das startups nesse sucesso. O êxito das startups depende tanto das suas características intrínsecas, como do ecossistema em que se inserem; ecossistemas mais inovadores podem proporcionar maiores oportunidades de crescimento. As hipóteses foram testadas com base numa amostra de 108.441 investimentos realizados em 39.502 startups de IA, fundadas entre 2000 e 2019, em 183 países. Esses países foram classificados de acordo com o Índice Global de Inovação da Organização Mundial da Propriedade Intelectual. Os resultados mostram que o grau de inovação do local onde as startups de IA estão inseridas influencia positivamente a sua probabilidade de sucesso, sobretudo quando se movem de áreas menos inovadoras para mais inovadoras. Adicionalmente, a presença do CVC aumenta significativamente a probabilidade de uma saída bem-sucedida das startups, moderando positivamente o efeito da localização.

INDEX

1. Introduction

Corporate Venture Capital (CVC) is formally defined as a “minority equity investment by an established corporation in a privately held entrepreneurial venture” (Dushnitsky, 2009, p. 387). It is an exploited practice that has exponentially grown since the beginning of the Century until 2021-2022 (PwC, 2021; CB Insights 2024). The highest peak of CVC investments occurred in 2021, reaching a $ 174.4 billion value; then a steady decrease began (CB Insights, 2024). The value of CVC's global investments was $55.1 billion at the end of 2023 (PwC, 2021; CB Insights, 2024); CVC is currently in the midst of a recession, across industries (EY, 2024). Nevertheless, CVC investments in the Information Technology (IT) and notably in the Artificial Intelligence (AI) Industries (also including AI’s subsets) enable a countertrend to arise: the amount of global VC investments in AI has grown from $7.1B in 2022 to $21.3B in 2023 and $15.3B of the former 2023 investments’ value depended on CVC investments in AI (EY, 2024). This attraction for AI mainly depends on the fact that investors “expect growth and change to happen in IT and AI” (Khaled Helioui, as cited in Fernandes & Leonard, 2024; International Monetary Fund, 2024). AI is “the ability of a software to perform tasks that traditionally require human intelligence” (Chui et al., 2023). It has a broad scope of application across industries and business functions and is reshaping the nature of work (Chui et al., 2023; International Monetary Fund, 2024). Used both as a substitute (Acemoglu & Restrepo, 2019) but mainly as a complement of human labor (Zhou et al. ,2021), AI enables companies to improve processes’ efficiency and to cut costs (Financial Times, Javier Espinoza, 2024), notably in the knowledge work context (Chui et al., 2023). It is indeed delivering huge value to global Economy and is forecasted to increase global GDP by 1.2 percent a year by 2030 (Bughin, et al., 2018). For the former reasons, AI solutions indeed attract several investors, among which Corporate Venture Capitalists (CVCs) (EY, 2024; Fernandes, & Leonard, 2024).

CVC investments generate twofold benefits: towards the investor and towards the funded startup (Chesbrough, 2002; Dushnitsky, 2012; Lantz et al., 2011; McKinsey & Company, 2023; Weniger & Jarchow; 2022). Corporations exploit CVC practice to access both to financial and strategic benefits (Dushnitsky, 2012), aiming to exploit synergistic benefits (Chesbrough, 2002). On the one hand, they access to financial returns from the equity investment in startups; on the other hand, they access to the innovative and disruptive solutions proposed by the funded startups (Dushnitsky & Lenox, 2006), enabling them to maintain their market positioning (Lantz et al., 2011; Dushnitsky & Lenox, 2003).

In turn, startups gain access to capital, from CVCs, which enables them to grow and scale (Gompers & Lerner, 1998; McKinsey & Company, 2023); finally, they gain access to CVCs' know-how of market or industry, expertise and assets, such as distribution channels or infrastructures (Weniger & Jarchow, 2022).

Within the IT and AI context, CVC investments still generate huge benefits; notably, CVCs benefit from accessing to disruptive technological innovations and organizational learning (Charron, 2020), in the new "Digital Era", (Morgan, 2016), while expecting for boosted Return On Investments' (ROI), thanks to AI's potential (IBM, 2022). Simultaneously, AI startups may find it crucial to gather corporate support, exploiting a coopetitive model, in order to navigate the sector's complexities (Mack Institute for Innovation Management, 2024), also considering the high costs of operating the business, including IT spending and costs of infrastructures or software development (Statista, 2023).

However, startups' growth and scaling in the market, beyond the receival of significant investments, mainly depends on additional internal and external factors: both internal startup's qualities and the external ecosystem in which the venture is located are relevant (Regions' Alliances for Interconnected Startup Ecosystems, 2024; Ziakis et al., 2022). Notably, an active ecosystem, where actors are co-located may enable open innovation (Ziakis et al. 2022) and may grow the pressure to innovate because of major and more innovative opportunities, thanks to knowledge exchange; startups' location is indeed relevant into the startups' growth context (Delgado et al., 2010; Porter, 2000).

Despite the existence of several studies on CVC practice and CVC practice in the new IT and AI disruptive context, this thesis aims to further contribute to future research, investigating the link between the presence of CVCs in an AI startups' equity, the startup's location and the consequent venture's success. Compared to previous research and differentiating from it, this study indeed aims to analyze the potential positive impact of CVC investments in IT and AI startups, while accounting for the degree of innovation of the startup's location, also investigating if the additional presence of a CVC investment within the startup's context, may moderate the location effect. This study will be conducted by firstly reviewing previous research and following adding new elements to it by exploiting a solid statistical analysis.

CVC investments may indeed be beneficial for startups' growth in general, as aforementioned. *May they additionally be beneficial for IT and AI startup's success?* Contemporarily, ventures' site and ecosystem, as again above mentioned, contributes to startups' growth: an ecosystem, constituted by various actors' interaction, is unavoidably linked to the concept of innovation as it hosts knowledge's exchange (Ziakis et al. 2022) and knowledge is the source from which innovation, on which entrepreneurship is based and build (Schumpeter, 1935, as cited in Śledzik, 2013), derives. At the same time knowledge tends to be geographically localized (Breschi & Lissoni, 2009). Moreover, according to the yearly Global Innovation Index (GII) by WIPO (WIPO, 2023), Countries' degree of innovation differs and this both depends on the countries' availability of inputs to innovate and the countries' output deriving from their innovative activities' results. *May, in these terms, a location's degree of innovation, additionally impact on the success of IT and AI startups there located*? *Moreover, is there any additional link between an AI startup's location and the capital raised, for its success: does CVC positively moderates location effect?*

Taking into account that AI world is relatively new and still to be explored, this thesis aims to investigate the above highlighted questions in order to analyze if CVC' s presence in an AI startup's context, and the firm's location, can significantly make the difference for the venture's probability of success. Success will be investigated in terms of succesful exit.

The *Research Question* (*RQ*), which is the focus of the study, is indeed defined as follows.

RQ:"Do Corporate Venture Capital Investments significantly increase AI & IT startups' probability of succesful exit, beyond or even positively moderating a potential existing location effect, determined by the degree of innovation of the site in which the startup is located?".

Therefore, in order to investigate the extent to which CVC investments have an impact on the success of AI startups, an empirical analysis will be carried out with four logistic regressions, including a moderation analysis

Literature Review

2. Corporate Venture Capital investments

CVC investments involve two actors: a venture, typically a startup, proposing an innovative solution and aiming to grow, and a corporation allocating money on the startup in exchange for equity (Dushnitsky & Lenox, 2006). Consequently, CVC investments deliver value in a biunivocal way: they do create value for the funded startup and for the investing corporation itself too (Dushnitsky, 2012; McKinsey & Company, 2023).

2.1 CVC functioning

CVC is a subset of Venture Capital (VC). VC is a type of private equity investing, mainly regarding early-stage equity investments (Loo). Venture Capitalists (VCs), also called General Partners (GPs), are external professional investors raising money from institutional investors, who act as Limited Partners (LPs), and allocating it on promising ventures through a Fund Vehicle.

On the other hand, CVC, as a branch of VC, refers to the use of corporate funds in ventures, by larger companies (Dushnitsky & Lenox, 2005). It is formally defined, as previously highilighted in the Introduction (section 1.), as a "minority equity investment by an established corporation in a privately held entrepreneurial venture" (Dushnitsky, 2009, p. 387), with the aim of accessing to ventures' innovative solutions, for both strategic and financial purposes. These purposes will further be explored in the following section (section 2.2).

This practice can be organized according to different forms. CVC can indeed both be direct and indirect. When referring to direct CVC, the most diffused practice entails the settlement of a corporate venturing unit (CVU), a vehicle to fund innovations. The CVU is an internal corporate division (Lantz et al., 2011).

Alternatively, if aiming at directly investing in external startups, an incumbent can also decide to settle spinoffs or can decide to cooperate with other private or public funds or with an innovative Small Medium Enterprise to jointly invest (Lantz et al., 2011).

When referring to indirect CVC, corporations do have the possibility to indirectly allocate money on startups leaning on an external VC fund (Lantz et al., 2011; Youssef, 2001).

CVC is an exploited practice which reached its first peak in 2000, when incumbents invested over $16 billion in CVC programs, representing around 15% of all venture capital investments. (Venture Economics, 2001). From that moment on, an exponential growth began (CB Insights, 2024). The 20-years trend, has nevertheless suffered from some relevant drops:

as it will be further analyzed (subsection 2.4), the current CVC investments' global value is experiencing a recession but some countertrends exist, which lay foundation for a recovery (EY, 2024).
This study will focus on Corporate Venture Capital investments on startups and notably on IT & AI startups.

2.2 CVC investments' purpose and underlying reasons

Strategic reasons are the primary drivers behind corporate venture investments (Dushnitsky, 2012).

First of all, established incumbents may decide to allocate part of their funds on emerging competitors in order to eliminate any potential threat, "accelerating their own market entry" (Kann, 2000) in an evolving and changing environment, by acquiring or leveraging value from promising ventures' new solutions. This is more likely to happen if the startup and the incumbent operate in the same industry; if the startup enters the industry with a disruptive innovation and technology, it consequently forces incumbents to adapt to changes and innovate to keep up with new industrial trends (Lantz, et al., 2011). If not able to adapt to changes, established firms risk being excluded from the marketplace (Eggers & Park, 2017). Therefore, laying on competitors' innovations, allocating money on them and acquiring stocks, may be a functional solution (Banholzer & Ramtri, 2023; EY Americas, 2020; Lantz et al., 2011; Vipond).

On the other hand, according to a study by Dushnitsky and Lenox (2006), incumbents may strategically invest on new ventures to build demand for their own technologies. As a matter of fact, startups may enter the market with complementary solutions to incumbents' existing ones. By acquiring these promising solutions and supporting their growth, incumbents can indeed indirectly support the growth of their own existing complementary solutions. The likeliness for an incumbent to support new startups is positively correlated with the degree of complementarity of their offerings (Dushnitsky, 2004, as cited in Dushnitsky & Lenox, 2006).

Finally, the third and most relevant reason for corporates to make a strategic CVC choice, is gaining access to new emerging technologies, that can indeed guarantee their market positioning and diversify their portfolio (Dushnitsky & Lenox, 2006; Lantz, et al., 2011), "filling gaps in the corporate technology portfolio" (Dushnitsky, 2012). These technologies can be exploited or licensed by investors, opening wide international business opportunities and keeping up with the innovative context (Dushnitsky, 2012).

Nevertheless, CVC investments are also pushed by financial underlying reasons (Lantz et al., 2011). In these terms, incumbents allocate money on promising ventures with the aim of obtaining positive financial returns on the stock they hold. In this case, investing corporations tend to leave when a positive financial exit for the funded startup becomes feasible (Dushnitsky & Lenox, 2006; Lantz et al., 2011).

All in all, CVC does effectively create value for incumbents when competitive success is built out of the strategic acquisition of ventures' complementary assets and resources (Teece et al., 1997, as cited in Dushnitsky & Lenox, 2006). Strategic CVC, as Dushnitsky & Lenox (2006) note, does indeed create firm value; instead, financial CVC alone is less likely to create firm value. Financial reasons for CVC need to be paired with strategic ones. CVC strategic reasons are indeed key for Corporate Venture Capitalists' success, enabling them to remain competitive and potentially gain new competitive advantage; innovation is the key to be competitive on the market (Dushnitsky & Lenox, 2006).

Finally, according to Vipond, Corporates may decide to invest on startups at an earlier or at a later stage. If investing in an earlier stage, beyond the advantages they can generate for themselves, incumbents also have a relevant role on the startups' survival and growth themselves (Vipond). Instead, according to Banholzer & Ramtri (2023), incumbents invest on later stage ventures because they see a lot of potential in obtaining returns. This happens because the startup has already gained a solid market positioning and consumer basis, reducing the overall risk for investors (Banholzer & Ramtri, 2023).

Beyond the value generated by CVC practice to the investors themselves, a dialogue can be opened up on the important role and impact that CVCs do also have on funded startups' growth.

2.3 CVC's relevance for startups

Corporate Venture Capitalists invest in startups for both personal returns and strategic purposes (Dushnitsky, 2012; Lantz et al., 2011). In doing so, they also create a huge impact on funded ventures, by providing them with access to both complementary assets (Rossi et al., 2022; Weniger & Jarchow, 2022) and financial support (Gompers & Lerner, 1998; McKinsey & Company, 2023).

2.3.1 Access to complementary assets

According to several studies (Bammens & Lilienweiss; Harlé et al., 2017; Pollman, 2020; Rossi et al., 2022; Weniger & Jarchow, 2022) CVCs, as being operating incumbents, can provide startups with various resources beyond access to fundings: complementary knowledge, know-how, expertise, mentoring, network and market access resources, through strong and established distribution channels and market knowledge. These resources benefit startups in terms of growth, expansion and market scaling.

First of all, according to various studies (Bammens & Lilienweiss; Harlé et al., 2017; Weniger & Jarchow, 2022), startups lack of experience and, beyond financial resources, they need for knowledge regarding the industry and the market where they operate and need for general and technological and technical expertise, in order to grow. Incumbents do have experience on being on the market, hold know-how, regarding how to deal with the changing environment and how to "do the business" (Bammens & Lilienweiss; Weniger & Jarchow, 2022) and own market access resources and market knowledge thanks to their solid marketing resources, that provide costumer data, strong distribution channels and sales capacity (Harlé 2017; Katila et al., 2008; Maula et al., 2005; Weniger & Jarchow, 2022). Through a CVC investment relationship with incumbents, startups can exploit the corporate parent's resources and market knowledge they lack of (Bammens & Lilienweiss; Harlé et al., 2017; Weniger & Jarchow, 2022).

In addition, in terms of knowledge, Harlé et al., (2017) note that incumbents can provide the startups they fund with additional and complementary technical know-how. As a matter of fact, big established firms have wider financial availability and spend more on R&D processes to gain technological advancement. Despite entering the market with disruptive technological innovations, startups may indeed need to lean on investors' complementary knowledge and on their advanced technical expertise (Harlè et al., 2017).

Thirdly, as noted by Weniger and Jarchow (2022), incumbents own developed internal processes and a huge array of assets to conduct the business (Maula et al., 2005, as cited in Weniger & Jarchow, 2022). They hold manufacturing sites and resources and hold distribution channels that enable them to stay competitive on the market. They also possess a solid know-how on manufacturing processes, supporting their competitive advantage (Maula et al., 2005, as cited in Weniger & Jarchow, 2022). In order to stabilize in the market, startups need for manufacturing and distribution assets; this is notably true for startups in capital intensive industries, such as Information Technology Industry. Startups may exploit incumbents' know-how and infrastructures to expand on the market, using the existing competitive advantage of their investors, instead of developing brand new alternatives from scratch (Weniger & Jarchow, 2022).

To follow, operating on the market has enabled incumbents to build a network of customers, suppliers, actors, which may become beneficial also for the funded startups (Bellavitis et al., 2014, as cited in Weniger & Jarchow, 2022). Networks guarantee access to additional resources and social capital and are one of the main reasons driving ventures to look for CVC's support (Weniger & Jarchow, 2022).

Finally, according to Pollman (2020), when entering a startup through an equity investment, investors also get access to the startup's board. Investors' accessing to startups' governance may provide additional value to the enterprise itself. Investors can indeed provide mentoring to founders, helping them to grow their experience in driving the business, and advisory services for the startup's administration (Pollman, 2020).

Overall, accessing to complementary investors' knowledge and assets is a benefit for startups' growth and solid positioning (Bammens & Lilienweiss; Harlé et al., 2017; Pollman, 2020; Rossi et al., 2022; Weniger & Jarchow, 2022).

2.3.2 Access to financial resources

On the other hand, according to studies by Gompers and Lerner (1998), McKinsey & Company (2023), and Ivanov and Xie (2010), startups also access to relevant financial resources and benefits, through CVC investments. This remains a key reason for startups to approach CVC investors (Gompers & Lerner, 1998; I. Ivanov & Xie, 2010; McKinsey & Company, 2023).

According to the research by McKinsey & Company (2023), the percentage of growing ventures also backed by corporate participation seems to be higher and their percentage of failure lower, compared to ventures only backed by other forms of investments. Companies both backed by Venture Capital and Corporate Venture Capital, grow more and faster and have higher probability of survival and of successful exit. Corporate participation can have a strong impact on promising ventures' future (*Figure 1.*, Appendix). Ventures also backed by CVC in their first, second, and/or third financing rounds are superior at successfully exiting through IPO, LBO or M&A by 7^{th} financing round compared to ventures backed by VC but non-CVC. The share of startups, also backed by CVC in their first three rounds or in one of the first three rounds and realizing successful exits by 7^{th} round, is respectively over 38%, 35% and 28%. On the other hand, the percentage of successful exits by 7^{th} round for startups funded by Venture

Capital only in the first three rounds, is equal to around 22%, 25% and 23%, clearly lower that CVC.
At the same time, the rate of ventures going out of business by 7th financing round is over 23% if the venture has been funded by VC only in the first round and around 15% if the venture was also CVC-backed, 15% if only VC-backed in the second round and 10% if also CVC-backed and finally 10% if VC-backed in the third round and 9% if also CVC-backed. Rate of success is higher for startups also having corporate participation.
Overall, despite the fact that VC-backed startups already have halved failure rates compared to non-VC backed ones, additional Corporate presence within these startups further reduces this rate. Having both VC and CVC support may heavily grow startups' survival horizon and success (McKinsey & Company, 2023).

Beyond the additional value that CVCs provide ventures with, through complementary assets and financial support, CVC investments can also provide ventures with a further benefit: a higher valuation in IPOs, as highlighted in the studies by Gompers & Lerner, (1998) and Ivanov & Xie (2010). This mainly lies on the fact that CVCs can exploit their own internal know-how, assets and strengths to support the funded startup and guide them towards exit. Nevertheless, an higher startup's IPOs valuation only occurs if a strategic fit between the two actors involved in the CVC partnership, exists. According to Ivanov & Xie (2010), CVC relationships are allocated as follows: 23.6% of startups have CVCs as suppliers, 30,1% have CVCs as users of their services, 26.8% of startups do have an agreement of engagement in product development and 17.9% an agreement of joint research with CVCs. Consequently, CVCs provide funded ventures with their own assets and knowledge but the value deriving from this practice can effectively grow ventures' valuation in IPOs only if CVC relationship is built out of a strategic choice. In this case, CVCs add value to startups because of the strategic overlap and beyond the value generated by the mere corporate alliance between the parties (Gompers & Lerner, 1998; Ivanov & Xie, 2010).

Finally, it is also crucial to state that the way how startups exploit investors' resources, also depends on the stage of the enterprise lifecycle. According to Rossi et al., (2022), CVC investments can work like real accelerators as they accelerate specific innovations' development. This is mainly true for earlier stage startups, as they are less solid; CVC relationships provide them with business experience.
CVCs' role of accelerators is particularly strong for startups at early stages operating in knowledge intensive industries and notably in new disruptive technologies ones. Due to the fact that CVCs provide complementary knowledge, expertise and assets to ventures, knowledge-

intensive industry benefits the most from this practice. As a matter of fact, knowledge spillovers flow from investors to startups. CVC investments in early stages, give a strong support to startups' survival and expansion (Rossi et al., 2022).

Nevertheless, CVC investments can also occur in a later stage; according to Munafo (2023) and Banholzer & Ramtri (2023), these kinds of investment have a different meaning. Later stage ventures do have more solid business models and customer bases. These ventures already had their value proposition validated; their offering has established and is finding a way to profitability. CVCs may indeed decide to allocate money on more advanced ventures to cut risks deriving from startups and to hope for better financial returns. These ventures still find it useful to obtain incumbents' support, which may be a driver for their scaling; nevertheless, this support is not a growth accelerator like it happens for early stage ventures (Munafo, 2023; Banholzer & Ramtri, 2023).

To conclude, CVC is double sided: it is practiced by incumbents to guarantee their own strategic and financial return, but also generates a lot of value for the funded startups.

It is crucial to highlight that startups and CVCs often have complementary resources, meaning that, as the startup can access to the CVC investor's resources, also the CVC investor can access to the startup's resources. Value creation goes in both directions (Weniger & Jarchow, 2022; Rossi et al., 2022; Gompers & Lerner, 1998; McKinsey & Company, 2023).

The only crucial element to effectively create value, is the necessary ability of parties to exploit synergies properly and align objectives and processes (Chesbrough, 2002; IESE Business School, 2017). A CVC investment is also lead by strategic reasons, because the choice of allocating money on a specific startup and solution is made knowledgeably (IESE Busines School, 2017). This does not mean that the CVC and the startup have to operate in the same specific industry or have a technological fit (Anokhin et al., 2016), but rather that the two parties' complementary assets must generate synergies and that the parties' final objectives have to be aligned (Chesbrough, 2002; IESE Business School, 2017)

If not, the CVC investment's potential cannot be exploited in either direction, neither investor to startup nor startup to investor (Chesbrough, 2002).

2.4 CVC's current activity

Considering the reasons driving CVCs to fund promising startups and the positive consequences generated by the former investments on startups' growth, it is relevant to analyze the evolution of CVC investments' value over the last decades, also to track their current activity and level.

The analyses of CVC's trends by PwC (2021), CB Insights (2021, 2024), show that CVC has had a boost between the beginning of the century and the immediate post-covid era: starting from $16.8 billion in 2000, the CVC-backed funding has steadily grown until $174.4 B in 2021. Some drops occurred but the general twenty-years trend was positive. The biggest drop, in this time bracket, occurred between 2018 and 2019, leading CVC fundings from $63.6 to $59.1 billion value; nevertheless, the drop was recovered with a 24% increase in 2020, leading to a $73.2 billion value and an amount of 3359 CVC-backed deals, 6 times higher than the amount of deals registered in 2000 (PwC, 2021). Again, between 2020 and 2021 the CVC-backed investments more than doubled, leading to 5142 deals, in 2021. Nevertheless, this continuous growth has undergone another significant stop in 2022 (in the last quarter of the year) which continued in 2023, leading to a final 46% drop from 2021 to 2023, with a final $55.1 B amount and 3545 deals in 2023 (CB Insights, 2024)

CVC current activity is indeed higher than the levels registered at the beginning of the century but its steadily growing path has suffered from an interruption (CB Insights, 2021; CB, Insights, 2024; PwC, 2021). This trend is in line with global VC investments' trend, which has suffered from a huge drop in 2023. From 51.894 deals and $531.4 B in 2022, the global VC investments dropped to 37.808 deals and $344B in 2023 (KPMG, 2023).

Both CVC and VC investments suffered from a drop in 2022 and 2023 mainly due to the irrational growth occurred during the Covid-19 pandemic, because of lower interest rates (EY, 2024; Gabrow, 2022). After the pandemic, the inflation and interest rates, which went back to more used and familiar patterns, drove investments down (EY, 2024; Gabrow, 2022).

A study by Fernandes and Leonard (2024), a press release by EY (2024) and a report by OECD (2021), show that, despite this general current decreasing trend of CVC and VC investments and of startups' access to capital, some exceptions exist. One of these exceptions lies in the Artificial Intelligence (AI), Deep Tech and Information Technology (IT) sector, which instead shows a countertrend.

Notably, the AI and IT markets are growing trends, which are expected to exponentially grow also in the next decade (EY, 2024; Fernandes & Leonard, 2024; OECD, 2021). Indeed, tech and deep tech companies saw unprecedent amounts of investments, mainly during pandemics, where digitalization of daily activities was a must for corporates to operate their business (Espinoza, 2024).

But this trend didn't stop after the end of pandemic era (EY, 2024; Fernandes & Leonard, 2024; OECD, 2021).

Artificial Intelligence is the key driver of the Deep Tech and IT market growth. Investors' interest is indeed primarily driven by AI. This depends on the fact that AI and its applications are extending beyond technology-focused industries; it is applied to several sectors disrupting them and leading them through an innovative growth (Cockburn et al., 2019; Espinoza, 2024).

In these terms, is relevant to define the concept of "AI startup": "AI startup or AI firm is considered to be a private company that researches and delivers all or part of an AI system or researches and delivers products and services that rely significantly on AI systems" (OECD, 2021, p. 5). An AI system, in turn, is a "machine-based system that is capable of influencing the environment by producing an output (predictions, recommendations or decisions) for a given set of objectives; it elaborates inputs or human-based data in order to sense real or virtual world and elaborate models out of it, with the aim of employing model inferences to create outcomes" (OECD, 2021, p. 5).

In the context of VC (Fernandes & Leonard, 2024; EY, 2024; OECD; 2021) and CVC investments (Fernandes & Leonard, 2024), IT and AI markets are indeed relevant. As a matter of fact, IT and notably AI startups, as above defined, have gathered increasing investments from VC and CVC, because of the trust investors place in them. The amount of investments allocated to IT and, notably, AI startups, has grown even in the last years (even in 2022 and 2023), in opposition to the general trend. Consequently, even though the average CVC and VC investments' value has dropped, because of the disseminated fall for all sectors, the specific IT and AI investments' value is not, and is driving the overall cumulative result. (Fernandes & Leonard, 2024; EY, 2024; OECD 2021). Over 35% of the global venture funding, has been catalyzed by AI startups in the second quarter of 2024 (CB Insights, 2024).

This depends on the idea that "Tech (notably AI) has come back in investors' appetite. This is where they expect growth to happen" (Khaled Helioui, as cited in Fernandes & Leonard, 2024). This countertrend mainly lies in companies producing innovative AI technologies, such as Generative AI (Gen AI), based on deep learning algorithms, and large language models (LLMs) (Fernandes & Leonard, 2024).

As the EY (2024) press release notes, the Global investments in AI startups and solutions (notably Gen AI solutions), has grown from $1 billion in 2018 to $21.3 billion in 2023; the $21.3B peak mainly depended on CVC's presence as it consisted of $6BVC investments and $15.3B CVC investments, thanks to the OpenAI-Microsoft $10B, the Anthropic-Amazon $4B and the Inflection-Microsoft $1.3B deals. The growth was continuous and exponential, showing only a minor drop in 2022 ($7.1 billion of value). Between 2020 and 2021, the investments' value went from $2.9 to $12.2 billion and, between 2022 and 2023, it went from $7.1 to $21.3 billion (EY, 2024).

As Fernandes & Leonard (2024) additionally note, the global VC funding has grown to $89B in the first quarter of 2024. In this context, the US Venture capital funding, representing around a half of the $89B VC Global Value, had a 72% growth quarter over quarter in 2024, mainly supported by IT and AI investments. Similarly, global CVC-funded deals have grown thanks to IT, AI and Gen AI startups', in the first quarter of 2024 (Fernandes & Leonard, 2024).

AI and IT sectors, and their following relationship with CVCs, will be further explored in the following sections (sections 3., 4.) as they constitute the main focus of this study.

The above – and short – analysis regarding CVCs presence within the IT and AI context is useful to introduce how attractive new disruptive technological solutions, notably AI, are becoming for investors. Those solutions can support corporations differently, such as increasing corporate processes' efficiency and efficacy, as well as cost cutting across sectors (Chui et al., 2023; Murray et al., 2020; Puranam, 2021).

It seems indeed clear that Corporate Venture Capital does have an important role in supporting startups in general, particularly in the IT and AI sectors, due to the rapid growth and increasing importance of these technologies (Fernandes & Leonard, 2024).

This also leads to the conclusion that, despite having suffered from a drop in the last two years, CVC investments' value has a potential for growth and this potential lies within the AI and technological sector (Fernandes & Leonard, 2024; EY, 2024).

3. The Artificial Intelligence and the Information Technology Sectors

As mentioned in the former subsection (subsection 2.4), CVC investments' overall value in the IT and AI context is very high. Beyond the advantages that Corporate Venture Capital is expected to have for startups in general (as mentioned in subsection 2.3), its role for IT and for AI startups may even be more impacting (developed in sections 3. and 4.).

As a matter of fact, the main strategic reason that justifies CVC investments is gaining access to new solutions, developed by startups (Dushnitsky & Lenox, 2006; Lantz, et al., 2011). In the IT and AI context, allocating CVC funds on a startup means accessing its technological, deep tech or AI solution (Dushnitsky & Lenox, 2006).

As above mentioned (observed by Fernandes & Leonard, 2024), the majority of IT investments, among VC, CVC and global venture funding, is allocated to AI solutions. AI solutions have a high potential because of the wide scope of application they can have across industries and business functions (Chui et al., 2023). Consequently, allocating money on IT startups but mainly on AI startups is a new growing trend, also practiced by corporate realities through CVC investments (Fernandes & Leonard, 2024). This practice enables investors to access promising tech solutions but at the same time guarantees a financial and experiential support to the development of new technological solutions, able to transform the competitive landscape and appliable in various industries (Bughin, et al., 2018).

For the former reasons, in order to better justify the growing amount of CVC investments on AI and IT startups and to better study the crucial role of CVCs in this context (beyond the reasons already introduced in section 2, subsection 2.3), an analysis of the AI's market and of AI's potential of application needs to be conducted.

3.1 AI's definition, subsets and market

Artificial Intelligence (AI) can be defined as "the ability of software to perform tasks that traditionally require human intelligence" (Chui et al., 2023).

Several forms and subsets of AI, with various applications, can be identified (as noted by research by Chui et al., 2023). A huge array of other different forms of AI exists, such as Machine Learning (ML) and Generative AI (Gen AI), as the main ones. ML is constituted by algorithms able to learn how to make effective recommendations and higher-precision pforecasting, exploiting their own experience and not having received explicit input and programming to do it. On the other hand, Gen AI is a more advanced form of AI, able to generate content. It is made of Foundation Models (FM). FM refers to Deep Learning models appliable to various tasks as trained on big amounts of unorganized data (Chui et al., 2023).

Deep Learning algorithms are ML's algorithms that exploit multiple levels to extract higher-level features from the raw input (Chui et al., 2023). On the other hand, Gen AI may also specifically be based on Large Language Models (LLMs), which are a class of FMs and are able to process huge volumes of unorganized text and "learn relationships between words, known as tokens" (Chui et al., p. 6, 2023) (IBM, 2023). Gen AI can indeed generate various content: images, music, but also text (IBM, 2023).When referring to AI, within this study, all AI's subsets and forms will be included in the broader AI definition.

According to Espinoza (2024), the practical scope of application of AI within corporate realities is broad. This potential of application also depends on AI's differentiation into its various branches and forms: Gen AI, ML and all the other AI's subsets can perform different tasks and overcome different challenges (in depth study at subsection 3.2) (Espinoza, 2024).

In this context, it is indeed crucial to highlight that AI can be intended as a specific form of disruptive technology. "Disruption describes a process whereby a smaller company with fewer resources is able to successfully challenge established incumbent businesses" (Christenses et al. 2015) and a disruptive technology is the "Effect of a new technology or a new way of operating a business model that leads to a change in the logic present in the market, introducing new behaviors and interactions, thus revolutionizing existing logic". (Christenses et al. 2015). Consequently, we may define new AI solutions as disruptive because they can lead to corporate business functions, industries and market's reshaping (Espinoza, 2024; Minevich, 2023).

Artificial intelligence can indeed be considered as one of the biggest contributors to the "Fourth Industrial Revolution", transforming global economy (Morgan, 2016). Consequently, when referring to Disruptive Technologies and to the potential of investing in the Technological Disruptive Innovative sector, AI solutions are included and are also the focus of this study.

AI's scope of application within companies, beyond being highly diversified, is also the reason why demand for AI solutions and AI market are so big: the broader the scope of application, the higher the potential. Because of its usage potential, AI is becoming an integrant part not only of businesses but even of our daily lives.

The global market size of AI was valued at $515.31 billion in 2023. It is expected to grow at a rate of over 20% in the period between 2024 and 2032, where $621.19B of value is projected (Fortune Business Insights, 2024). To provide more comprehensive numerical results, AI contributes to global economic activity and is forecasted to boost global GDP by 1.2 percent a year by 2030 and to deliver $13 trillion additional economic output (Bughin et al., 2018). AI's growing demand, market and potential open a window of opportunity for ventures to enter the

AI-producing market and for established corporations to invest in them through CVC, also contributing to the ventures' scaling.

3.2 AI's scope and potential of application

AI's potential and scope of application in the corporate context, as noted by Espinoza (2024), is broad and has exponentially grown in recent years. In line with the division of AI into several subsets made by Chui et al., (2023), AI and its branches can effectively be applied across different functions and industries, thanks to their different capabilities. Firms exploit AI's broad potential of application, integrating it within their corporate realities, in order to create value and build competitive advantage. Nevertheless, in order to effectively leverage and grow this value, it becomes necessary to exploit a combined approach between AI technologies and human capital (Chui et al., 2023; Espinoza, 2024).

As a matter of fact, according to Paul et al., (2022), several corporate tasks require the interpretation of massive amounts of data, which may challenge human rational and limited capabilities; loss of time and money is likely to follow. However, some different kinds of task, requiring human creativity or memory, need to rely on human effort and cannot be automated. Consequently, while AI is better at performing information processing, data analysis and more complex analytical tasks, humans are better at dealing with uncertaint situations and contexts with "a more holistic approach" (Paul et al., 2022, p.430). Together human and technology can address complex tasks (Paul et al., 2022).

According to several studies (Acemoglu & Restrepo, 2019; Autor, 2015; Murray et al. 2020; Paul et al., 2022; Puranam, 2021; Shrestha et al., 2019; Zhou et al., 2021), humans and machines, having different capabilities and strengths, can act complementarily, performing different tasks, or can collaborate on the same task.

"Automation does indeed substitute for labor. However, automation also complements labor, raises output in ways that lead to higher demand for labor and interacts with adjustments in labor supply" (Autor, 2015, p.,3). Technology unavoidably restructures the job market, roles and responsibilities; nevertheless, AI is not only aiming to substitute human work but mainly to boost its performance and grow human productivity, supporting and complementing it.

Automation is the "development and adoption of new technologies that enable capital to be substituted for labor in a range of tasks" (Acemoglu & Restrepo, 2019, p. 2) but Augmentation means "enhancing and elevating human ability, intelligence and performance with the help of information technology" (Zhou et al,2021).

Capital and labor can indeed be integrated differently and for several purposes, in order to improve processes' efficiency by cutting costs, risks, time or by tailoring firm's offering, consequently improving it. AI's scope can thus be exploited differently (Chui et al., 2023; Murray et al., 2020; Shrestha et al, 2021).

In these terms, according to Chui et al., (2023), AI and its Gen AI branch may have a strong impact on various corporate functions. AI can indeed optimize back-end and front-end activities pertaining to various business functions, such as Software engineering, R&D, Marketing and customer operations (Chui et al., 2023).

All these applications may find fertile ground across industries, mainly in the context of knowledge work; this happens because AI is designed to mainly perform cognitive tasks (Chui et al., 2023; Fortune Business Insights, 2024).

To go more in depth, into specific corporate processes in which AI, if properly exploited, can add value, a research by Shrestha et al., (2021) notes that AI may guarantee relevant improvements of decision-making processes and an associated risk cutting. "Decision-making is the process whereby an individual, group or organization reaches conclusions about what future actions to pursue given a set of objectives and limits on available resources" (Russo, 2014, p.1). Shrestha et. al (2021) note that decision-making processes can be maximized in terms of precision and time when AI comes into play. In order to guarantee their maximization by exploiting AI, decision making processes can be boosted through a full human to AI delegation, a hybrid human to AI or an aggregated human-AI decision making approach. In the first case, human intervention becomes absent and AI becomes the decision maker: human activity is substituted. In the hybrid structure, AI and human decisions are taken consequentially: the decision made by the machine becomes input so that the human decision-making process is built on the machine's decision, or the opposite; AI and humans cooperate. In the aggregated structure, human and AI elaborate decisions together according to their specific and respective capabilities and competencies: they are complementary (Shrestha et al., 2021).

Similarly, according to Murray et al. (2020), AI can also impact on routines' predictability and degree of routines' changes and responsiveness (Murray et al., 2020)

Consequently, it is crucial to better study the ways how AI can be used and integrated within companies, across functions and industries, to understand some of the underlying reasons why incumbents may want to acquire new AI solutions, consequently supporting their growth.

3.2.1 Generative AI’s impact on industries and business functions

To conclude the explanation of the reasons why the demand for new AI technologies and solutions is so wide, an in depth focus on the corporate potential of Generative AI as a branch of AI should be done.

To begin with, according to Chui et al. (2023), AI has a huge impact on several business functions. Across business functions, AI can be applied to improve activities’ efficiency or to reduce time and costs. To go more in depth in the specific functions on which AI can impact, creating value, it is possible to state as follows.

In the context of Customer Operations, Gen AI can improve customer experience and digital productivity by cutting time spent to handle customers’ issues. In addition, technology supports the retrieval of data guaranteeing targeted services and consequent growing sales.

Secondly, Marketing and Sales operations can become more functional and create more value too because of AI’s ability to tailor customers’ preferences and customize content; both time and costs are cut.

In addition, Gen AI enables to reduce time spent on code corrections and on generating drafts or system design, impacting of Software Engineering activities (Chui et al., 2023).

Finally, R&D activities may exploit AI too (Chui et al., 2023). AI can be used to design products, enhancing their performance, guaranteeing more efficiency of materials’ usage, improving their quality and also cutting costs (Minevich, 2023).

All in all, as noted by Chui et al. (2023), Gen AI can impact on various industries, providing them with huge value, because of its broad scope of application on several business functions, as above highlighted.

Among all the industries that AI can benefit thanks to its features, Banking, Pharma, Retail and Consumer packaged goods are the three industries where AI may have the strongest impact.

The highest value potential by function, within each of these industries, is delivered by AI to Product R&D and Software engineering.

Within the banking sector, Gen AI can optimize and fasten the transition of legacy systems, which are obsolete systems currently used for banking activities such as daily market transactions or back-end operations, towards more updated and digital business models. On the other hand, in the Retail context, Gen AI is able to guarantee a better and faster research of consumer and customer targeting by creating a prototype of potential customer to have practice with. In addition, Generative AI is also able to aggregate data in order to come up with models’ testing and to customize goods and services. Finally, in the Pharma industry, Gen AI can be exploited to make the selection process of molecules for new drugs faster and more precise. SOM Biotech is a good example for that: it is a newly Spanish founded venture that exploits Gen AI to identify potential in existing drugs and recombine molecules in order to develop new drugs against orphan diseases (SOM Biotech, website)

Overall, by guaranteeing better precision, costs and time reduction and other advantages, AI is able to grow one company's performance and attractiveness on the market (Chui et al., 2023)..

Overall, AI generates impact on processes: above all, it also additionally improves decision-making processes and routine activities (Murray et al., 2021; Shrestha et al., 2019). Moreover, it defines and improves activities pertaining to several corporate functions (Chui et al., 2023). These capabilities can be applied to several industries (Chui et al., 2023). Still, according to Chui et al. (2023), knowing that AI is often used as a complement more than as a substitute of human capital, it is also possible to state that the impact it has on knowledge work is higher, because it is designed to perform cognitive tasks (Chui et al., 2023; Fortune Business Insights, 2024). Consequently, corporates, mainly the ones operating in knowledge work sectors, do often want to exploit AI to create value, leveraging the advantages it creates. For these reasons the market of AI is growing and remains a great opportunity both for startups to penetrate and for investors to allocate money.

To conclude, AI's broad potential of application across sectors, beyond growing AI's demand and market, calls for investments in AI startups; CVC investments grow (Chui et al., 2023).

After a detailed analysis on AI's features and potential, it is indeed possible to study the role of CVC investments and how they do create value within the AI and IT context, bidirectionally to startups and to investors themselves.

4. CVC's value creation in the specific AI and IT context

Beyond a general analysis (section 2.) of CVC investments across industries, with a specific focus on the underlying reasons driving corporate investors to allocate money on firms and notably startups (subsection 2.2) and with a focus on the benefits that CVCs do have on ventures themselves (subsection 2.3), CVCs investments in IT and AI context call for a more detailed analysis.

As a matter of fact, our Society is evolving into the "Fourth Industrial Revolution" and "Digital Era", where technological innovating, and notably AI innovating, are crucial (Morgan, 2016).

For these reasons, CVC in IT and notably CVC in AI are the focus of this study.

According to research by experts, presented at the Spring Conference 2024 by Mack Institute for Innovation Management (2024), corporate innovation was perceived as an "in-house project", however "today's disruptive technologies are so complex and capital intensive that neither corporations nor startups can deal with them alone". The main idea is that value deriving from disruptive technologies can be captured only through entrepreneur-investors' engagements. The new needed model of innovation in the "Big Tech era" should be based on a form of "coopetition" (Mack Institute for Innovation Management, 2024), involving the creation of innovative ecosystems, enabling the proper interplay between the investors, the startups and other actors. This model should indeed be built out of partnerships or other strategic alliances and modes of entry (Mack Institute for Innovation Management, 2024). That may be a good reason why CVC practice in the IT and AI market, where AI and IT startups and investing incumbents are engaged, is a growing practice (EY, 2024; Fernandes & Leonard, 2024; Mack Institute for Innovation Management, 2024).

On the one hand, accessing disruptive IT and AI solutions is relevant for incumbents to access emerging technologies and grow their own performance and future perspectives (Benson & Ziedonis, 2009). Taking into account that for incumbents seems usually easier to cooperate with startups and acquire something rather than internally develop it, CVC investments are highly diffused in this context, on the demand side (Agarwal & Helfat, 2009; Benson & Ziedonis, 2009). As a matter of fact, having the internal capabilities and competencies to develop AI solutions may be rare (Banholzer et al., 2019; Benson & Ziedonis, 2009). Thus, allocating money on new entrants and penetrating such a growing market, may leverage a huge potential to create and capture value, both in financial and strategic terms (Benson & Ziedonis 2009; Charron, 2020; IBM, 2022). Corporations, mainly the ones already operating in the sector, can gain advantages from investing in promising and/ or performing technologies (Benson & Ziedonis, 2009; Charron, 2020; IBM, 2022).

On the other hand, on the supply side, deep-tech and AI startups and ventures find it crucial to count on CVC support, which may be relevant not only for their survival but mainly for their expansion, within this new technological world (Guo et al., 2015; Harlé et al., 2017; Kagan et al., 2021; Mack Institute for Innovation management, 2024; O'Brien, 2023).

Because of the growing practice of CVC investments', their overall value is indeed expected to rebound and to grow back from its 46% drop occurred between 2022 and 2023 (CB Insights, 2024; subsection 2.4). This room for improvement and recovery lies in the IT and notably AI sectors' potential, which are continuously innovating and becoming more and more relevant because of the direction our Society is taking and because of the ways in which they can be applied and create value (CB Insights, 2024; Chui et al., 2023; Morgan 2016).

Consequently, it is possible to state that while CVC can in general create benefits for both demand and offering sides across industries, these effects exist and are strong also in the IT and AI sector (Kagan et al., 2021). As a matter of fact, observing a sample of startups located in US, which indeed represent over a half of the current global $89B venture capital funding (Fernandes & Leonard, 2024), corporate investors in US fund top AI startups on a more regular basis than other ventures; furthermore, the number of investors for top AI startups tend to be higher than for top startups operating in other sectors (Kagan et al., 2021).

4.1 Potential of investing in Artificial Intelligence and Information Technology startups

CVC investments are both guided by financial and strategic reasons (subsection 2.2).

When entering the IT and AI context, some additional elements, regarding benefits and potential that investors can leverage from CVC investments, must be analyzed, beyond the ones already studied in section 2.

4.1.1 CVC investing to leverage financial potential

IT and notably AI demand and market are growing, opening a window to high potential financial returns if investing in IT and AI startups (KPMG, 2019; Ashoori et al., 2022, IBM 2023). As formerly introduced (subsection 3.1 and subsection 3.2), the enormous growth of current IT market value mainly lies into AI (Cockburn et al., 2019; Espinoza, 2024); in addition, the growth of AI market value mainly lies into AI solutions' potential of application. Consequently, AI's potential of application (subsection 3.2) is also the root cause of CVC investments in AI and IT (Charron, 2020; Chui et al, 2023; KPMG, 2019; Ashoori et al., 2022; IBM, 2023).

In financial terms, according to studies by KPMG (2019), Ashoori et al. (2022; IBM) and IBM (2023), investing in an exponentially growing market opens a window to higher returns. Investments in innovative technologies are indeed expected by experts to generate positive Returns on Investments (ROI). Research by KPMG (2019), explores ROI's expectations in IT innovations by ten Tech Giants. The ten incumbents are indeed interviewed: according to the research results, 44% of the interviewees expect a meaningful ROI on investments in innovative tech within 6 months; 71% expects significant results by the first 12 months. The expectations on disruptive technologies' market, notably AI, are high (KMPG, 2019). To go more in depth, additional analyses reported in IBM Reseach Institute (Ashoori et al.,2022; IBM, 2023) need to be highlighted: ROI grows with AI maturity. The average ROI on global AI investments, in 2021, was around 5.9%; on the other hand, the "Best-in class"(Ashoori et al., 2022, p. 4) companies delivered a 13% ROI, which was double compared to the average and even higher than the average cost of capital for companies, equal to 10%. Nevertheless, in 2022, the average went up from 5.9% to 8.3%. It's all about "Disrupting yourself" (IBM, 2023); companies technologically innovate to adapt to changes and to seize context's opportunities, building ambidextrous organizations. Innovating is however not enough: as also noted in research by IBM (2023), IT and AI innovations have to integrally become part of the company's business in order to create value and generate better firm advantages. AI and IT investments do deliver value and financial returns; however, properly integrating the tech with the business, is an unavoidable condition (in depth analysis in subsection 4.1.2). Consequently, in order to fully integrate AI within one corporate reality, the development of proper capabilities and methodological approach, building the proper analytical skills, training teams and creating a corporate internal environment for a proper human-AI collaboration, is crucial.

Once the AI is embedded within the organization, it has matured and is used in the activities and functions it can effectively boost, ROI soars. AI and IT investments may indeed lead to high returns. (Ashoori et al., 2022; IBM, 2023).

4.1.2 CVC investing to access new technologies, grow organizational learning and lead competition

"Companies that treat AI as a 'technology thing' struggle to deliver value: An IT focus on AI tends to generate less value than a broad strategic focus" (Ransbotham et al., 2019). Accessing or acquiring AI and IT solutions is not only a financial matter, but mainly a strategic one (Ransbotham et al., 2019). In strategic terms, investing in technological solutions, which can be applied across business functions and improve them also exploiting a human-technology collaboration, opens a window to a boosted corporate performance (Benson & Ziedonis, 2009; Chui et al., 2023). All in all, beyond expected high financial returns (KPMG, 2019; Ashoori et al., 2022; IBM, 2023), investing in AI is indeed mainly pulled by strategically accessing to new tech solutions (Ransbotham et al., 2019, 2020).

Because of the current digital revolution, and within a fast-changing environment, which begun at the beginning of the 20s, several companies aspire to grow by exploiting technologies and disruptive technologies mainly (Morgan, 2016). In this context, taking into account that building value out of technology by internally developing it requires a lot of expertise and high degree of innovation, the majority of corporates prefers to exploit a B2B strategy, externally acquiring it (Charron, 2020; Dierickz & Cool, 1989; Richard and Devinney, 2005).

Innovative technologies, between which AI is one of the most relevant, can indeed provide several advantages and are a crucial source of competitive advantage; that is the reason why acquiring them can be a strategic move (Agarwal & Helfat, 2009, Benson & Ziedonis, 2009).

On the one hand, AI can be used to improve or fasten processes, cut costs, improve precision by analyzing huge amounts of data and enabling people and teams to make optimal decisions (Chui et al., 2023). All AI's applications, described in subsection 3.2, are applicable here to explain how much value AI can take to corporations and why corporations may want to access to it.

On the other hand, access to IT and AI innovations is directly and strongly linked to the concept of *organizational learning* (Benson & Ziedonis, 2009; Charron, 2020; Dushnitsky & Lenox 2005).

CVCs find in corporate venturing a driver to learn about disruptive solutions and technologies (Benson & Ziedonis, 2009). In fact, managers of CVC Programs tend to highlight the corporate exposure to new technologies as the main aim for them (Benson & Ziedonis, 2009).

The interaction with startups, producing innovative IT and AI solutions, can grow the investors' knowledge of the disruptive tech market and its evolving dynamics (Benson & Ziedonis, 2009), building corporate renewal and competitive edge (Agarwal & Helfat, 2009). The tech and market exposure and the acquisition of knowledge regarding innovative disruptive technologies, additionally grow incumbents ability to recognize successful solutions and ventures, identifying proper acquisition targets out of which synergies and higher financial returns can be built (Benson & Ziedonis, 2009).

According to Leithwood et al., (2001), Organizational Learning entails the concept of "knowledge acquisition and retention". Organizational Learning refers to "the activities through which organizational members construct new knowledge or reconstruct existing knowledge in order to improve the functioning of individual organizational members and the organization as a whole" (Leithwood et al., 2001, as cited in Sleegers & Leithwod, 2010, pp. 557-562). At the same time, knowledge plays a crucial role for firms, supporting them into value creation, to seize internal and external opportunities; it is a corporate asset (Benson & Ziedonis, 2009; Charron, 2020).

As noted by Argote (2013), organizational learning tends to happen through three sequential processes: knowledge creation, retention and transfer. Within the specific CVC investments in AI context, investors do acquire general and commercial knowledge and the organizational learning process occurs through the transfer of knowledge and innovation between the venture and the corporation so that the corporation subsequently transfer it to the whole organization, as according to Argote (2013) and as also noted by Charron (2020).

According to Argote (2013), as precisely reported by Charron (2020), the process is the following. Incumbents invest in IT and AI startups through CVC. The AI solution and the attached knowledge regarding AI, AI's market, trends and applications are retained by the incumbent and transferred to it.

Knowledge Retention refers to "actions taken to develop and maintain the organization's knowledge base" (Levallet & Chan, 2016, p.97-111).

Knowledge transfer is instead defined by Argote & Ingram (2000, p. 151) "As the process through which one unit of an organization is affected by another unit", simplified into indirectly learning from others, by Argote & Miron-Spektor (2011).

Consequently, the transfer occurs only if knowledge is effectively retained (Argote, 2013).

Additionally, in order to enable knowledge retention and transfer, regarding the acquired tech solutions, investors need to integrate it within their own operations and business strategy, to allow it spreading within the organization, as noted by Benson & Ziedonis (2009). To make this happen, in order to exploit the value of knowledge, investors do have to use R&D and absorptive capabilities for the integration (according to the study by Benson & Ziedonis , 2009). Consequently, beyond the acquisition, the assimilation through internal capabilities and R&D is a must to enable knowledge retention and organizational learning process completion. Consequently, the role of internal R&D, within this context, remains crucial. CVC investments and internal R&D are indeed unavoidably linked. They are complementary; this complementarity is a key element for incumbents to effectively leverage value and benefits deriving from disruptive technological solutions acquired through CVC (Benson & Ziedonis, 2009).

Having internal solid R&D means having robust knowledge and notably robust absorptive capacity. Absorptive capacity is "the ability of a firm to recognize, assimilate and commercialize the value of external knowledge" (Cohen & Levinthal, 1989). It is about developing ambidexterity, creating value out of existing competencies, while creating new ones contemporarily (Kolte et al.,2023).

CVC investments in tech and deep-tech can indeed generate huge value for incumbents; nevertheless, they can effectively grow an incumbent's performance, building competitive advantage, if complemented by a solid R&D level (Benson & Ziedonis, 2009; Dushnitsky & Lenox, 2005).

Overall, the linking between CVC investments in AI and IT and R&D is two-fold: an incumbent needs a proper level of R&D to integrate new tech capabilities (Benson & Ziedonis, 2009); on the other hand, the technology's complexity forces market players to access to external solutions in order to innovate, avoiding explosive R&D costs (Chesbrough 2003, as cited in Benson & Ziedonis, 2009). Accessing to external solutions supports internal limited R&D; R&D capabilities support the integration of external technologically innovative solutions (Chesbrough 2003; Rindfleisch & Moorman, 2001). On the other hand, the technical knowledge, referring to the specific AI solution, often remains tacit and embedded within the AI startup's context and is not transferred to the corporation (Charron, 2020).

All in all, the only needed element to create value (as previously highlighted, at subsection 2.3), is indeed a strategic and objectives alignment and fit, enabling synergies to leverage value from the CVC relationship (Chesbrough, 2002).

Overall, strategically talking, corporations do have interest into acquiring AI solutions mainly to grow their available stock of knowledge on disruptive technologies, growing their own organizational learning. This also enables them to reuse and build up on acquired and retained knowledge and assets and remain competitive on the market. CVCs in the IT and AI market have indeed several opportunities: acquire applicable solutions which generate value across activities and business functions, learn about successful innovations and consequently acquire the most promising solutions while contemporarily growing the potential of their financial returns, reuse knowledge to build out of it (subsections 4.1.1,4.1.2). Nevertheless, this is possible if the proper absorptive capabilities, through R&D exist. (Benson & Ziedonis, 2009).

4.2 CVC's value creation in the AI and IT context

In subsection 2.3, an in-depth analysis of all the advantages that startups can derive from CVCs both in financial and strategic terms, has been done. The former highlighted advantages for ventures, operating across industries, are also valid for IT and AI ventures; nevertheless, some clarifications are to be done.

A form of investor-AI startup collaboration is relevant in order to enable also startups to capture value from and within the current disruptive and technologically innovative context (Mack Institute for Innovation Management, 2024). As a matter of fact, and in line with various researches (O'Brien, 2023; Statista 2023, 2024), compared to other industries, the technological sector is more complex. In order to develop and scale an AI and IT solution, enhanced capabilities, expertise and infrastructures are needed.

In fact, settling technical infrastructure and a proper data architecture is complex and the costs, mainly the operating ones, are very high. IT spending is very high in general. It has reached a level of over $4.5 trillion in 2023 (O'Brien, 2023) and is projected to reach over $5 trillion by the end of 2024 (Statista, 2024). Over 30% of these expenditures depends on communication services; additional 30% depends on IT services; 20% depends on software; the remaining part is occupied by devices and communication services (Statista, 2024). In addition, from a comparison with other industries, IT spending as share of the revenues of companies that operate in software or tech/cloud hosting sectors, represents really high percentages. In 2023, software companies spent over 19%, while tech hosting ventures spent 18% of their revenues on IT. In comparison, Financial Services, had on average 15% of revenues allocated on IT spending, Telcom 14% and Healthcare 13%. (Statista, 2023).

Therefore, within the IT and AI context, also ventures need the "coopetition model" of reciprocal support, in order to grow (Mack Institute for Innovation Management, 2024); this need for cooperation is indeed furtherly driven by the AI and IT context's complexity (Mack Institute for Innovation Management, 2024; O'Brien, 2023; Statista 2023, 2024).

Consequently, CVC investments in the tech and deep-tech context are not only useful to investors to help them to adapt to the changing environment, but also crucial for start-ups themselves to navigate the complexities of the sector where they operate (Mack Institute for Innovation Management, 2024, O'Brien, 2023; Statista 2023, 2024).

On the one hand, in financial terms, CVC-backed ventures across industries, see their probability of survival and successful exit increase (Guo et al., 2015; McKinsey & Company, 2023). Corporate investors are significant players for startups and for AI startups too (Kagan et al., 2021). According to previous literature (Guo et al., 2015), the odds of exit and the exit strategy of ventures, across industries, also strongly depends on the investments' amount they have raised and on their duration, which represents how much time a venture survives since the foundation moment to the exiting one.

Several studies (Hellmann 2002; Masulis & Nahata, 2009) demonstrate that startups gain bigger amounts of investments from CVCs than they do from VCs. CVC-backed startups receive $52B on average compared to $26B received by VC-backed startups (Gompers & Lerner, 2000; Guo et al., 2015). Secondly, CVC-backed startups' duration is 1.938 days; VC-backed startups' duration is 1.642 (Guo, et al., 2015).

Therefore, CVCs indirectly impact startups' exit strategy (Guo et al., 2015). In these terms, IPOs tend to occur when the investment amount received is bigger and the startup's duration is shorter (Cumming, 2008; Hellmann, 2002; Riyanto & Schwienbacher, 2006). On the other hand, acquisitions are more likely to occur to startups with lower raised investments and longer durations: longer durations indeed guarantee a better diffusion of startups' information on the market and available to potential acquirers (Chemmanur & Loutskina, 2008; Gompers & Lerner, 2000). CVCs provide startups with higher investments' amounts but longer duration; as a consequence, the presence of CVCs does not significantly unbalance startups towards IPO or acquisition exiting, nevertheless it significantly impacts on the rates of startups' succesful exit, in one way or another (Guo et al., 2015).

Consequently, accessing to additional financing round is crucial for startups across industries but can indeed be key also for AI and IT startups, notably to cover costs and to support the product launching on the market and the generation of margins out of it (McKinsey & Company, 2023; as above introduced, in subsection 2.3). Also, CVC-backed startups tend to gain financing rounds of higher value, compared to non-CVC-backed; this also impacts on their exit strategy (Guo et al., 2015; O'Brien, 2023). Within the AI and IT context also considering that AI startups tend to attract more corporate investors (Kagan et al., 2021), this higher value may be extremely relevant for them to navigate the industrial complexities.

On the other hand, startups can gain additional huge strategic benefits from CVC funding (as above introduced, in subsection 2.3), mainly based on the acquisition of Industrial and Market Know – how and assets (Harlé et al., 2017; Weniger & Jarchow, 2022). This "intangible support" is exemplified in Corporate assets: Market data, Trend data, distribution channels, infrastructure. Due to the high IT costs of operating in deep-tech businesses., the exploitation by startups of incumbents' assets may indeed cut costs, that can be focused on the launch of the AI solution, fastening the process of growth and scaling. This may also grow life expectancy for AI startups. It is indeed clear that CVCs do have a positive impact on AI startups and on their growth and success' expectations.

Additionally, according to the BCG-Hello Tomorrow deep-tech survey (Harlé et al., 2017), deep-tech startups aim to access fundings from various partners for different reasons. The six main needs driving deep-tech startups (AI is a deep-tech innovation) to look for partnerships are identified as: financial resources (funding), market access, technical knowledge and expertise, access to facilities and talent acquisition. Startups look for different types of partners according to their priorities; nevertheless, accessing to corporate fundings is a strong driver for each of the above six identified deep-tech startups' needs: corporate fundings are crucial when looking for market access but relevant also when looking for technical and business knowledge and expertise. Indeed, while incubators and accelerators remain among the most relevant partners for deep-tech startups, CVCs are extremely important partners mainly in terms of accessing to parents' complementary assets (Harlé et al, 2017).

Consequently, CVC orientation towards AI has grown. A good and famous example of a CVC investment in AI is Microsoft's investment of $10 B on OpenAI, in 2023(Bass, 2023). The Incumbent had already allocated $1B on OpenAI in 2019 but kept acquiring equity stake on it because of the AI's market potential (Bass, 2023).

Besides this example, other huge and relevant CVC investments in AI have been concluded or are being concluded. Describing the most relevant among them, may be useful to better highlight their relevance in AI and IT context.

As reported in the IBM newsroom (2023), IBM launched a $500M venture fund, in November 2023, aiming to invest in AI ventures. IBM is pursuing a portfolio diversification strategy, supporting several businesses into realizing their potential. IBM's fund also aims to support promising solutions both from newly founded startups and high growth ventures (IBM, 2023).

To additionally highlight the relevance that is placed on AI, Google, has announced a $75B investment on Google AI Opportunity Fund, which aims to collaborate with Google.org, Google's philanthropic branch, in order to provide one million Americans with AI skills (Porat, 2024).

The former examples regard Tech Giants investing in AI and IT solutions (Bass, 2023; IBM 2023; Porat, 2024). Nevertheless, relevant examples of incumbents not operating in the IT sector, but investing in AI and IT, exist (Bass, 2018). Toyota Research Institute developed the Toyota AI Ventures division for CVC investments, allocating $100M on it, in 2017. The division invests on disruptive technologies (Toyota, 2018). Toyota, operating in the automotive industry, now holds a portfolio of over 50 innovative solutions, notably in AI and robotics (Lavine, 2024).

CVC investments in AI and IT are indeed huge in terms of sizes and a lot in terms of numbers (Bass, 2023; IBM, 2023; Kagan et al., 2021; Porat, 2024); we expect this to be an additional reason for CVC to significantly contribute to AI startups' support, growth and consequent succesful exit, mainly due to IT and AI context's complexities.
This is aim of the current study: to demonstrate the effective impact that CVC investments can have on AI startups.
For startups which are new in the market being associated with an incumbent may be beneficial to access complementary expertise and resources (Guo et al., 2015; Kagan et al., 2021). As a matter of fact, as noted by Benson & Ziedonis (2009), newly born ventures have innovative and competitive ideas but tend to lack of the array of resources needed to grow on the market. It is not enough to have a good proposal; ventures also have to survive the competitive landscape. An effective access and use of resources is crucial to survive. Enterprises do indeed need to look for investors that can provide them with support and with the most valuable benefits beyond financial support (Benson & Ziedonis, 2009. On the other hand, CVC investors, as also holding equity stakes in a startup, have interest in its long-term success and success on the market (Graumann, 2024).
This study's empirical analysis, starting from previous research, indeed aims to better observe to which extent also IT and AI startups find it relevant to be CVC-backed.

However, before developing the statistical analysis, an additional element is to be added. As a matter of fact, the above sections (sections 2., 3., 4.) have opened a dialogue on the relevance for newly founded ventures and deep-tech ventures to gather financial and strategic external support, with a specific focus on CVC. As additionally aforementioned, according to previous research, when referring to CVC it is possible to state that incumbents derive several benefits from CVC practice and startups derive several benefits from CVC investments.
Nevertheless, startups' success may also depend on additional factors: among them, we also have the ecosystem and site where one startup is located (Regions' Alliances for Interconnected Startup Ecosystems, 2024; Ziakis et al., 2022). The venture's geographical location indeed calls for an additional detailed analysis.

5. CVC investments and startups' exit – The role of startups' geographical location

Previous literature (Breschi & Lissoni, 2009; Delgado, et al., 2010; Feldman et al., 2005; Mason & Brown, 2014; Porter, 2000) has deeply studied the existence of location effects and how they drive entrepreneurship.

First of all, the regional economic environment can differently impact entrepreneurship: actors' co-location increases the pressure to innovate while increasing the perception of existing innovation opportunities; some locations, with higher co-location effects, have higher degree of innovation (Delgado et al., 2010; Porter, 2000). Following, arising clusters in specific location further grows additional entrepreneurship, guaranteeing easier access to resources, inputs and complementary products while lowering business entry costs (Feldman et al., 2005). According to Delgado et.al (2010), entrepreneurship's growth rates are much higher in those regional industries that are located in a relatively strong cluster; proximity of actors is relevant (Baskin, 2023).

To go more in depth, innovating "consists of a recombination of conceptual and physical materials that were previously in existence" (Nelson & Winter, 1982, p. 130). This definition lays foundation on the idea that innovation derives from reshuffling existing and new knowledge. Innovation, which is based on knowledge, according to Schumpeter's theories and view (Schumpeter, 1935, as cited in Śledzik, 2013) is the driving force of development and economic development: entrepreneurship and startups are generated out of knowledge, build knowledge and are assimilated with the concept of knowledge and knowledge creation. Startups are indeed built out of an innovative idea; similarly, AI startups are built out of an IT and deep tech innovative idea.

According to a study by Breschi and Lissoni (2009), knowledge refers to a corporate asset that flows. However, despite flowing, it turns out to be localized. As a matter of fact, knowledge flows depend on workers' mobility; knowledge workers, which are the actors through which knowledge flows, tend to move without effectively relocating in space but remaining in the same area or even region. All in all, the moving of knowledge workers across organizations enables connections between different inventors, but because movements are space bounded, they make knowledge localized (Breschi & Lissoni, 2009). Additionally, according to Barbulescu et al., (2023), the co-location of Knowledge sources into innovation clusters, enables the creation of "startup or entrepreneurial ecosystems", which can be defined as "sets of interconnected entrepreneurial actors (both potential and existing), entrepreneurial organizations (firms, investors), institutions (universities) and entrepreneurial processes, which formally and informally coalesce to connect, mediate and govern the performance within the local entrepreneurial Environment" (Mason & Brown, 2014, p. 5).

Overall, according to the above cited studies (Breschi & Lissoni, 2009; Delgado, et al., 2010; Feldman et al., 2005; Mason & Brown, 2014; Porter, 2000), actors co-location enables knowledge flow and knowledge localization and generates additional innovative opportunities, consequently driving entrepreneurship and startup ecosystems' settlement. Areas where knowledge flows faster and more easily indeed tend to be more innovative and to be site for additional innovation and entrepreneurship development (Breschi & Lissoni, 2009; Delgado, et al., 2010; Feldman et al., 2005; Mason & Brown, 2014; Porter, 2000).

World areas and Regions can host a more or less active co-location and innovative ecosystem. Regions indeed also differ in terms of their degree of innovation (better explained in sections 7., 8.): some sites seem to be more likely to host increased levels of innovation and entrepreneurship compared to others (GII, WIPO; 2023)

It is indeed crucial to observe whether a start-up, based in a location with a higher degree of innovation (subsections 7.4, 8.), has higher likelihood of growth and exit, notably thanks to better opportunities to continuously innovate.

Moreover, previous literature (Chen et al., 2010), also studied that VC firms tend to locate in areas where previous VC-backed investments have obtained a high rate of success. If a specific area is a VC center, new VC investments in that area are likely to additionally outperform; consequently, investments tend to locate next to other succesful investments (Chen et al., 2010).

It is then crucial to study if interactions between investments, notably CVC (as they are the focus of this study), and one startup's location exists and if the additional presence of a CVC, in a startup operating in an already outperforming area, increases the startup's chances to outperform too.

The following statistical analysis will indeed take also these elements into account when investigating the defined *RQ*.

6. Summary

To conclude, as noted by previous sections (see sources at sections 2., 3., 4., 5.), investors gain both financial returns and strategic benefits from CVC practice (Dushnitsky, 2012; Dushnitsky & lenox, 2006; Lantz et al., 2011). The same happens to funded startups.
In the specific AI and IT context, incumbents, as investors, obtain again financial returns and positive projections for enhanced ROI from investing in AI and IT solutions (Ashoori et al., 2022; IBM, 2023; KPMG; 2019), which have high market potential. Also, they obtain strategic benefits mainly linked to the technology and organizational transfer, through integration, helping them to adapt to a disruptive environment (Agarwal & Helfat, 2009; Benson & Ziedonis, 2009; Charron 2020; Dushnitsky & Lenox 2005; Ransbotham et al, 2019). When acquired and properly absorbed through R&D internal capabilities (Argote, 2013), a specific disruptive tech can also be exploited as basis to build additional value. On the other hand, AI & IT startups gain financial support, crucial to overcome huge costs and complexities deriving from IT spending (Statista 2023, 2024). On the other hand, they gain know how and experience regarding the Market and general trends (Weniger & Jarchow, 2022). They also gain access to incumbents' already established networks and technical expertise (Harlé et al., 2017) through knowledge workers mainly. Finally, they gain access to distribution channels and other subsidies and facilitations of the investors, that startups can exploit to grow their competitiveness on the market; these last benefits occur also to CVC-backed startups operating in other industries (see sections 2., 3., 4. For sources; as also noted by Bammens & Lilienweiss; Harlé et al., 2017; Pollman, 2020; Rossi et al., 2022; Weniger & Jarchow, 2022).

The following Statistical analysis aims to additionally investigate how all these benefits, driven by CVC investments in startups, and notably AI & IT startups, also support startups' likeliness to successfully exit. Within this context, it is to be taken into account an additional element: the startups' geographical site. Knowledge, from which Innovation arises, is the basis for entrepreneurship's development (Nelson & Winter, 1982; Schumpeter, 1935, as cited in Śledzik, 2013. Locally bounded knowledge flows (Breschi & Lissoni, 2009) tend to drive the creation of entrepreneurial ecosystems and the attraction of investors (Barbulescu et al, 2023; Delgado et al. 2010; Feldman et al., 2005; Porter, 2000). This is valid for startups in general (section 5.).Remembering that a coopetition investor-startup model, which can also be exemplified into the CVC practice, is optimal in the "Fourth Revolution" era (Mack Institute for Innovation Management, 2024), in order to analyze CVC's impact on IT and AI startups, the geographical factor needs to be taken into account.

Empirical analysis

7. Model and Hypotheses

The aim of this study is to investigate the relevance of CVC investments in AI and IT startups, with a specific focus on the crucial role that these investments do have on AI startups' exit. The efforts are exclusively on CVC investments in IT and notably AI startups because of the growing relevance that AI and its branches are gaining nowadays.

Additionally taking into account that some Regions of the World and locations are more likely to host the development of innovative solutions because of the ecosystem they host (Breschi & Lissoni, 2009; Delgado, et al., 2010; Mason & Brown, 2014; Porter, 2000), the site where a venture is founded needs to be taken into account. To make the model more solid, it is indeed crucial to observe if a more innovative ecosystem/site, impacts on one startup's growth and consequent probability to exit. After having analyzed this, the study will analyze if the additional presence of CVC investments in startups remains one of the most relevant factors for an AI startup's successful exit. The model also aims to study is CVC's presence positively moderates the location effect on startups' odds of successful exit. This study is set up also both taking into account that CVCs generate big value to investors and startups and that investments tend to locate next to other successful investments (Chen et al., 2010).

The analysis also takes the foundation time of the analyzed ventures into account; it may indeed impact on startups' maturity and consequent exit (subsection 7.1.1)

The aim of this thesis is to analyze if Corporate Venture Capital Investments do have a relevance on AI startups, increasing their probability of successfully exiting (*Research Question*) and accounting for the degree of innovation of startups' geographical location. To deal with the *Research Question*, the former Question is broken into four hypotheses:

Hypothesis A: Corporate Venture Capital Investments increase the probability of ventures' successful exit.

Hypothesis B: The degree of innovation of AI startups' geographical location increases ventures' probability of a successful exit.

Hypothesis C: When accounting for CVC Investments and location effect together, both effects independently increase ventures' probability of exit.

Hypothesis D: Corporate Venture Capital Investments positively moderate the location effect.

Consequently, the *Hypotheses* aim to investigate if there is a positive relationship between a startup's geographical location and its success, if CVC does have a positive relationship with an AI venture's successful exit too, and finally if CVC also positively moderates location effect.

This study aims to lay the foundation for additional future research, shedding light on the fact that CVC investments do have a significant positive impact on AI startups' successful exit.
As analyzed within the Literature review, incumbents do have several strategic and financial reasons to allocate money on startups and mainly on startups operating within the IT and AI-market on the supply side. At the same time startups have several advantages from gathering incumbents' corporate investments. The study *Hypotheses* that CVCs, thanks to the strategic and financial benefits they generate for startups, grow their probability of successfully exiting.

7.1 Data

In order to develop this analysis and support and add on what mentioned in the Literature Review, three different datasets, assembled from "Pitchbook: Venture Capital, Private Equity and M&A Database", are used and two regression analyses and a moderation analyses to test for CVC contribution to probability of successful exit for startups, accounting for startup's site, is conducted.
The first dataset contains data regarding 39,502 startups. These startups have disruptive technologies and notably AI production as their core activity: they are indeed defined as AI startups (OECD, 2021). The solutions these ventures produce are various and can be differently applied across industries. Most of them are applied in the Financial Services and in the Productivity Software Sectors.
The second dataset regards Deals done by the above-mentioned ventures; 108,441 deals have been identified. These deals represent all the external investments that companies have received. These investments pertain to different classes, going from private and individual to institutional investments.
The third dataset regards Investors. This dataset is indeed the joining link between the other two datasets; it contains data regarding investors that allocated money on the startups, of the first dataset, through the deals, of the second dataset. These investors pertain to various "types". Above all classes of investors, CVCs are the key element of our analysis.

The three datasets are merged into a final aggregated dataset. It contains the startups, paired with the total amount of Deals/investments they have received; these deals are in turn associated with the Investors that concluded them. The data are aggregated, to guarantee a correct merging between all the datasets.

The final merged and aggregated dataset contains several variables. These variables can be divided into three major groups: variables containing descriptive elements of the startups, variables representing deals' descriptive elements and variables regarding investors' features.

7.1.1. Variables

Ventures' variables hold data regarding firms' business and performance.

The *CompanyID* and *CompanyName* variables represent details regarding startups and their denomination.

PrimaryIndustrySector, represents to sector to which each startup pertains. As we are exclusively analyzing AI startups, we only have ventures operating in the Information Technology Sector.

YearFounded represents the foundation year of enterprises. All ventures were founded between 2000 and 2019. Therefore, some of them are in a more advanced stage of their life.

between 2000 and 2019. *YearFounded* is additionally associated with the *Time* variable, representing the life length of each venture since its foundation to current year (2024). These two variables, as will also be deepen in the following Methodology and Descriptive Statistics subsections (subsections 7.2, 7.3), are crucial to take the impact of time into account in the analysis and to allocate startups across various temporal Cohorts.

TotalRaised represents the amount of fundings gathered by each startup over the years, starting from their foundation year. It is a cumulative financial numeric variable expressed in million dollars, fluctuating a minimum of $50k and a maximum of over $12B.

LastFinancingDealType indicates the type of last financing round that startups have reached. It can be broken into different components, as Table 1. (Table 1., Appendix) shows. Ventures may be in an earlier or later stage; may be failing and going Bankruptcy or may be scaling and Exiting. It is to be highlighted that a company has had an exit and notably a successful exit if its *LastFinancingDealType* coincides with Merger/Acquisition (M&A), Buyout/LBO or IPO.

Employees is a numeric variable representing the number of employees working for each venture.

WorldArea is a categorical variable representing the Area in which startups are located: Africa, America (containing North America, including Canada, Central America and South America), Asia, Europe, Oceania; it is associated to the *HQLocation* variable, which indeed precisely lists the City, and to the *Country* variable, representing the country where each startup is sited. Each Country is also associated to an additional variable, GII_byCountry, which allocates scores of "degree of innovation", according to the Global Innovation Index, defined by WIPO (WIPO, 2023).

The dataset also includes both quantitative financial data, regarding ventures' financial performance, and qualitative ones, containing additional descriptive data regarding the ventures' business. For example, *NetIncome* and *EBITDA* (Earnings Before Interests, Taxes, Depreciations, Amortization) are numeric variables in millions measuring for ventures' profitability and operational performance. On the other hand, *Description* is a categorical variable providing information regarding ventures' activities and businesses, while *FinancingStatusNote* provides information regarding features of the fundings raised by each venture. Nevertheless, these additional variables are not the focus of our analysis.

Deals' variables regard the concluded deals between startups and investors.

The *DealID* variable represents the code of the specific deal received by a specific startup in a specific time (*DealDate* variable). We also have numeric data (*DealSize* variable), representing the size of each deal.

Each Deal is associated with the Investor that concluded it (*InvestorName* variable). The *DealID* variable is the merging variable between the three datasets, because it enables us to exactly know which investor has conducted which deal for which company.

For what concerns Investors' variables, beyond *InvestorName*, the dataset contains an additional key variable: *PrimaryInvestorType*. *PrimaryInvestorType*, represents which type of investor has concluded each specific deal. It can be divided into various subgroup, as shown in Table 2. (Table 2., Appendix). As investors can be of various types, they can also enter the enterprises' business and /or stake differently.

7.2 Methodology

Four logistic regression analyses, one of which is a moderation analysis, are run through Stata in order to test the defined *Hypotheses*.

The first analysis (answering to *Hp A*) aims to isolate CVC's effect on the startups' probability of success. The second analysis aims to observe the location effect on AI startup's probability to succeed (answering to *Hp B)*. The third regression aims to take into account both CVC and location effects but studying their effects independently (answering to *Hp C)*. The moderation analysis instead aims to observe if an interaction between the two effects exists and notably if CVC, positively moderates location effect (answering to *Hp D*).

LastFinancingDealType, from the dataset, is used to generate the dependent variable of the regression, *ExitSuccess*. *LastFinancingDealType* has a categorical nature; that is why the *ExitSuccess* dummy is created out of it. When *LastFinancingDealType* is equal to Merger/Acquisitions, IPO or Buyout/LBO, meaning that the venture has received a successful exit, the corresponding *ExitSuccess* dummy is equal to 1. Elsewhere it is equal to 0. M&A, IPO and LBO are indicators for successful exit, because they represent the stage at which the venture, thanks to both its financial performance and its strategic and business success' features, is acquired or goes public. It is relevant to specify that we assume to refer to the concept of "Successful exit" in financial and life stage terms. Consequently, only acquired or going public companies are considered as successfully exiting.

To follow, from *PrimaryInvestorType,* the *CVC* dummy variable is generated: *CVC* is used as the independent variable to answer to *Hp A*; is then used, together with location variable, within the third regression analysis, to answer to *Hp C;* is finally used as the moderator variable to answer to *Hp D*. *CVC* variable indeed corresponds to 1 when the investor (*PrimaryInvestorType)*, who allocates money on the corresponding deal and venture, is a Corporate Venture Capitalist, and 0 elsewhere.

Thirdly*, GII_byCountry* variable, reflecting the innovation's score of countries where ventures are allocated, is used as the independent variable when answering to *Hp B, Hp C* and *Hp D*. *GII_byCountry* depends on *Country* variable. To each *Country* is then assigned a specific score of Innovation, according to the Global Innovation Index (GII) (WIPO,2023) and through *GII_byCountry* variable. There is indeed a clear ratio behind this scores' allocation: this Study investigates *CVC* impact on AI startups also accounting for the innovative degree of the startup's geographical location; the foundation of a startup is unavoidably linked to the concept of "innovation" (Schumpeter,1935, as cited in Śledzik, 2013), from which new solutions and enterprises arise. In these terms, each Country, also depending on its internal ecosystem in terms of, for example, the number of startups or investors that it hosts, can have a higher or lower "degree of innovation" and can be assigned an Innovation score. The most representative index for a location's innovation score, according to its ecosystem, is the Global Innovation Index. The GII is built out of over 80 indicators from both public and private sources and aims at establishing the degree of innovation, assigning scores to each Country. It is based on two sub-indices: The Innovation Input Sub-Index and the Innovation Output Sub-Index. The Innovation Input Sub-Index captures economies' elements that facilitate innovative activities. It involves Infrastructure (including Tech infrastructure, General infrastructure and Ecological Sustainability), Human capital and research, Institutions, Business sophistication (mainly regarding knowledge work) and Market sophistication (mainly regarding the availability of an easy access to the international market) data (WIPO, 2023). The Innovation Output Sub-Index involves the results that innovative activities have within the economy, involving Knowledge and Technology outputs and Creative Outputs.

The simple average of the two sub-indices, corresponds to the final GII score, for each country (WIPO,2023). GII does indeed become a proxy for the geographical variable; using this numerical indicator as a proxy for *Countries*, enables us to overcome the problem of the categorical nature of the geographical variable.

It is crucial to include this proxy in the model to include in our results the location effect. As a matter of fact, we may expect more innovative world's areas to more easily support startups into successfully exiting.

The Research Question has been broken into four hypotheses, in order to investigate CVC impact on increased probability of exit after investigating if location effect is additionally increasing exit probability while being moderated by CVC. Consequently, the first regression is run with *CVC* alone, to study its independent effect on *ExitSuccess*; the second one is run with *GII_byCountry* alone, in order to study location effect; the third regression includes both location effect and CVC; the fourth regression has instead *CVC* as moderator. With the first regression we want to study if CVC increases AI startups' probability of exit. With the second regression, we want to study if a location effect on AI startups' probability of exit exists, according to one site's degree of innovation. With the third regression we aim to confirm that CVC does have a positive impact on AI startups' probability of success and the impact holds, beyond location effect. The purpose of this is to ensure that the effect of CVC, remains relevant, thereby adding additional robustness to the model. Finally, the moderation analysis, again including CVC and also a CVC-location interaction term, aims to study if *CVC* positively moderates *GII_byCountry's* impact on *ExitSuccess.*

Finally, the model also incorporates additional control variables to strengthen causal conclusions and ensure the model's validity.

First of all, time cohorts, generated from *YearFounded* are used to control the whole model. Our sample contains ventures founded between 2000 and 2019: 20 cohorts are indeed created. Older ventures are more likely to be exiting; younger startups, at an early-stage, more likely are in a growth stage, far from exit. Controlling the regression for time is indeed crucial. The aim is to include time effect within the regression, in order to understand if a cohort effect, linked to startups' foundation time, exists and is relevant within our analysis.

An additional reason for considering time effect in our analysis is the fact that it is assumed that only ventures under financial deals, such as M&As, IPOs or LBOs, are successfully exiting: newly founded ventures are in an initial lifecycle stage so it is almost impossible that they already have had a successful exit.
TotalRaised is used as an additional control variable. Higher total raised may indeed predict for a better venture's performance and higher probability of success. It is relevant to control the model through this variable to avoid confounding effects.
Employees is used as control variable too because a venture of a bigger size may be index of a more solid corporate growth and scaling: a bigger size may indeed mean that the venture is already well established on the market, evoking investors' trust. The variable's impact on the increased probability of successful exit needs indeed to be controlled.

Before studying the regression analyses' results, to answer to our *Hypotheses*, based on the Study's *Research Questions*, some descriptive statistics are run, in order to better analyze potential existing cohorts' time effects and to better support the model's results.

7.3 Descriptive statistics

The descriptive statistics aim to shed light on existing relationships among the main variables. In these terms, as the startups' sample includes ventures founded in different periods and currently in different lifetime stages, it is also relevant to study if specific trends, determined or influenced by time, exist. As above mentioned (subsection 7.2), startups are divided into time Cohorts according to the *YearFounded* variable. The following descriptive statistics indeed also aim to analyze potential existing patterns across *ExitSuccess* and capital raised (*TotalRaised* and *DealSize*) by startups, according to the ventures' foundation time and stage of lifecycle.
Overall, on the one hand, these descriptive statistics present relevant results regarding variables' relationships. On the other hand, they are also useful to better understand the reasons why some variables are or are not included within the final model (subsection 7.4) and notably the reasons why time effect is among the crucial variables that have to be included in the final Regression analyses, to answer to the RQ, in order to avoid confounding effects.
The complete development of the Descriptive Statistics' will not be presented in this subsection (subsection 7.3) but will instead be attached in the Appendix, at the end of this Study; nevertheless, the main points of discussion and the conclusions derived from the statistics, are here reported (subsections 7.3.1, 7.3.2, 7.3.3). Instead, for the in depth analysis, consult the Descriptive Statistics section in Appendix (Descriptive Statistics, Appendix).

7.3.1 ExitSuccess

First of all, a descriptive summary of *ExitSuccess* by cohort is run. It enables to study the percentage of successful exits for each cohort and to conclude that time impacts the percentage of AI startups successfully exiting. When moving from older to younger cohorts (e.g from 2000 to 2019 cohorts), the *ExitSuccess*' mean drops year by year: younger startups are less likely to exit and to already have exited because they still are in their growing stage of lifecycle. The older cohort (2000 cohort) does indeed present a percentage of ExitSuccess=1, above the 50% percentile. Then, this percentage steadily drop, as moving towards younger cohorts: cohorts between 2001 and 2009 present succesful exits above the 75% percentile; for cohorts between 2010 and 2016 the rate of succesful exits drops to the 90% percentile; 2017 and 2018 cohorts have succesful exits above the 95% percentile; 2019 cohort, above the 99% percentile.

On the other hand, the number of newly founded startups steadily grows when moving from older to younger cohorts, notably thanks to the context. In this regard, the amount of startups founded by cohort seems to strongly depend on the cohort's historical context. According to the results, it is clear that years/cohorts in which several and/or relevant innovations were drafted or improved, were more likely to host increased amount of startups' births. Innovation drives further entrepreneurship (Nelson & Winter, 1983; Schumpeter, 1935, as cited in Śledzik, 2013): the more the context evolves, the more startups are founded. In addition, 2004, 2007, 2010, 2011, 2012 and 2014 cohorts present significantly higher growths in the number of founded startups, compared to other cohorts; this may be expected to mainly depend on the innovative context that those specific time cohorts have hosted. 340 papers were submitted (17^{th} Australian Joint Conference on Artificial Intelligence, 2004) and Facebook was invented in 2004 (Webb & Yu, 2004). The first Iphone was invented in 2007 (Consoli, 2007). 3D bioprinter, Apple Ipad and Google Driveless car were invented in 2010 (The New York Times, 2010), together with the first self-replicating synthetic bacterial cell (J. Craig Venture Institute, 2010). Novel Protease Inhibitor for Treatment of Drug-Resistant HIV-1 (National Institutes of Health, 2011) and Siri were invented in 2011 (Brookings, 2001). The first foundation for the development of Machine Learning was laid in 2012 (Van der Made, 2023; Waters, 2023). Improvements of IoT and Cloud Computing technologies were made in 2014 (Newmann, 2015). The innovative and specific historical context appears to stimulate entrepreneurship. All in all, moving from older to younger startups, the percentages of exiting startups drops but the percentage of founded startups grows.

Overall, looking to the summary data for *ExitSuccess (*Table 3., Appendix*)*, the mean of the rate of successful exits is equal to 0.163, showing that only 16.3% of the sample's startups have made successful exit. This percentage is lowered by the presence in the whole sample of more recent startups. Taking these trends into account, time effect impacts on exit; using time to control the final model and regressions is indeed relevant and aims to account for confounding effects.

7.3.2 TotalRaised

To follow, the amounts of *TotalRaised* by time cohorts are analyzed. *TotalRaised* variable is expressed in millions. Going in depth, into single cohorts' results, it is possible to observe that each cohort tend to have low values of the median and few huge outliers, notably above the 99% percentile, that inflate the means and also increase the dispersion of results around the means (see Appendiz, Descriptive Statistics for in depth analysis). The outliers, among all time cohorts, tent to have values included between $1B and $3B. However, two exceptions exist. Firstly, 2004 cohort hosts a specific *TotalRaised* value equal to $12B and corresponding to the overall equity gathered by Meta Platforms. Secondly, 2015 cohort hosts the $11.3B *TotalRaised*, gathered by OpenAI; this amount of money allocated on OpenAI was mainly provided by Microsoft, operating as a CVC, between 2019 and 2023.

All in all, looking to the aggregated summary table of *TotalRaised* by time cohort (Table 4., Appendix), a $18.4M mean can be observed, with a $146.9M standard deviation. It can be inferred that the majority of startups have gathered, on average low amounts of capital, as all cohorts' median tend to be extremely low compared to cohorts' means, but few isolated outliers across time cohorts influence and inflate the aggregate mean.

Within this context, does time have a relevance? Time seems to be impactful on *TotalRaised* too: by making a comparative analysis between the oldest and the youngest cohort (2000 vs 2019), we obtain that 2000 cohort has a mean value equal to $34.76M while 2019 cohort has a mean value equal to $6.44M. In these terms, despite the fact that between 2000 and 2009 cohorts there is not a clear path determined by time (means tend to float), notably because of the strong presence of outliers, after 2009 the mean steadily drops year by year, keeping a descendant pattern. The inability to determine a clear path for the cohorts between 2000-2009, allows to assume that time is not the only crucial factor impacting on capital raised by AI startups (as will be further analyzed below in subsection,7.3.3; as also previously demonstrated by various studies: Gennaioli et al., 2015; Montanaro et al., 2024); nevertheless, as above demonstrated time still impacts on *TotalRaised*.

On the other hand, looking to an aggregated statistic showing the mean and standard deviation of *TotalRaised* by *CVC* variable (Table 5., Appendix*),* it is possible to notice that CVC-backed startups have a mean of TotalRaised qual to $45.57B while non-CVC-backed only have a $17.7M mean value, confirming that CVCs appear to allocate higher total investments on startups, despite a higher volatility (373 standard deviation vs 136); this confirms what mentioned by previous literature (Guo et al., 2015).

7.3.3 DealSize

To conclude the descriptive analysis, an additional statistic of single deals' size by cohort is run. The aim is twofold: going more in depth on the contribution that CVCs give to ventures into gathering higher investments raised on average, while looking for potential time trends and impact that time cohorts can have on this.

Analyzing *DealSize* by cohort, it can be observed as follows. *TotalRaised and DealSize* are interrelated: *TotalRaised*, is a cumulative variable for the total value raised, *DealSize* represents the amount of money that ventures have received through a specific deal.

TotalRaised is indeed the aggregated result deriving from the sum of all the Deals gathered by a venture (within our dataset we lack some minor deals; consequently, *TotalRaised* may be higher than the sum of single registered deals). The bigger the size of single deals gathered by a venture, the bigger the *TotalRaised*; but the lower the amount of *Deals* accessed, the lower the *TotalRaised*. As for *TotalRaised*, even for *DealSize,* each cohort holds low Median values and few high values and outliers above the 95% and /or the 99% percentiles, driving the cohorts' means up. As for *TotalRaised*, the majority of ventures have tendentially gathered deals of lower size: the aggregated mean is instead inflated by outliers. Cohorts indeed follow similar behaviors. The biggest outliers have values above $1B (a specific analysis of all the Deals above $1B, by cohort, is presented in the Appendix, in Descriptive Statistics section). Among them, the most relevant is the $10B investment allocated on OpenAI by Microsoft, as CVC, in 2023.

Overall, looking to the aggregated *DealSize*'s results for all cohorts (Table 6., Appendix), the mean is equal to $18.6M, while the median is equal to $1.65M. The median is strongly lower than the mean showing that the majority of startups have received smaller deals and investments in terms of size; however, few outliers boost the mean of *DealSize*. The standard deviation, equal to 86.1, is high, furtherly witnessing that data dispersion around the mean is big because of a lot small values flanked by a few big values.

Furthermore, running a summarized descriptive statistics of *DealSize* for *CVC* (Table 7., Appendix), it is possible to observe that CVC-backed AI startups tend to gather bigger deals compared to non-CVC-backed: the mean of *DealSize* for CVC-backed startups is 25.289, while the mean for non-CVC-backed is 18.418.

In contrast to the cumulative *TotalRaised*, *DealSize* appears to be less affected by time: there is not a clear path, determined by time effect; nevertheless, cohorts between 2000 and 2011 on average have mean values beyond $20M, while cohorts between 2011 and 2019 only include means with values below this threshold (between $15M and $18M). So, time effect, despite not clear, still exist and impacts also on this variable.

Despite the fact that the above analyzed descriptive statistics do not allow us to derive causal conclusions, observing the results and analyzing them in the light of previous studies and literature, it is possible to derive as follows.

Time seems to impact *ExitSuccess*; we expect this to happen because time grows ventures' maturity and consequently increases the percentage of ventures closer to a potential exit. Consequently, going through the statistics, a single path, affected by time effect, has been identified across time cohorts: the amount of exiting startups drops with time. The more recent the startup is, the less likely it is to have exited. The exit phase occurs when the startups' service or product has established in the market; startups at early stages tend to only see their products start making profits and achieving first milestones (Telefónica, 2023).

On the other hand, beyond time effect, also the technological context in which a startup grows needs to be taken into account: a more innovative context may stimulate investors and entrepreneurship to flourish (Regions' Alliances for Interconnected Startup Ecosystems, 2024; Ziakis et al., 2022), resulting into more founded startups.

Secondly, *TotalRaised* and *DealSize* seem to be impacted by time variable too. According to the statistics' results, beyond the outliers' presence and influence, younger startups tend to present, on average, lower *TotalRaised* and *DealSize*. Nevertheless, opposed to the *ExitSuccess* variable by time cohort, *TotalRaised* and *DealSize* present no linear paths across all cohorts. According to previous studies, it is possible to derive that the amount of investments gathered by a startups strongly depends on several factors; among them, there is investors' expectations (Gennaioli et al., 2015). In addition, it has indeed been demonstrated by a study by Montanaro et al. (2024) that capital gathered by AI startups through VCs investments (which CVC is a branch of) is positively moderated by both the ventures' stage of life and the investors' previous experience. As a matter of fact, older startups guarantee better information on their business activities and reduce the information asymmetry with investors. On the other hand, investors tend to allocate money according to their previous experience (Montanaro, et al., 2024). All in all, investments are driven by investors' expectations (Gennaioli et al., 2015), investors' experience and also ventures' stage of lifecycle (Montanaro, et al.,, 2024). Therefore, also according to previous literature, time is one of the factors influencing the amount of capital raised by companies, but not the only one. The statistics show that, even though the values of means for older startups are higher both in cumulative (*TotalRaised*) and single (*DealSize*) terms, there are no clear paths due to outliers. It is possible to expect that these outliers incorporate the fact that investment decisions are influenced by a wide range of factors, including time, that make it impossible to predict specific paths. Nevertheless, time remains significant in this context.

On the other hand, CVCs' presence has a positive linkage with *TotalRaised* and *DealSize*. Within the AI-IT context, CVC practice is diffused, notably for strategic reasons. All in all, CVC-backed AI startups are more likely to access larger Total raised and to funding/deals of a greater magnitude than non-CVC backed ventures (Guo et al., 2015). This is also confirmed by the statistics' results.

All in all, leaning on previous literature and as also demonstrated by the descriptive statistics' results, taking the impact of time into account for ventures' growth and capital raised is crucial. Starting from this, the Study will now investigate, through the regression analyses (subsection 7.4), if and how CVCs' presence and locations' degree of innovation affect ventures' probability of exit.

7.4 Results

The *Hypotheses* are investigated using three logistic regressions and a moderation analysis on the dependent variable *ExitSuccess*. The Logistic regressions, used because *ExitSuccess* is a dummy variable, are run using the "Logit" command on Stata; the "Logit" command enables to obtain the log-odds coefficients and is a more effective way to study the direction and strength of variables' relationships. On the other hand, to better observe the percentage increases or drops of the dependent variable, deriving from unitary increments of the other model's variables, a log-odds transformation into odd ratios is performed (odd ratio= e^(log-odd)); the odd increase of the dependent variable, depending on other variables' unitary changes, is equal to (odd ratio-1)*100.

7.4.1 Regression analysis with CVC

The first regression has *CVC* as independent variable and *YearFounded*, *Employees*, *TotalRaised* as control variables.

It is to underline, in light of the aforementioned descriptive statistics, that *DealSize* variable is excluded from all the model's regressions, to circumvent the potential risks associated with multicollinearity with *TotalRaised*. *DealSize* indeed represents a singular funding episode across all capital received by a startup; *TotalRaised* variable instead represents the cumulative amount of capital gathered by the same startup. *TotalRaised* needs to be employed in the model, thereby confirming that the potential influence of Corporate Venture Capitalists on *ExitSuccess* is not limited to the higher capital they provide (subsection 7.2). *TotalRaised* is used to control the model to prevent the confounding effects and *DealSize* is excluded to avoid leading to erroneous conclusions.

Looking into the results of the first regression, provided below (Table 8.; Appendix), the following statements can be done.

Table 8.

Regression analysis with CVC

Logistic regression

LR chi2(22) = 8574.92
Prob > chi2 = 0.0000
Log likelihood = -38851.491
Pseudo R2 = 0.0994

ExitSuccess	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
CVC	.5934658	.0476226	12.46	0.000	.5001272	.6868044
TotalRaised	-.0000312	.0000348	-0.90	0.370	-.0000993	.000037
Employees	-7.80e-06	5.61e-06	-1.39	0.164	-.0000188	3.19e-06
YearFounded						
2001	-.2636258	.0955802	-2.76	0.006	-.4509595	-.0762921
2002	-.4333582	.0952218	-4.55	0.000	-.6199895	-.246727
2003	-.5955183	.0929237	-6.41	0.000	-.7776454	-.4133913
2004	-.5400184	.0886727	-6.09	0.000	-.7138137	-.3662231
2005	-.5461298	.084711	-6.45	0.000	-.7121603	-.3800993
2006	-.8188551	.0848624	-9.65	0.000	-.9851824	-.6525278
2007	-.8807772	.0807128	-10.91	0.000	-1.038971	-.722583
2008	-.9090298	.0783472	-11.60	0.000	-1.062588	-.7554721
2009	-.931941	.0762981	-12.21	0.000	-1.081483	-.7823996
2010	-1.152135	.0742921	-15.51	0.000	-1.297744	-1.006525
2011	-1.122116	.0718118	-15.63	0.000	-1.262865	-.9813675
2012	-1.392312	.0706819	-19.70	0.000	-1.530846	-1.253778
2013	-1.587591	.070753	-22.44	0.000	-1.726264	-1.448917
2014	-1.739369	.07034	-24.73	0.000	-1.877233	-1.601505
2015	-2.152777	.0714514	-30.13	0.000	-2.292819	-2.012735
2016	-2.313994	.0721901	-32.05	0.000	-2.455484	-2.172504
2017	-2.72585	.0753095	-36.20	0.000	-2.873454	-2.578246
2018	-3.199358	.0822266	-38.91	0.000	-3.360519	-3.038197
2019	-3.407408	.0894067	-38.11	0.000	-3.582641	-3.232174
_cons	.1897188	.0646951	2.93	0.003	.0629187	.3165188

Note. [95% conf. interval]= confidence interval with lower and upper limits

Starting from the *CVC* variable, it presents a 0.5935 coefficient, with a high statistical significance (p-value< .001). The 95% confidence interval (between 0.500 and 0.687), not including 0, reinforces the results, confirming that *CVC*, as impacting on the dependent variable *ExitSuccess*, is statistically significant. Additionally, the standard error is equal to 0.0476; its value is relatively small, meaning that the coefficient's estimation is precise. This demonstrates that Corporate Venture Capital investments do have a significant positive impact on AI startups' successful exits, meaning that the presence of CVCs significantly increases the likelihood of ventures to exit through M&A, IPO, LBO.

Moving to the control variables, the following results are obtained.

TotalRaised presents a coefficient of -0.0000312 with a p-value of 0.370. The coefficient is indeed negative and shows that a low increase of *TotalRaised* may slightly decrease the odds of successful exit. Nevertheless, the p-value is significantly above 5%, meaning that there is no significance of *TotalRaised* on *ExitSuccess*. The non-significant impact is even smaller, taking the scale of *TotalRaised's* values into consideration.The regression model presents a different result compared to what mentioned by previous literature. Experts have previously observed the relevance of higher total investments for ventures' exits (Guo et al., 2015). In order to better explain our model's results, an additional analysis needs to be done. To begin with, the Descriptive statistics have indeed shown that time negatively impacts on *TotalRaised*. To follow, an additional correlation matrix between *TotalRaised* and *YearFounded* is run: the two variables present a low negative correlation, equal to -0.0855. Also, running a simple regression with *TotalRaised* as independent variable and *YearFounded* as dependent variable, it is possible to observe a highly significant negative coefficient of *YearFounded*, equal to -5.634, with a <.001 p-value. We confirm that *YearFounded* has a negative impact on *TotalRaised*. Taking into account that there is no collinearity between the two variables, as demonstrated by the low correlation between them (-0.0855), it is indeed possible to say that including time effect within the regression can reveal different dynamics of exit according to the stage of lifecycle of startups. For younger startups, additional capital raised is not necessarily driving a venture towards a successful exit. Older startups, if proposing promising solutions, are more likely to need less additional capital to scale and exit. Time's negative effect on *TotalRaised* explains these results.

On the other hand, as previously observed (Section 7.3), it was derived that also *CVC* variable is linked to *TotalRaised*; this is an additional reason that calls for the inclusion of *TotalRaised* in the model to guarantee that an eventual effect of *CVC* on *ExitSuccess* is not exclusively dependent on *TotalRaised*.

To follow, *Employees* has negative coefficient, equal to -7.80e-06, with a 0.164 p-value, meaning no statistical significance. The *Employees* variable, which indeed represents the concrete size of the venture, has a tiny coefficient and is not significant. As for *TotalRaised*, the inclusion of time variable within the model reduces or cancel the effect of *Employees* and ventures' sizes on their probability of exit. Overall, the size of a venture may be an indicator for its lifecycle stage and a potential prediction of the distance between the current company's state and its withdrawal from the market. Nevertheless, taking time into account, it does not appear to be a significant indicator to predict if a venture is more likely to successfully exit or not.

Finally, *YearFounded* is analyzed. The variable is not showing collinearity with other model's variables; it is indeed crucial to control the results for it because not doing it may wrongly estimate the effect of other variables.

Going more in depth into time variable, we obtain that coefficients of all time cohorts are negative and significant. The confidence intervals do not contain 0 for any observations, confirming the high significance of the coefficient. The cohort coefficient decreases steadily as we move from the older to the younger time cohorts. This confirms previous descriptive analyses, that the time of founding is a good indicator of the distance between the firm and its exit, and thus, when shorter, reduces the likelihood that the firm has already gone public or been acquired. We move from a -0.2636 coefficient's value with a 0.006 p-value in 2001, to a - 3.407 value with < .001 p-value in 2019.

The Pseudo R2 is around 0.0994, meaning that the model has explanatory power but there is a proportion of the dependent variable that remains unexplained.

On the other hand, the Prob>chi2 equal to 0.0000 shows a high significance of the model, as the model's variables have a collective high significant effect on the independent variable.

CVC does indeed increase AI startups' probability of exiting. The *Discussion* section (section 8.) will in deep analyze these results.

It is consequently crucial to observe if an additional location effect on AI startups' probability of exit exists, and if a location-CVC relationship exists.

Going through the second regression (Table 9.; Appendix), it can be observed as follows.

7.4.2 Regression analysis with GII_byCountry

The second regression has *GII_byCountry* as independent variable and *YearFounded*, *Employees*, *TotalRaised* as control variables (Table 4.; Appendix).

The following statements can be done.

Table 9.

Regression analysis with GII_byCountry

Logistic regression

	LR chi2(22)	= 8981.43
	Prob > chi2	= 0.0000
Log likelihood = -38648.237	Pseudo R2	= 0.1041

ExitSuccess	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
GII_byCountry	.0257336	.0011695	22.00	0.000	.0234414	.0280258
TotalRaised	-.0000651	.0000346	-1.88	0.060	-.000133	2.81e-06
Employees	-4.21e-06	5.10e-06	-0.83	0.409	-.0000142	5.79e-06
YearFounded						
2001	-.2677644	.0957694	-2.80	0.005	-.455469	-.0800598
2002	-.4269717	.0954796	-4.47	0.000	-.6141082	-.2398352
2003	-.5835973	.0931872	-6.26	0.000	-.7662409	-.4009537
2004	-.5308711	.08891	-5.97	0.000	-.7051315	-.3566106
2005	-.5361484	.0849104	-6.31	0.000	-.7025697	-.3697271
2006	-.803173	.0850392	-9.44	0.000	-.9698467	-.6364992
2007	-.8736435	.080893	-10.80	0.000	-1.032191	-.7150961
2008	-.8567068	.0785793	-10.90	0.000	-1.010719	-.7026941
2009	-.9161011	.0764681	-11.98	0.000	-1.065976	-.7662264
2010	-1.112273	.0744989	-14.93	0.000	-1.258288	-.9662579
2011	-1.087733	.072001	-15.11	0.000	-1.228853	-.9466139
2012	-1.350933	.0708706	-19.06	0.000	-1.489837	-1.212029
2013	-1.534062	.0709516	-21.62	0.000	-1.673125	-1.395
2014	-1.689892	.0705334	-23.96	0.000	-1.828135	-1.551649
2015	-2.092485	.0716474	-29.21	0.000	-2.232911	-1.952059
2016	-2.243715	.0724017	-30.99	0.000	-2.385619	-2.10181
2017	-2.666861	.0754948	-35.33	0.000	-2.814828	-2.518893
2018	-3.140996	.0824012	-38.12	0.000	-3.3025	-2.979493
2019	-3.347432	.0895788	-37.37	0.000	-3.523003	-3.17186
_cons	-1.338931	.0959712	-13.95	0.000	-1.527032	-1.150831

Note. [95% conf. interval]= confidence interval with lower and upper limits

Starting from *GII_byCountry* variable, the model presents a 0.0257 coefficient, with a high statistical significance (p-value < .001 and < .05). The 95% confidence interval (between 0.02344 and 0.0280), not including 0, reinforces the results, confirming *that GII_byCountry,* as the independent variable, is statistically significant. Additionally, the standard error is low, with a value equal to 0.001169; the coefficient's estimation is precise.

We indeed derive that the site where a startup is located, positively impacts on the startups' probability of exiting, even though its effect is small. The low coefficient does indeed demonstrate that the degree of innovation of countries, as a proxy of location effect, has a small but significant value on the odd of exit. Notably, there are different levels for the *GII_byCountry* variable: each *Country* is indeed assigned to its *GII* value (and this assignment happens under the *GII_byCountry* variable) according to the report by WIPO (WIPO; 2023). There are 107 levels of *GII_byCountry:* the amount of *Countries* in which the startups' sample are founded are 183; 15 of them are not assigned with any GII, as WIPO does not register any GII for those *Countries* (which are Chad, Monaco, Palestine, Seychelles, Gibraltar, Liechtestein, Tanzania, Venezuela, Gabon, Myanmar, Sierra Leone, Vanuatu, Belize, Andorra, Marshall Islands); 61 *Countries* are instead all included, according to WIPO, under the United States' GII, which includes North America and few islands and is calculated as a weighted index(WIPO; 2023). This allocation of GII by WIPO, leads to 107 levels of *GII_byCountry;* the analysis automatically organizes these levels on a scale from the lowest (lowest degree of innovation/GII among the sample's Countries) to the highest (highest GII). Consequently, AI startups located in a specific more innovative area see their probability of exit growing, compared to startups located in the area pertaining to the level below. This odd is supposed to grow by (e^(*GII_byCountry's* coefficient) -1)*100 when the GII index unitary changes; consequently, if the difference between GII indices of two countries pertaining to subsequent levels is 1, the startups' odd of succesful exit grows by (e^(0.0257336)-1)*100 when moving from the least to the most innovative of the two countries. However, as GII variable is continuous, the jump between one level and the subsequent one may not be unitary; for example Switzerland is the country assigned to the highest GII value, corresponding to 67.588, and Sweden follows (is the country with the 2^{nd} largest GII), with a GII equal to 63.22. In light of these non-unitary jumps, instead of considering the *GII_byCountry's* coefficient alone (0.0257336), it is instead necessary to consider (0.0257336* the difference in the degrees of innovation between a Country and the Country pertaining to the level below) = (0.0257336*Δ degree of innovation). We are indeed calculating the odd ratio on *GII_byCountry*' s coefficient, according to the difference in the countries' degrees of innovation. From this value, is possible to generate the odd ratios and subsequent odds' changes: referring back to the previous example, startups located in Switzerland, beyond any other factor or variables except for control ones, have a (e^[2.5%*(67.588-63.22)]-1)*100= 11.9% increased probability of success compared to startups located in Sweden. The same happens when moving between the other GII levels.

Moving from a location with a higher degree of innovation's level, to the location with the level over, the probability of success grows of the exponential of (2.5%* Δ degrees of innovation).

Taking into account that *GII_byCountry* represents startups' site according to the site's degree of innovation, the results demonstrate that being located in a more innovative area has a positive and significant effect on startups. A more active ecosystem may enable a startup to access more knowledge and expertise, to grow faster and be more successful, thanks to greater proximity to other entrepreneurs or actors.

Moving to the control variables, we can observe as follows.

TotalRaised presents a coefficient of -0.0000651 with a p-value of 0.06. The p-value is significant at 6% level, above 5%, meaning that there is no significance of *TotalRaised* on *ExitSuccess*. Beyond the low significance, its negative sign again depends on time effect.

Employees has a negative coefficient, equal to -4.21e-06, with a 0.409 p-value, meaning no statistical significance.

YearFounded has consistently negative coefficients when moving from older to younger cohorts: 2001's coefficient is -0.2677 with a p-value of 0.005, while 2019 cohort has a value of -3.347 with a p-value < 0.001.

The Pseudo R2 is around 0.104, meaning that the model has explanatory power but there still is a proportion of the dependent variable that remains unexplained.

The Prob>chi2 is equal to 0.0000 and shows a high significance of the model.

GII_byCountry does indeed influence AI ventures' probability of exiting.

Going through the third regression (Table 10.; Appendix), we have and observe as follows.

7.4.3 Regression analysis, including both CVC and GII_byCountry

Table 10.

Regression analysis including both CVC and GII_byCountry

Logistic regression

LR chi2(23) = 9120.54
Prob > chi2 = 0.0000
Log likelihood = -38578.682 Pseudo R2 = 0.1057

ExitSuccess	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
GII_byCountry	.0256254	.001171	21.88	0.000	.0233303	.0279204
TotalRaised	-.0000723	.0000347	-2.08	0.037	-.0001403	-4.28e-06
Employees	-4.03e-06	5.09e-06	-0.79	0.429	-.000014	5.95e-06
CVC	.58106	.0477478	12.17	0.000	.4874761	.674644
YearFounded						
2001	-.2643283	.0959213	-2.76	0.006	-.4523307	-.0763259
2002	-.4184839	.0956077	-4.38	0.000	-.6058715	-.2310963
2003	-.5705209	.0933198	-6.11	0.000	-.7534244	-.3876173
2004	-.5235277	.0890434	-5.88	0.000	-.6980495	-.3490059
2005	-.5330028	.0850508	-6.27	0.000	-.6996993	-.3663062
2006	-.8004441	.0851784	-9.40	0.000	-.9673907	-.6334974
2007	-.8675221	.0810224	-10.71	0.000	-1.026323	-.708721
2008	-.8571573	.0787086	-10.89	0.000	-1.011423	-.7028913
2009	-.9126899	.0765915	-11.92	0.000	-1.062806	-.7625734
2010	-1.104822	.0746144	-14.81	0.000	-1.251063	-.9585803
2011	-1.082615	.0721169	-15.01	0.000	-1.223962	-.9412686
2012	-1.344523	.0709822	-18.94	0.000	-1.483646	-1.205401
2013	-1.528973	.0710636	-21.52	0.000	-1.668255	-1.389691
2014	-1.681909	.0706427	-23.81	0.000	-1.820366	-1.543452
2015	-2.086999	.0717551	-29.09	0.000	-2.227637	-1.946362
2016	-2.236034	.0725077	-30.84	0.000	-2.378147	-2.093922
2017	-2.65903	.0755971	-35.17	0.000	-2.807198	-2.510862
2018	-3.130641	.0824958	-37.95	0.000	-3.29233	-2.968953
2019	-3.332675	.0896678	-37.17	0.000	-3.508421	-3.15693
_cons	-1.358033	.0961256	-14.13	0.000	-1.546436	-1.16963

Note. [95% conf. interval]= confidence interval with lower and upper limits

First of all, in order to contemporarily observe the coexistent impact of *CVC investments* and *location effect* on the model, both *CVC* and *GII_byCountry* are used within this regression. *GII_byCountry* coefficient remains positive, with a value of 0.0256, and significant (p-value <.001). Indeed, the Location effect remains relevant even when accounting for CVC investment in the model.

Secondly, *TotalRaised* has a coefficient of -0.0000723; its negative sign depends on time effect. *Employees* coefficient takes the value of -4.03e-06 at a 0.429 p-value showing no statistical significance.

Time effect (*YearFounded*) keeps holding decreasing coefficients when moving from older to younger cohorts.

Finally, moving on to the CVC variable, it is possible to observe that it has a coefficient of 0.581 with high statistical significance (p-value <.001). Also CVC does indeed have a positive and significant impact on the probability of succesful exit. The presence of a CVC investment within an AI startups, increases the probability for the startup to exit by 78.8%, calculated through the e^(*CVC's* coefficient)= e^(0.58106). Changing log-odds into odd ratios consists of the aforementioned formula; as CVC is a dummy variable, it means that the odd of succesful exit grows of 78.8% when moving from non-CVC backed to CVC-backed startups.

Adding CVC to the model demonstrates that Corporate Venture Capital investments do have a significant positive impact on AI startups' successful exits, beyond location effect.

Overall both CVC and location, independently impact AI startups' probability of succesful exit: the degree of innovation of one startup's site independently increases startup's odd of exit, beyond CVC effect; CVC independently increases startup's odd of exit, beyond location effect. On the other hand, the model hardly changes. Nevertheless, the pseudo R2 is equal to 0.1057, showing that the inclusion of both variables within the model increases the explanation power of results; however, the value is still small. On the other hand, part of the independent variable still remains unexplained; we derive that the probability of a successful exit not only depends on the type of fundings received or on the startup's location but also on additional features, such as investors' expectations (Weniger & Jarchow, 2022).

All in all, *CVC* is the variable presenting the highest significant coefficient and the highest impact on the probability of exit, among the ones analyzed.

The Prob>chi2 remains equal to 0.0000, showing a high significance of the model.

Taking into account that both location and CVC presence impact on startups' success, running a moderation analysis is relevant. The moderation analysis enables to understand if CVC positively impacts on the location variable (*GII_byCountry*), positively moderating it by increasing the effect of location on exit success. The results obtained are presented in Table 11.

7.4.4 Moderation analysis

Table 11.

Moderation analysis

Logistic regression

LR chi2(24) = 9127.20
Prob > chi2 = 0.0000
Log likelihood = -38575.349
Pseudo R2 = 0.1058

ExitSuccess	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
GII_centered	.0251019	.001185	21.18	0.000	.0227793	.0274245
TotalRaised	-.0000728	.0000347	-2.10	0.036	-.0001408	-4.83e-06
Employees	-3.98e-06	5.07e-06	-0.78	0.433	-.0000139	5.96e-06
CVC	.5359843	.0518769	10.33	0.000	.4343075	.6376612
interaction_GII_CVC	.0184282	.0074006	2.49	0.013	.0039234	.032933
YearFounded						
2001	-.2642628	.0959413	-2.75	0.006	-.4523042	-.0762213
2002	-.4174932	.0956152	-4.37	0.000	-.6048957	-.2300908
2003	-.5713045	.0933275	-6.12	0.000	-.7542231	-.388386
2004	-.5231184	.0890575	-5.87	0.000	-.6976679	-.3485689
2005	-.5333239	.0850619	-6.27	0.000	-.7000421	-.3666057
2006	-.8006391	.08519	-9.40	0.000	-.9676085	-.6336698
2007	-.8683422	.0810346	-10.72	0.000	-1.027167	-.7095172
2008	-.8559876	.0787203	-10.87	0.000	-1.010276	-.7016987
2009	-.9128665	.0766009	-11.92	0.000	-1.063002	-.7627315
2010	-1.104718	.0746214	-14.80	0.000	-1.250973	-.9584625
2011	-1.083062	.0721254	-15.02	0.000	-1.224425	-.9416989
2012	-1.344272	.0709895	-18.94	0.000	-1.483408	-1.205135
2013	-1.529389	.0710711	-21.52	0.000	-1.668685	-1.390092
2014	-1.682105	.0706496	-23.81	0.000	-1.820576	-1.543635
2015	-2.08717	.0717619	-29.08	0.000	-2.227821	-1.94652
2016	-2.235931	.072514	-30.83	0.000	-2.378056	-2.093806
2017	-2.659482	.0756041	-35.18	0.000	-2.807663	-2.5113
2018	-3.131567	.0825032	-37.96	0.000	-3.29327	-2.969864
2019	-3.333011	.0896733	-37.17	0.000	-3.508767	-3.157254
_cons	.1087961	.0650824	1.67	0.095	-.0187631	.2363552

Note. [95% conf. interval]= confidence interval with lower and upper limits

The *interaction_GII_CVC* variable, indicating the interaction term between *location* and *CVC*, is indeed generated with the aim of studying the combined effect of *CVC investments* and the degree of innovation of one startup's *location*. The interaction term is generated out of the combined effect of *CVC* and *GII_centered. GII_centered* corresponds to the centering of *GII_byCountry* variable on its mean: *GII_byCountry's* mean is subtracted from its values to generate *GII_centered*. The *interaction_GII_CVC* variable is indeed obtained by multiplying "*CVC* GII_centered*" variables. It is used to additionally control the model, where *ExitSuccess* remains the dependent variable, *GII_centered* is the independent variable, *CVC* is the moderator variable, *TotalRaised* and *Employees* the control variables. With the moderation analysis we indeed aim to study if *CVC* moderates location effect.

Consequently, beyond the combined effect, both the original variables (*CVC* and *GII_centered)*, which *interaction_GII_CVC* is extracted from, needs to be included in the model.
Notably, *GII_centered* is used in place of *GII_byCountry,* in order to give the model more stability and to reduce multicollinearity's problems. Indeed, taking into consideration that the interaction term and the two variables, from which the term is generated, have to be included in a moderation model, some multicollinearity problems may seem to arise. As a matter of fact, the interaction term, for definition, is function and product of the two variables from which it derives. Nevertheless, according to several studies (Allison, 2012; Johnston, 2017), the multicollinearity arising from the product of other model's variables is "not something to be concerned about" (Allison, 2012) because is not affecting the p-value of the combined variable. Despite this, centering variables may still be a good option to try reducing eventual problems. In this specific study, we center *GII_byCountry* only, because *CVC* is a dummy variable.
Going through the results it is observed as follows.
To begin with, *TotalRaised* and *Employees* have results similar to the ones observed in the former three logistic regressions: low negative coefficients with respectively low, for *TotalRaised*, and absent, for *Employees*, statistical significance (p-values equal to 0.036 and 0.433). This again mainly depends on time's presence within the model.
Following, looking to the effect of *GII_centered*, a positive coefficient, equal to 0.0251, with high statistical significance (p-value < .001) is observable. Considering that we are now looking at the combined effect of CVC and location, the single *location*'s coefficient here again demonstrates that the degree of innovation of a startup's site, increases the venture probability of success by 2.5%, even when CVC investments corresponds to 0. Indeed, a location's degree of innovation still increases the probability of a startup success, beyond the eventual presence of a CVC investment in the startup.
Similarly, CVC's coefficient is equal to 0.53598 with a high statistical significance (p-value < .001); even when the degree of innovation of the location is 0, CVC-backed startups still have increased probability of successfully exiting.
Finally, looking to the combined term, *Interaction_GII_CVC* presents a positive coefficient (0.01843) with high statistical significance (p-value < .001). This shows that the presence of *CVC, which is the moderator,* increases the location effect (*GII_centered*) on *ExitSuccess*; as the value of *CVC* increases, the effect of the independent variable on the dependent variable becomes stronger. CVC presence positively moderates and increases the effect that location has on the probability of success. These results confirm that the moderator (*CVC)* both increases

the probability of successful exit of AI startups and also contributes to increase the probability of exit of AI startups, after accounting for their location. This means that CVC strengthens the relation between the degree of innovation of a startup's location and its probability of successfully exiting. Taking the effect of the location on the startup's probability of exit into account, the additional presence of a CVC investments in the startup, furtherly increases the startup's odd of succesful exit by 1.83%. This leads to the fact that CVC furtherly grows probability of success of ventures located in more innovative locations and therefore already exposed to higher exit probabilities. The presence of a CVC investment amplifies location effect on exit probability by [1.843%*(GII changes, when moving between two locations pertaining to subsequent levels)]. Taking into account, as aforementioned (subsection 7.4.2), that location effect grows AI startups' probability of [e^(2.5%*Δ degree of innovation)-1]*100 when moving from startups located in a location with a certain degree of innovation to startups located in the area that have the GII immediately below, the CVC's presence furtherly grows the odds of exit by [e^(1.83%*Δ degree of innovation)-1]*100 when moving from one GII's level to the one immediately over.
The combined effect between CVC investments and startups' location creates a synergistic impact on *ExitSuccess*. All in all, a CVC investment moderates the effect that a location's degree of innovation has on the probability of success of startups located in that area.

Going through the four regressions' results it is indeed possible to observe that, on the one hand, both location and CVC's presence increase the AI startups' probability of success; on the other hand, additionally exploiting the interaction term is possible to observe that, if CVC and location are combined, the probability of exit of startups, which is already increased by the location effect, additionally grows by 1.843% thanks to CVC.
All in all, the independent effect of CVC investment, may increase the probability of success of AI startups by 58%, beyond location effect. Additionally, location has a positive effect too on success and the odds of successful exit are high already for startups located in more innovative areas; the additional presence of a CVC may, nevertheless, furtherly grow this probability.
The *Discussion* section (section 8.) will in deep analyze the results from all the four logistic regressions, including moderation one. Notably, the analyses need to receive a further explanation: CVC increases the probability of success of startups both located in areas with low and with high degree of innovation. This demonstrates the validity of the Study in answering to the *RQ* but also incorporate one model's limitation; this limitation will be better exposed in the following section (section 8.).

8. Discussion and limitations

The model setup with regressions and with the inclusion of a moderation analysis (subsection 7.4), enables to demonstrate a threefold effect: location effect on exit success, CVC effect on exit success and further CVC effect on location.

Building on the Literature review and the results obtained, it is possible to derive and open up some potential elements of discussion.

The first logistic regression, aims to answer to *Hp A*. According to the results, CVC's presence positively increases an IT -AI startup's probability of exit. We may expect that CVC-backed AI startups are more likely to succeed, notably thanks to the benefits that CVC can generate in ventures: financial support, (McKinsey & Company, 2023; Statista 2023, 2024) that tends to guarantee higher investments amounts also compared to VCs' support, (Gompers & Lerner, 2000; Guo et al., 2015) and the strategic support, consisting of investors' internal know-how, networks, expertise and assets, accessible by ventures when being funded (Weniger & Jarchow; sections 2., 4.). These benefits may also be driven by the huge costs of investing and operating in IT (Statista 2023, 2024), notably in AI and all its subsets, which concern several functions and scopes (Chui et al., 2023).

The second logistic regression instead aims to answer to *Hp B*. The results show that the location's degree of innovation positively increases a venture's probability of exit. Consequently, an AI startup located in a more innovative region, is more likely to successfully exit, being acquired or going public, independently from being CVC-backed. *GII_byCountry*, used as independent variable, represents Regions' degree of innovation according to GII scores and is a proxy for the location variable. Knowledge, on which innovation is based and from which startups derive and on which startups are build (Schumpeter, 1935, as cited in Śledzik, 2013), tends to be geographically localized in areas where there is an increased workers' mobility (Breschi & Lissoni, 2009). Additionally, areas that host actors' clusters increase pressure to innovate (Porter, 2000; Delgado et al., 2010) and tend to favor the diffusion of additional entrepreneurship because of better perceived innovation opportunities, easier access to complementary products, resources and lower costs of entry (Feldman et al., 2005). It can indeed be expected that a venture, located in a more active innovative area, where knowledge flows easily and where actors' co-location furtherly drives entrepreneurship, has a higher probability of successfully exiting.

To follow, according to the results of the third regression, that answers to *Hp C (subsection 7.4.3), location effect* presents a positive significant impact on probability of successful exit, beyond C*VC effect and CVC* presents a significant positive correlation with AI startups' odd of succesful exit, beyond location effect.

Finally, the fourth regression (for *Hp D*) shows that *CVC* positively moderates *location effects* on exit. It can again be expected that the further positive effect of CVC on startups located in highly innovative area, mainly depends on the financial and strategic benefits that CVC can drive in the entrepreneurship's context (sections 2., 4.). Overall, AI startups located in more innovative areas are more likely to have success; on the other hand, the further presence of a Corporate Venture Capitalist in an AI startup's equity tends to improve its chances to succeed. But, CVC's impact on AI ventures positively grows their exit probabilities anyway.

Despite being robust, the model still holds some additional limitations that would need further investigation. As a matter of fact, part of our *ExitSuccess* variable remains unexplained. This firstly depends on the fact that AI world is growing but a huge part of it is still unknown and the availability of public data is overall low. On the other hand, this may also lie on an additional element: the endogenous nature of CVC; this CVC's nature can be observed from the obtained results: the presence of Corporate Venture Capital in AI startups increases startups' probability of exit but furtherly increase by 1.843% the probability of exit of startups located in innovative areas and already having more chances of success, compared to startups located in less innovative areas. May we indeed investigate and say that CVC investments also have success and increase funded startups' success because of CVCs' ability to allocate money on startups that already had higher probabilities of success? CVC investments are not allocated on a random basis.

Consequently, this Study opens a dialogue on the two-fold effect of CVCs in the context of AI startups. As a matter of fact, on the one hand, we can therefore say that big players and incumbents strongly contribute, through CVC, to AI startups' access to exit. On the other hand, a positive moderation effect of *CVC* on *location,* exist. Investments indeed tend to locate in more succesful areas, where other succesful investments have previously located; investors tend to co-locate, as entrepreneurship does (Chen et al., 2010). This Study indeed opens up a dialogue on the fact that incumbents, acting as CVCs, may contribute to startups' success while contemporarily operating in World Areas that already are more promising to succeed and innovate.

The following example is explanatory. OpenAI, proposing one of the most succesful AI solutions of the last decade, is based in San Francisco (CA), whose southern Bay Area is occupied by Silicon Valley. Silicon Valley is an entrepreneurial ecosystem, both hosting promising ventures and top incumbents (San Francisco Innovation Hub, 2024). Top Big tech firms too (eg. Google, Facebook as Meta) have major sites in Silicon Valley (Kagan, Gelles & Arnold, 2021). It is indeed an innovation hub, where ventures have better growth and scaling possibilities and where “Many large corporations are creating offices to spot new trends” because “It’s no longer good enough to wait for change. You need to be out there where it’s happening. And a lot is happening in San Francisco” (Brad Power, 2013). OpenAI has initially exploited Silicon Valley’s innovative and active ecosystem to gather support and scale (Linley, 2024). Microsoft has funded OpenAI with over $11B. Microsoft funding rounds have grown OpenAI’s valuation, in 2019, to over $29B and are supporting OpenAI into its growth and success (Novet, 2023). Microsoft investments on OpenAI additionally maks up almost half of the global investments in Gen AI (Waters & Thornhill, 2023).

OpenAI consequently operates in an innovative World Area. Considering Silicon Valley’s potential, is it possible that Microsoft is acting as CVC in a World Area that already hosts more promising startups and is consequently investing on a venture that already had higher probability of exit?

As demonstrated through the run analyses and through Microsoft’s example, beyond the benefits generated by CVCs, also the World Location of a startup, according to its degree of innovation, does have an impact and influences the startup’s probability of exit. These two bound aspects, if investigated, may enable us to hypothesize on the endogenous nature of CVCs and CVC investments: CVCs do not allocate money on random startups, instead, they make carefully considered evaluations. These evaluations, reflecting CVCs’ ability to select promising startups, do have their contribution to the final increased odd of a funded startup to successfully exit.

To better investigate this aspect, additional analyses on our final merged dataset need to be run, in order to study the potential likeliness of startups to locate and of CVCs to invest in specific areas. In addition, the likelihood of successful exit of startups located in specific areas is examined.

A first analysis, showing us the cities (Table 12., Appendix) by frequencies in which startups are located, according to the dataset, is run: we obtain a table showing the ten cities (1/10 frequencies’ analysis) with higher frequencies. These ten cities represent the locations in which the highest amount of AI startups, according to our dataset, is founded and based, worldwide. The results show that San Francisco (CA), is the city with the highest amount of AI located startups, with around 2000 ventures, across the ones present in our dataset sample. New York (NY), London (UK), Beijing (CHI), Paris (FRA), Shanghai (CHI), Singapore (Singapore), Tokyo (JP), Seoul (South Korea) and Tel Aviv (Israel), follow. Secondly, a statistic on the frequencies of startups by *Country* is conducted (Table 13., Appendix). Overall, at aggregated level, the areas where AI startups are more likely to grow and flourish correspond and tend to be aligned to the statistic of cities. As a matter of fact, the Countries with more AI startups are California (CA), with over 5,900 observations, New York (NY) and Texas (TX), in the United States (US), the United Kingdom, China, Canada, France, India, Germany, and Israel. Comparing the frequencies by city (*HQLocation*) with the frequencies by *Country*, it is found that startups are more likely to flourish in North America (CA, NY, MA), Western Europe and South-Eastern Asia (with the exception of Israel, in the Western Asian side).

The main reason for startups to notably flourish in these areas is linked to the innovative footprint that these areas have. Looking to the degree of innovation by country (exploiting the Global Innovation Index, GII) (WIPO, 2023) and to the activity of the startup and accelerator ecosystems by country (exploiting the Global Startup Ecosystem Index) (StartupBlink, 2024), some clarification can be obtained.

As explained in the Methodology subsection (subsection 7.3), GII establishes the degree of innovation of Countries. According to the GII scores (WIPO, 2023; Merged Dataset), the US (North America) present a weighted average index equal to 63.5. China has a GII equal to 55.31, the UK have 62.44, Canada has 53,79, France has 56.02, India has 38.11, Germany has 58.76 and Israel has 54.31. Among the 132 Countries analyzed by the GII, these ten *Countries/Regions* are in the top 15; India only is instead ranked 40th. According to our dataset and to Table 13., the areas that most likely host new startups are also the ones with highest GII.

On the other hand, exploiting the Global Startup Ecosystem Index (StartupBlink,2024), is possible to study the startups' ecosystem by *Country* and classify each Country with a score, between a maximum of 215, in the US, and a minimum of 0.32, in Kyrgyzstan. The Index is made out of "hundreds of thousands of data points processed by an algorithm which takes into account several parameters"; StartupBlink collaborates with institutional partners to guarantee its results (e.g. the United Nation Development Program, the UNDP). The index aims to observe the value of startup ecosystems in each Country. As above mentioned (Section 5.; Mason & Brown, 2014), a startup or entrepreneurial ecosystem is a set of interconnected entrepreneurial actors. Considering its complexity, the Startup ecosystem index is indeed based on a Quantity score, a Quality score and a Startup Business Environment score. Regarding Quantity, the index considers the number of startups, investors, coworking spaces, accelerators and startup-related meetups activities within each country. Also, the number of Unicorns, Pantheon firms and influencers are included in the index. Unicorns are private exiting startups with a valuation over $1b; Pantheon refers to over 250 organizations that no longer are unicorns or startups but

continue to significantly impact their startup ecosystem. Influencers are startup influencers which impact goes beyond their own local ecosystem; they can be individual investors or entrepreneurs who impact areas even across local boundaries.
As far as Quality is concerned, its score is based on variables like the total raised by Private sector, the amount of R&D centers by country, the amount of accumulated employees in the startup sector, the total accumulated value of exits below $1B valuation, the number and market capitalization of listed company in tech sectors, and so no. All variables are matched together by algorithms in order to calculate the overall quality score of the ecosystem.
Finally, the Startup Business Environment score is based on indicators of one country's infrastructure and general business environment. It is the weighted average of elements that can boost or slow down one country's innovation growth (e.g. The presence of Top Universities, R&D investments, Internet speed, Corruption perception index, Diversity index etc.) (StartupBlink, 2023). According to the Global Startup Ecosystem Index, taking only the scores of Countries with higher frequencies (Tables 12., 13.) in our dataset into account, it is observed as follows. The US presents a 215 aggregated value; Canada presents a 38.254 score. Moving to Asia: Singapore has a 37.736 score, China has 18.46, South Korea has 13.41, Japan has a 13.312 score, Israel presents a score equal to 51.557 and India a score of 13.529. The UK has a value corresponding to 55.995. Germany has a score equal to 25.830 while France has a score of 24.894. All countries are positioned in the top 25 of the Global Startup Ecosystem Index (StartupBlink,2023).
All in all, the Countries and Regions where AI startups are primarily located, also are the ones with the highest both GII and Global Startup ecosystem indices. We also obtain that Countries with more active ecosystems, notably thanks to the presence in their territory of highly innovative cities (e.g. San Francisco in US, London in UK), are more likely to attract new ventures.
To follow, in order to observe a link with *CVC*, an additional frequencies' analysis, regarding the Countries where CVCs invest more, is run (Table 14., Appendix) The results represent the locations where the majority of CVC investments in AI startups, of our sample, are based. These results are consistent with Table 12. and Table 13., which represent the cities and countries where AI startups are primarily based.
As a consequence, it can be inferred that CVC investors are more likely to penetrate the AI and IT sector, allocating money on startups based in areas that teem with newborn ventures and have higher levels of innovation. CVC investments are highly diffused in California, New York, Massachusetts and Texas: the United States remains one of the primary subjects of our

investigation. Also, Canada hosts a very high amount of CVC investments. As far as Asia is concerned, China, Japan and Israel remain the places where CVCs invest the most. Finally, also the UK and Germany remain in the top 10. It is possible to notice that, although the exact listing order of frequencies is partially rearranged when we move from the locations of AI startups to the locations of CVC investments, the specific areas and countries do not change. As supported by the GII and by the Global Startup Ecosystem Index, the areas where enterprises and also CVC investments are mainly located are the most innovative ones.

To introduce a last element, a statistic highlighting the frequencies by *Country* for successfully exiting startups is run (Table 15., Appendix). Beyond time effect, the Countries with startups registering the highest number of exits are again California, New York, Massachusetts, Texas, Canada, the UK, China, Israel, France and Germany. This also confirms our Regressions' results, according to which the degree of innovation of one location impacts on startups' succesful exit.

Overall, according to these additional statistics (Table 12., 13., 14., 15.), it is found that startups are more likely to locate in certain Areas, with already active and innovative ecosystems. Innovation and innovation opportunities are a driver of entrepreneurship (Barbulescu et al., 2023). In addition, actors tend to co-locate and this co-location furtherly grows pressure to innovate (Delgado et al., 2010; Porter, 2000). Ventures locate next to other ventures; according to research by Ziakis et al. (2022), cooperation for innovation is a key driver of success. Collaboration between parties generates knowledge's exchange, resulting into open innovation, driving sustainable entrepreneurship (Ziakis et al. 2022). In these types of ecosystems, experts and human capital flow easily, knowledge flows because linked to human mobility, notably localized (Breschi & Lissoni, 2009). Startups' success both depends on startups' qualities (Regions' Alliances for Interconnected Startup Ecosystems, 2024) and on the ecosystem where the startup is located (Regions' Alliances for Interconnected Startup Ecosystems, 2024; Ziakis et al., 2022). A startup's internal capabilities, organizational structures and resources, in terms of human capital, technological ones and financial ones are indeed major factors of one startup's success (Regions' Alliances for Interconnected Startup Ecosystems, 2024). On the other hand, being located in an entrepreneurial ecosystem may additionally contribute to startups' success (Regions' Alliances for Interconnected Startup Ecosystems, 2024; Ziakis et al., 2022).

Contemporarily, CVC investments tend to locate in the same areas; according to a research by Li & Wang (2018), institutions and investors tend to locate in the same areas as entrepreneurs, supporting innovations and contributing to startups' support and success, also due to the fact that geographic proximity enables easier access to information and reduces information asymmetry and agency problems (Li & Wang, 2018). Finally, these areas are also the ones with the highest exit frequency of AI startups; investments locate where previous investments had high rate of success (Chen et al., 2010).

Looking to CVCs, it can be inferred that, beyond the positive effects that CVC investments do have on AI startups and on their probability of successful exits, an internal endogeneity effect also exists. As a matter of fact, also according to Tables 12., 13., 14., 15., CVCs tend to allocate money on startups operating in highly innovative and successful areas, where the degree of successful exits is already higher. Indeed, on the one hand CVC investments do have a significant positive impact on AI startups' exit, both beyond location effect and positively moderating it; on the other hand, CVCs also have an intrinsic capacity to identify and select the most successful or the most promising ventures, also depending on the context where these ventures have grown, which is a predictor of a venture's success.

In general terms VC investments' success, also strongly depends on their initial success (Nanda et al., 2020). The initial VCs' ability of identifying promising startups with higher odds of success is also a predictor for the investment's future success and the startup's successful exit. CVC, as a branch of VC, can be assumed to behave similarly. While CVCs have a significant impact on startups and contribute to their success (Results, subsection 7.4), also accounting for location effect, the initial choice of startups in which they invest is also crucial (Nanda et al., 2020). In general, good startup ecosystems may outperform big corporations and incumbents in terms of speeding up innovation cycles and improving existing business models or creating new ones through technological innovation; CVC investments is a highly diffused practice (IESE business school, 2017). In these terms, taking into account that the existence of a strategic fit between the two parties tend to grow the investment's probability of success, CVCs have to be able to make strategic decisions and also align their internal strategy with startup's strategy in order to exploit synergies (IESE Business School, 2017). CVCs tend to use the five Ps framework to assess a proper investment strategy: they aim to access startups that guarantee an alignment of objectives and processes, that can be integrated in the corporate reality through the internally available or developable skills and capabilities, that can provide benefits and accelerate internal innovation, and that can guarantee a successful performance. CVCs are indeed able to select promising startups ex ante: they select startups that propose disruptive solutions and startups with which synergies can be built (Khuong & Nguyen, 2022).

General Investors ability to select ex-ante also contributes to the success of the investments ex post (Nanda et al., 2020).

In conclusion, CVC investments do have success not only because they generate benefits for startups and help them to grow but even because of Corporate Venture Capitalists ability to select promising startups when choosing where to invest their money (Khuong & Thanh Van, 2022).

Looking to statistics' results and to previous literature, it is possible to derive that startups and investors continuously attract themselves. AI startups located in active entrepreneurial ecosystems have easier access to education, training, workforce, market and support; these factors contribute to grow the probability of entrepreneurial success (Ziakis et al. 2022). CVCs are indeed likely to invest in promising startups that have this successful perspective. Overall, innovative areas attract increasing amounts of entrepreneurs, which attract increasing amounts of investors, and so on.

Consequently, both the results from the moderation analysis (subsection 7.4.4) and the ones regarding the statistics of geographical locations' frequencies (above, in this section 8.), also leaning on previous literature review, enable us to observe and investigate CVC's endogeneity. In these terms, Corporate Venture Capitalists have the ability to select successful startups (*Statistics*, subsection 8.), also according to their geographical location. As a matter of fact, a more innovative location with a more active ecosystem is a signal of a higher probability of a successful exit for the startups located there (*Results*, subsection 7.4.2). This indeed is also a predictor of a higher probability of success of the CVC investment through a successful startup's exit. On the other hand, the concrete benefits that CVCs generate on the AI startup they fund, both in financial and strategic terms, additionally grow the probability of startups to have success and to successfully exit, beyond the geographical location. The two elements are interrelated.

The model indeed highlights that being CVC-backed, always increases one startup's probability of success, even in less innovative areas (*Results*, 7.4.4). Nevertheless, as CVCs not randomly select target startups on which to invest, they tend to select more promising startups ex ante; this non-random selection furtherly grows the ex-post probability of success of CVC investments (as also previously noted by Nanda et al., 2020). CVC indeed tend to support startups that are usually located in more innovative ecosystems, as the external ecosystems of one startup's is also a strong determinant of its success, and that already have higher probabilities of success.

This model's limitation, intrinsic to CVCs' features, is here signaled and must be taken into account; future research should build on the present findings, better studying *CVC* endogeneity on startups' probability of success. Nevertheless, the presented results (as above demonstrated, Results, subsection 7.4) remain solid. All in all, CVC positively moderates location effects but is also endogenous to them. The presence of CVC investments increases the probability of success of startups well and strategically located. But this also occurs because of CVCs ability to locate their investments in innovative areas. CVC positively moderates location effects but is attracted by them.

In conclusion, despite the CVC's endogenous effect, the final results shed light on the *RQ* and provide support to the *Hypotheses*.

9. Conclusion

This study aims to add and investigate new elements regarding CVC investments in the IT and AI context, building on existing literature. In order to answer to the RQ that guides the whole setting, a robust statistical model has been developed: four *Hypotheses* were investigated through four logistic regressions, among which a moderation analysis. Through database analysis, it was possible find the following results. Firstly, there is a positive and significant relationship between the presence of CVC investments in AI startups and their probability of successful exit exist. Secondly, there is a location effect on AI startups' probability of successful exit: the degree of innovation, as measured by the GII index (WIPO, 2023), of the site where an AI startup is located (used as a proxy for location), positively and significantly impacts on the startup's success. Overall, taking into account that 107 levels of *GII_byCountry* (which is the proxy for the location effect and indicates the degree of innovation by Country) exist, the probability of successful exit for startups located in the upper level of innovation, grows compared to the probability of exit of startups in the level immediately below. Finally, a moderation analysis has demonstrated that CVC's presence within an AI startup furtherly increases the venture's probability of success, positively moderating location effects. Looking at the CVC-location combined effect it can be observed that CVC's presence furtherly increases an AI startup's probability of success, after accounting for startups' location, and furtherly boosts the location effect, by a value equal to [e^(1.843%*Δ degree of innovation between two countries pertaining to subsequent levels, considering that *GII_byCountry* variable is ordered in ascending order)-1]*100.

The solid conclusions drawn from this study enable to positively answer to the *Research Question;* CVC is demonstrated to positively impact and significantly increase AI startups' probability of exit. Furthermore, as the degree of innovation of an AI startup's location is also relevant for its success, CVC positively moderates the location effect.

Moreover, this study also opens a dialogue on a model's limitation, consisting of the endogenous nature of CVCs: CVCs do not invest randomly; they look for strategic and synergistic opportunities when investing and make careful assessments and valuations of startups to invest in (IESE business school, 2017). Running additional statistics (subsection 8.) it has indeed been possible to demonstrate that the majority of AI ventures (from our sample) tend to be founded and located in regions and countries with higher degrees of innovation, both according to the GII (WIPO; 2023) and to the Global Startup Ecosystems Index (StartupBlink, 2024). These countries also coincide with the sites where most of CVC investments are located and where the majority of successful exits has occurred (Tables 12.,13.,14.,15). Investments, in general, tend to locate in sites where other and previous investments had already been successful (Chen et al., 2010). It is indeed possible to derive that CVCs are able to select promising startups ex-ante, also according to those startups' location, because the degree of innovation of a startup's location is a predictor of the startup's success (sections 7.4, 8.; Regions' Alliances for Interconnected Startup Ecosystems, 2024). CVCs, because of a conscious ex-ante selection, consequently tend to allocate money on promising startups and contribute to drive to success the startups that already had higher chances to succeed. Additionally, taking into account that investments' success also strongly depends on investors' initial success (Nanda et al., 2020), it may be expected that CVCs' ex-ante ability to select promising startups is also an additional driver for their investments' ex-post success. The CVC's two-fold effect is intrinsic to CVCs' features and objectives.

All in all, despite this endogenous effect which future research should consider and build on, the statistical analysis is solid enough to answer to the initial *RQ*. The model's results are indeed solid enough to underline the crucial relevance of CVCs' presence in AI startups, as CVC investments significantly increase ventures' probability of success.

Appendices

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Appendix

Figure 1. McKinsey & Co, 2023, CVC-backed startups

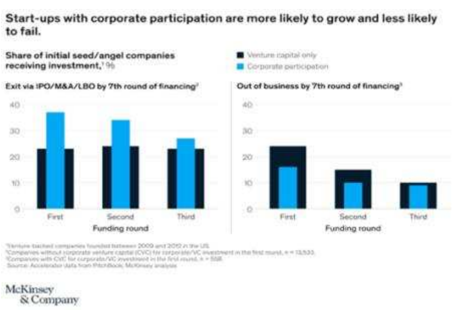

Table 1. Dataset, LastFinancingDealType variable

LastFinancingDealType
Accelerator/Incubator
Angel (individual)
Bankruptcy: Admin/Reorg
Bankruptcy: Liquidation
Bridge
Buyout/LBO
Capitalization
Convertible Debt
Corporate
Debt - General
Debt - PPP
Debt Refinancing
Debt Repayment
Dividend Recapitalization
Early Stage VC
Equity Crowdfunding
Grant
Investor Buyout by Management
IPO
Later Stage VC
Leveraged Recapitalization
Merger of Equals
Merger/Acquisition
Mezzanine
Out of Business
PE Growth/Expansion
PIPE
Product Crowdfunding
Public Investment 2nd Offering
Restart - Angel
Reverse Merger
Revolving Credit Line
Secondary Transaction - Open Market
Secondary Transaction - Private
Secondary Transaction - Stock Distribution
Seed Round
Share Repurchase

Table 2. Dataset PrimaryInvestorType variable

PrimaryInvestorType
Accelerator/Incubator
Angel (individual)
Angel Group
Asset Manager
Business Development Company
Corporate Venture Capital
Corporation
Family Office
Fund of Funds
Government
Growth/Expansion
Hedge Fund
Holding Company
Impact Investing
Infrastructure
Investment Bank
Lender/Debt Provider
Limited Partner
Merchant Banking Firm
Mezzanine
Mutual Fund
Not-For-Profit Venture Capital
Other
Other Private Equity
PE-Backed Company
PE/Buyout
Real Estate
SBIC
Secondary Buyer
Sovereign Wealth Fund
University
VC-Backed Company
Venture Capital

Table 3.Descriptive statistics, summary of ExitSuccess

Variable	Mean	p50	SD
ExitSuccess	.1629538	0	.3693282

Table 4. Descriptive statistics, summary of TotalRaised

Variable	Mean	p50	SD
TotalRaised	18.40316	.79	146.9616

Table 5. Descriptive statistics, TotalRaised's mean and standard deviation by CVC

	Mean	Standard deviation
CVC		
0	17.70835	136.2421
1	45.57268	373.752
Total	18.40316	146.9616

Note. Mean and Sd of TotalRaised, for CVC-backed (CVC=1) and non CVC-backed (CVC=0) startups

Table 6. Descripitve statistics, summary of DealSize

Variable	Mean	p50	SD
DealSize	18.61985	1.649999	86.1237

Table 7. DealSize's mean and standard deviation by CVC

	Mean	Standard deviation
CVC		
0	18.41791	77.87709
1	25.2896	228.1791
Total	18.61985	86.1237

Table 8 Regression analysis with CVC

Logistic regression

LR chi2(22) = 8574.92
Prob > chi2 = 0.0000
Log likelihood = -38851.491 Pseudo R2 = 0.0994

ExitSuccess	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
CVC	.5934658	.0476226	12.46	0.000	.5001272	.6868044
TotalRaised	-.0000312	.0000348	-0.90	0.370	-.0000993	.000037
Employees	-7.80e-06	5.61e-06	-1.39	0.164	-.0000188	3.19e-06
YearFounded						
2001	-.2636258	.0955802	-2.76	0.006	-.4509595	-.0762921
2002	-.4333582	.0952218	-4.55	0.000	-.6199895	-.246727
2003	-.5955183	.0929237	-6.41	0.000	-.7776454	-.4133913
2004	-.5400184	.0886727	-6.09	0.000	-.7138137	-.3662231
2005	-.5461298	.084711	-6.45	0.000	-.7121603	-.3800993
2006	-.8188551	.0848624	-9.65	0.000	-.9851824	-.6525278
2007	-.8807772	.0807128	-10.91	0.000	-1.038971	-.722583
2008	-.9090298	.0783472	-11.60	0.000	-1.062588	-.7554721
2009	-.931941	.0762981	-12.21	0.000	-1.081483	-.7823996
2010	-1.152135	.0742921	-15.51	0.000	-1.297744	-1.006525
2011	-1.122116	.0718118	-15.63	0.000	-1.262865	-.9813675
2012	-1.392312	.0706819	-19.70	0.000	-1.530846	-1.253778
2013	-1.587591	.070753	-22.44	0.000	-1.726264	-1.448917
2014	-1.739369	.07034	-24.73	0.000	-1.877233	-1.601505
2015	-2.152777	.0714514	-30.13	0.000	-2.292819	-2.012735
2016	-2.313994	.0721901	-32.05	0.000	-2.455484	-2.172504
2017	-2.72585	.0753095	-36.20	0.000	-2.873454	-2.578246
2018	-3.199358	.0822266	-38.91	0.000	-3.360519	-3.038197
2019	-3.407408	.0894067	-38.11	0.000	-3.582641	-3.232174
_cons	.1897188	.0646951	2.93	0.003	.0629187	.3165188

Table 9. Regression analysis with GII_byCountry

Logistic regression

LR chi2(22)	= 8981.43
Prob > chi2	= 0.0000
Log likelihood = -38648.237 Pseudo R2	= 0.1041

ExitSuccess	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
GII_byCountry	.0257336	.0011695	22.00	0.000	.0234414	.0280258
TotalRaised	-.0000651	.0000346	-1.88	0.060	-.000133	2.81e-06
Employees	-4.21e-06	5.10e-06	-0.83	0.409	-.0000142	5.79e-06
YearFounded						
2001	-.2677644	.0957694	-2.80	0.005	-.455469	-.0800598
2002	-.4269717	.0954796	-4.47	0.000	-.6141082	-.2398352
2003	-.5835973	.0931872	-6.26	0.000	-.7662409	-.4009537
2004	-.5308711	.08891	-5.97	0.000	-.7051315	-.3566106
2005	-.5361484	.0849104	-6.31	0.000	-.7025697	-.3697271
2006	-.803173	.0850392	-9.44	0.000	-.9698467	-.6364992
2007	-.8736435	.080893	-10.80	0.000	-1.032191	-.7150961
2008	-.8567068	.0785793	-10.90	0.000	-1.010719	-.7026941
2009	-.9161011	.0764681	-11.98	0.000	-1.065976	-.7662264
2010	-1.112273	.0744989	-14.93	0.000	-1.258288	-.9662579
2011	-1.087733	.072001	-15.11	0.000	-1.228853	-.9466139
2012	-1.350933	.0708706	-19.06	0.000	-1.489837	-1.212029
2013	-1.534062	.0709516	-21.62	0.000	-1.673125	-1.395
2014	-1.689892	.0705334	-23.96	0.000	-1.828135	-1.551649
2015	-2.092485	.0716474	-29.21	0.000	-2.232911	-1.952059
2016	-2.243715	.0724017	-30.99	0.000	-2.385619	-2.10181
2017	-2.666861	.0754948	-35.33	0.000	-2.814828	-2.518893
2018	-3.140996	.0824012	-38.12	0.000	-3.3025	-2.979493
2019	-3.347432	.0895788	-37.37	0.000	-3.523003	-3.17186
_cons	-1.338931	.0959712	-13.95	0.000	-1.527032	-1.150831

Table 10 Regression analysis with CVC and GII_byCountry

Logistic regression

LR chi2(23)	= 9120.54
Prob > chi2	= 0.0000
Log likelihood = -38578.682 Pseudo R2	= 0.1057

ExitSuccess	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
GII_byCountry	.0256254	.001171	21.88	0.000	.0233303	.0279204
TotalRaised	-.0000723	.0000347	-2.08	0.037	-.0001403	-4.28e-06
Employees	-4.03e-06	5.09e-06	-0.79	0.429	-.000014	5.95e-06
CVC	.58106	.0477478	12.17	0.000	.4874761	.674644
YearFounded						
2001	-.2643283	.0959213	-2.76	0.006	-.4523307	-.0763259
2002	-.4184839	.0956077	-4.38	0.000	-.6058715	-.2310963
2003	-.5705209	.0933198	-6.11	0.000	-.7534244	-.3876173
2004	-.5235277	.0890434	-5.88	0.000	-.6980495	-.3490059
2005	-.5330028	.0850508	-6.27	0.000	-.6996993	-.3663062
2006	-.8004441	.0851784	-9.40	0.000	-.9673907	-.6334974
2007	-.8675221	.0810224	-10.71	0.000	-1.026323	-.708721
2008	-.8571573	.0787086	-10.89	0.000	-1.011423	-.7028913
2009	-.9126899	.0765915	-11.92	0.000	-1.062806	-.7625734
2010	-1.104822	.0746144	-14.81	0.000	-1.251063	-.9585803
2011	-1.082615	.0721169	-15.01	0.000	-1.223962	-.9412686
2012	-1.344523	.0709822	-18.94	0.000	-1.483646	-1.205401
2013	-1.528973	.0710636	-21.52	0.000	-1.668255	-1.389691
2014	-1.681909	.0706427	-23.81	0.000	-1.820366	-1.543452
2015	-2.086999	.0717551	-29.09	0.000	-2.227637	-1.946362
2016	-2.236034	.0725077	-30.84	0.000	-2.378147	-2.093922
2017	-2.65903	.0755971	-35.17	0.000	-2.807198	-2.510862
2018	-3.130641	.0824958	-37.95	0.000	-3.29233	-2.968953
2019	-3.332675	.0896678	-37.17	0.000	-3.508421	-3.15693
_cons	-1.358033	.0961256	-14.13	0.000	-1.546436	-1.16963

Table 11. Moderation analysis

Logistic regression

LR chi2(24)	= 9127.20
Prob > chi2	= 0.0000
Pseudo R2	= 0.1058

Log likelihood = -38575.349

ExitSuccess	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
GII_centered	.0251019	.001185	21.18	0.000	.0227793	.0274245
TotalRaised	-.0000728	.0000347	-2.10	0.036	-.0001408	-4.83e-06
Employees	-3.98e-06	5.07e-06	-0.78	0.433	-.0000139	5.96e-06
CVC	.5359843	.0518769	10.33	0.000	.4343075	.6376612
interaction_GII_CVC	.0184282	.0074006	2.49	0.013	.0039234	.032933
YearFounded						
2001	-.2642628	.0959413	-2.75	0.006	-.4523042	-.0762213
2002	-.4174932	.0956152	-4.37	0.000	-.6048957	-.2300908
2003	-.5713045	.0933275	-6.12	0.000	-.7542231	-.388386
2004	-.5231184	.0890575	-5.87	0.000	-.6976679	-.3485689
2005	-.5333239	.0850619	-6.27	0.000	-.7000421	-.3666057
2006	-.8006391	.08519	-9.40	0.000	-.9676085	-.6336698
2007	-.8683422	.0810346	-10.72	0.000	-1.027167	-.7095172
2008	-.8559876	.0787203	-10.87	0.000	-1.010276	-.7016987
2009	-.9128665	.0766009	-11.92	0.000	-1.063002	-.7627315
2010	-1.104718	.0746214	-14.80	0.000	-1.250973	-.9584625
2011	-1.083062	.0721254	-15.02	0.000	-1.224425	-.9416989
2012	-1.344272	.0709895	-18.94	0.000	-1.483408	-1.205135
2013	-1.529389	.0710711	-21.52	0.000	-1.668685	-1.390092
2014	-1.682105	.0706496	-23.81	0.000	-1.820576	-1.543635
2015	-2.08717	.0717619	-29.08	0.000	-2.227821	-1.94652
2016	-2.235931	.072514	-30.83	0.000	-2.378056	-2.093806
2017	-2.659482	.0756041	-35.18	0.000	-2.807663	-2.5113
2018	-3.131567	.0825032	-37.96	0.000	-3.29327	-2.969864
2019	-3.333011	.0896733	-37.17	0.000	-3.508767	-3.157254
_cons	.1087961	.0650824	1.67	0.095	-.0187631	.2363552

Table 12. Stata, HQLocation variable's frequencies

	HQLocation	freq
1.	San Francisco, CA	1887
2.	New York, NY	1622
3.	London, United Kingdom	1620
4.	Beijing, China	1109
5.	Paris, France	688
6.	Shanghai, China	580
7.	Singapore, Singapore	574
8.	Tokyo, Japan	523
9.	Seoul, South Korea	512
10.	Tel Aviv, Israel	481

Table 13. Stata, Country variable's frequencies

	Country	freq2
1.	CA	5973
2.	China	3082
3.	United Kingdom	2836
4.	NY	1832
5.	Canada	1476
6.	France	1452
7.	India	1258
8.	Germany	1230
9.	TX	994
10.	Israel	961

Table 14. Stata, Country variable's frequencies by CVC

```
. list Country cvc_freq in 1/10
```

	Country	cvc_freq
1.	CA	662
2.	China	469
3.	United Kingdom	217
4.	Japan	145
5.	NY	141
6.	Israel	99
7.	MA	99
8.	Germany	87
9.	Canada	72
10.	TX	69

Note. Frequency of CVC investments's location by AI & IT startups' foundation Country

Table 15. Stata, Country variable's frequencies by ExitSuccess

	Country	exit_f~q
1.	CA	1520
2.	United Kingdom	406
3.	NY	385
4.	MA	278
5.	Canada	273
6.	China	238
7.	France	236
8.	Germany	214
9.	TX	192
10.	Israel	168

Note. Frequency of AI & IT startups' ExitSucess by startups location

Source 16. Descriptive Statistics

15.1 Descriptive Statistics: ExitSuccess

To begin with, a descriptive summary of the *ExitSuccess* variable by cohort, allows to study the amount of ventures doing successful exit by cohort.

Plotting the former descriptive statistics and summaries, the following results are obtained: time cohorts follow five different trends regarding the percentage of successful exits, so they can be divided into five subgroups.

The first group contains the cohort of startups founded in 2000. Those startups have indeed had a huge percentage of successful exits. As a matter of fact, all the percentiles above the 50% percentile are equal to 1, meaning that over 50% of the startups within each cohort have had a successful exit.

The second group of cohorts holds startups between 2001 and 2009. The cohorts pertaining to this group have had a lower percentage of successful exits compared to 2000's cohort but still have high values, having successful exits over the 75% percentile.

Thirdly, for cohorts with startups founded between 2010 and 2016, the rate of successful exits drops to the 90% percentile.
Afterwards, startups pertaining to the 2017 and 2018 cohorts do have a successful exit rate above the 95% percentile.
Finally, the 2019 cohort only have a small rate of successful exits and over the 99% percentile.
The younger the cohorts of startups are, the lower percentage of exiting startups they host. If the startup is young it still is in its growing phase, so it is unlikely that is has had an exit. That is why, controlling the following regression analyses for time cohorts is crucial.
We will now go more in depth in these descriptive results.
Looking into the 2000's cohort we can observe as follows. The cohort holds 505 ventures' observations. The ExitSuccess variable's mean is equal to 0.5327, meaning that around 53,3% of the cohort's startups had a successful exit. At the same time the median, represented by the 50% percentile, is equal to 1, showing that at least 50% of the cohort's startups had a successful exit, confirming the mean's results. The Median is equal to 1 because we are in presence of a dummy variable's distribution; with this kind of distribution, if over 50% of the observations are equal to 1, also the median is equal to 1.
The skewness is equal to -0,1309, showing a negative asymmetry, meaning that we have more startups with *ExitSuccess*=1 than *ExitSuccess*=0. In order to better interpret these values, an additional operation is done on the sample. Only 2000's cohort is kept, momentarily focusing the analysis on its specific *ExitSuccess*, excluding other cohorts. This specific cohort's analysis is done by tabulating 2000's cohort *ExitSuccess*. According to the specific 2000's cohort analysis, 236 startups, corresponding to 46,73% of the cohort's sample, had *ExitSuccess*=0, while 269 had a positive successful exit. The reason why the cohort holds a negative Skewness lies in the tail of the observations' distribution. As a matter of fact, the majority of observations show a successful exit equal to 1 and the skewness is equal to -0,1309 because the distribution's tail extends through 0, generating a negative asymmetry. To conclude, the results coexist and show a successful rate over 50% for 2000's cohort.
To follow, we go through the second group of observations (2001-2009), beginning from the 2001 cohort. It presents 371 observations and a rate of *ExitSuccess* over the 75% percentile. The mean has a value of 0,4609 and the Median of the dummy variable has a value of 0; these results both show that less than 50% of the startups had a succesful exit. The skewness is indeed now positive, with a value equal to 0.1568.
The same path occurs in the cohorts between 2002 and 2009. The median remains equal to 0 and the mean drops year by year from a value of 0.445 in 2022, to a value of 0.289 in 2009.

Also, the skewness grows because the tail lengthens towards the right side meaning that the amount of *ExitSuccess* =1 decreases. On the other hand, the total amount of founded startups tend to grow over the years: the context evolves towards a more technological world, opening a window of opportunity for several potential new entrants; the AI market value is indeed growing steadily (Fortune Business Insights, 2024). In these terms, taking the situational context into account, a focus can be done on 2004 and 2007, which can be shortly analyzed. We are analyzing startups operating within the AI and IT sector and we may expect that the historical context has an impact on our descriptive statistics' results.

In these terms, as also the 17th Australian Joint Conference on Artificial Intelligence witnesses, 2004 was a relevant year for advancements in IT and notably AI research: over 340 were submitted, representing a substantial increase, compared to number of previous submissions (Webb & Yu, 2004). In 2004, referring to progress in IT, Facebook was launched by Mark Zuckerberg (Allison, 2007). To follow, 2007 is an important year for new emerging technologies, such as nanotechnologies (Consoli, 2007). In the same year, the first Iphone was invented. Finally, from 2007 on, there was an allocation of billions of euros to support R&D linked to these innovative areas (Commissione Europea, 2007). All in all, we may expect the 2007 cohort to present a countertrend and to oppose to the constant drop of the mean and of exiting startups, occurring year by year in this time interval of 5 years (2002-2007). Nevertheless, this drops still occur in 2007, as we go from a 0,367 mean in 2006 to a 0,331 mean in 2007. Despite the fact that this drop is significantly lower than the drops formerly occurred year by year between 2003 and 2006, it still is relevant.

Despite still presenting drops of the mean and of exiting startups, the 2004 and 2007's contexts surely offered a fertile ground and stimulating context for AI and IT innovations to emerge. Both in 2004 and 2007 the total amount of founded startups, compared to the number of startups in the other cohorts, significantly grew. Between 2001 and 2002 the total amount of founded startups have grown of 0.5%, going from 371 in 2001 to 373 in 2002. Between 2002 and 2003 a 11% growth occurred, moving from 371 founded startups in 2002 to 415 in 2003. Between 2003 and 2004 there was a 26% growth, going from 415 to 523 startups. Between 2004 and 2005 there only was a 12% growth, going from 523 to 587. Between 2005 and 2006, the growth was instead equal to 10%, moving from 587 to 648 observations. Between 2006 and 2007 there was a 25% growth, going from 648 to 813 founded startups. Between 2007 and 2008 there was a 9%, moving from 813 to 819 startups. Finally, between 2008 and 2009 cohort there was a 19% growth, going from 891 to 1.067 founded startups. Growths registered between 2003-2004

and 2006-2007 cohorts were indeed significantly higher than growths occurred between other cohorts, in the same group of observations.
All in all, between 2001 and 2009 there is a drop of the mean value from 0,461 to 0,289, despite a continuous growth of the number of startups over the years.
Afterwards, moving to the third group identified, starting from 2010 cohort, we observe that it presents an *ExitSuccess* equal to 1 only from the 90% percentile on. The mean value is equal to 0.24, with a positive skewness equal to 1.208. Cohorts between 2011 and 2016 similarly behave and follow a similar trend to the cohort of the second group: the mean steadily drops, moving from a value of 0.235 in 2011 to a value of 0.11 in 2016. In addition, similarly to 2004 and 2007 cohorts, also 2010, 2011 and 2012 cohorts present significantly higher increase in the number of founded startups, compared to the other group's cohorts. In 2009-2010 period, a 40% growth (from 1.067 to 1.495 startups) occurred. In 2010-2011 period a 29.6% growth happened (from 1.495 to 1.937 founded startups). In 2011-2012 a 37.6% growth occurred (from 1.937 to 2.666 startups). In 2012-2013 a 13% growth, going from 2.666 to 3.017 startups happened. In 2013-2014, going from 3.017 to 3.694, a 22% growth happened. In 2014-2015, from 3.694 to 4.116 startups, a 12.78% growth occurred. In 2015-2016, a 3% growth happened, moving from 4.116 to 4.292 startups. A significant growth in the number of founded startups, occurred in 2010, 2011 and 2012 compared to the lower growth of the other cohorts, again depends on the disruptive technological context. The first self-replicating synthetic bacterial cell was invented (J.Craig Venter Institute, 2010). Also, the first 3D bioprinter, Google Driverless car and Apple Ipad were invented in 2010 (The New York Times, 2010) (Time Magazine, 2010). A Novel Protease Inhibitor for Treatment of Drug-Resistant HIV-1, HPV Vaccines Based Upon Recombinant Papillomavirus Capsid Proteins (National Institutes of Health, 2011) but also Siri were invented in 2011 (Brookings, 2001). In addition, according to a report by Deloitte (2010), that was also a biennium in which businesses evolved. Several already existing technological innovations were improved and matured; their potential of application evolved and changed and was integrated with corporate processes, supporting their advancement. Process automation evolved towards information automation through business intelligence and analytics; Cloud computing was adopted in businesses, supporting scalability, cost efficiency and flexibility processes (Deloitte, 2010).
2012 was a breakthrough year for AI: AlexNet, a neural system by Alex Krizhevsky, Ilya Sutskever and Geoffrey Hinton, was trained on millions of images on the web and became able to recognize objects with great accuracy, compared to previous machines, reducing error from

26% to 16.4%; it laid foundations for machine learning's diffusion (Van der Made, 2023; Waters, 2023).
Finally, also 2014 cohort deserve a short focus: despite the 22% growth is notably lower than the ones occurred in 2010, 2011 and 2012, it still is signifcanlty higher thn the ones of the remaining group's cohorts. According to Newmann (2015), in 2014 indeed, several startups operating in the area of Internet of Things, Cloud Computing and innovative deep technologies started to emerge. Again, the context was appropriate to make existing AI startups flourish (Newmann, 2015). The context and ecosystem in which one startup grows can determine its growth and success (Regions' Alliances for Interconnected Startup Ecosystems, 2024). Additionally, as reported by EuropeanCeo (2014), according to studies by National Venture Capital Association, PwC and Thomas Reuters, it is also to be highlighted that the amount of investments on tech startups and mainly deep tech, grew. For example, according to National Venture Capital Association and to PwC, US venture capital investments grew in 2014 to $48.39 billion from a value of $29.96 billion in 2013; $19.8bn of the $48.39 amount was addressed to tech startups (EuropeanCeo, 2014).
To conclude, going more in depth, the amount of fintech Investments in the US tripled in 2014, going from $3.39 billion in 2013 to $9.89 billion in 2014 (Accenture, 2015).
Following, 2017 and 2018 cohort show positive *ExitSuccess* from the 95% percentile, with means respectively equal to 0.0762 and 0.051 and a skewness respectively equal to 3.193 and 4.079. 2018 is the first year in which a drop in number of startups, compared to the previous year, is registered: from 4.366 in 2017 to 4.015 in 2018.
Finally, the 2019 o cohort only has a minor number of exiting startups, over the 99% percentile, with a mean around 0.04 and a 4.685 skewness. Again 2019 shows a drop in the startups number, compared to 2018's amount: from 4.015 to 3.711.
Looking to the statistics, it is indeed possible to conclude that time inevitably impacts the percentage of AI startups successfully exiting because younger startups are less likely to exit. Trends over time cohorts are linear and there are no significant countertrends. The number of newly founded startups constantly grows across years: 2004, 2007, 2010, 2011, 2012, and partially also 2014, show positive jumps across this linear trend. On the other hand, the number of exiting startups constantly drops across years.
Overall, looking at the overall aggregated values for all cohorts, across the 39,502 observations, the mean of rate of successful exits corresponds to 0.163, having 16.3% of the startups making successful exit. This value is lowered by the presence in the sample of more recent startups.

Time effect indeed impacts on exit; it is consequently used to control the final regression, aiming to account for confounding effects.

15.2 Descriptive statistics: TotalRaised

Additional analyses are to be run, in order to also better support the final regression analyses. We have above observed a high variability of both the amount of startups' births and the probability of successful exits across time cohorts.

TotalRaised (expressed in millions) by time cohorts is analyzed. The older cohort, the 2000 one, presents a mean equal to 34.76 (corresponding to $34.76M). Looking into percentiles, it is possible to observe that under the Median (50% percentile) we only have values of *TotalRaised* under $5M. This means that, above the 50% percentile, some higher values, outliers, grow the overall mean. The positive skewness, tending to right, confirms it: the majority of observations register low values, while few outliers grow the result; the standard deviation is consequently high, equal to 147.81, showing high dispersion around the mean. Our highest values find place above the 99% percentile. The first value we encounter above this percentile is the 1.834M amount leveraged by AvidXchange. The venture was founded in Charlotte (NC) and operates in the financial sector, providing businesses and suppliers with a software to automate payable and boost speed and efficiency (AvidXchange website). On the other hand, the highest value (max) of this cohort is instead equal to over $2,3B, corresponding to the amount raised by the venture E2Open, founded in Austin (TX), which offers an integrated platform that enables businesses to monitor the whole supply chain, as an E2E process, supporting them also to take quick actions in case of challenges (E2Open website).

The 2001 cohort does instead have a lower mean, equal to 26.84 a median equal to 3M and a 99% percentile equal to 323M. Nevertheless, the highest value coincides with the $2B amount received by Vonage Holdings, which business consists of bringing "VoIP to families and small businesses and making communications more flexible, intelligent, and personal to help stay ahead" (Vonage Holdings).

The following cohorts from 2002 on, follow the same "trend" as 2000 and 2001 cohorts: the majority of ventures within each cohort presents lower amounts of *TotalRaised;* nevertheless, some isolated cases, above the 99% percentile, exponentially grow the overall mean. Notably, the outliers that contribute to increase the mean of each cohort tend to be aligned in terms of size, all resulting into values between $1B and $3B. The only exceptions are included in the 2004 and 2015 cohorts; these cohorts indeed host investments with values over $10B.

The 2004 cohort sees the invention of Meta Platforms (founded in Melo Park, CA): since its foundation, Meta Platforms has gathered over $12B investments. Indeed 2004 cohort presents this amount as the biggest value and outlier.

In 2015 instead, OpenAI was founded in San Francisco (CA). Overall, the venture has gathered $11.3B ($11.300M) of investments, mainly provided by Microsoft. OpenAI is an "AI research venture ensuring AI benefits humanity" (OpenAI, website).

To conclude, in order to better analyze time effect on *TotalRaised*, the 2000 and 2019 cohorts, which respectively are the oldest and the youngest cohorts, are compared. 2000 cohort as already been above analyzed. On the other hand, as far as 2019 cohort is concerned, the mean is equal to $6.44M in 2019; the standard deviation is instead equal to $25.12M. The highest value corresponds to $679M, leveraged by Deel, a startup that offers a platform with tools and resources aiming to remove barriers to hiring and administration and to facilitate teams and businesses collaboration across geographical borders (Deel, website).

The 2019 cohort's mean is markedly lower than 2000's one, meaning that startups have cumulatively gathered lowered TotalRaised, also accounting for outliers. Similarly, looking to the other cohorts, beyond 2000 and 2019 ones, and moving from older to younger ventures, the *TotalRaised's* mean tend to decrease; it is indeed easier for more solid and established companies to access more funding rounds and leverage final higher *TotalRaised*. Cohorts between 2000 and 2008 tend to have *TotalRaised*'s means above 30M, except for 2001, which presents a $26.84M mean; after 2008, means' values tend to drop: from 2009 to 2019 there is a steadily descending pattern, going from a mean equal to $27.58M In 2009, to a mean equal to $6.44M om 2019. Nevertheless, the value of the means also strongly depends on outliers too: cohorts holding only a few startups that have received huge amounts of money, may find their average grown by few outliers. This result notably occurs in the 2004 cohort, in which the investments gathered by Meta Platform alone lead the mean to a value of 60.69, while over 50% of the startups have gathered around $2M of *TotalRaised*. When few outliers boost the mean, the standard deviation exponentially grows: in 2004 cohort the standard deviation corresponds to $1568.87M.

All in all, looking at aggregated amount of *TotalRaised* for cohorts, the final mean is equal to $18.403M, with standard deviation equal to $116.921M. All the cohorts tend to present, below the 95% percentile, values of total startups' investments raised below $150M. The mean of each time cohort is highly influenced by a few isolated cases, meaning that the majority of startups in each cohort has cumulative amounts raised below the mean.

Between the 2000 and the 2009 cohorts there is not a clear mean's path, due to the presence of outliers; on the other hand, after 2009, the mean drops year by year following a decreasing path. We may assume that time has an impact on capital raised but the inability to determine a clear path over time cohorts makes it clear that time is not the only relevant factor impacting ton the amount of money gathered by an AI startup.

On the other hand, running an aggregated table of *TotalRaised* value, analyzing it for the *CVC* variable, enables to study the differences among the aggregated amount of investments raised by CVC-backed AI startups and by the ones non-CVC-backed. From the $18.403M aggregated mean, we find that CVC-backed startups hold a mean equal to $45.57B, among the 985 observations, while non-CVC-backed hold a $17.7M mean, among the remaining 38.517 observations. This confirms that CVCs tend to contribute to higher total investment amounts gathered by AI startups, despite a higher standard deviation (around 373 vs 136) and volatility of results around the mean.

In conclusion, time seems to impact the overall total amount raised by ventures. On the other hand, also CVCs' presence impacts *TotalRaised* amounts, as CVC backed AI startups gather, on average, higher amounts.

15.3Descriptive Statistics: DealSize

To conclude a statistic of single deals' size by cohort is run.

DealSize variable is expressed in millions; its descriptive statistics are observed, starting from the 108,441 deals gathered by the ventures. The following results were obtained.

From the 2000 cohort, we register 1.049 observations (*DealSize* variable's availability of data is limited so we lack data for some of the 180,441 deals), with a value of the mean equal to $15.13M. The Median is instead equal to 5. Looking at the percentiles we can observe that 75% of the cohort's observation do have a deal's size lower than $10.5M; at the same time, few values over the 99% percentile contribute to boost the mean: the largest value registered within the last quartile is $951M. The overall standard deviation is equal to 58.64. Furthermore, going into the analysis, it is noticeable that the 2000 cohort is the one with "most aligned" values; as a matter of fact its relatively low standard deviation is definitely lower than the remaining cohorts' corresponding values (which are included between a minimum of 65.125, in 2019, until a maximum of 107.992, in 2007), showing a relatively low dispersion around the mean.

For the remaining cohorts, the results, in terms of size, are aligned with *TotalRaised* variable. The majority of ventures across all cohorts have relatively low values of deals' sizes. Nevertheless, larger values, as outliers, are inflating the mean, making the overall distribution by cohort positively asymmetric and dispersed.

Going more in depth, 2001 cohort has values above $648M in the 99% percentile and a highest value equal to $955M. The 2002 cohort has values below $45.64M until the 95% percentile and over $402M beyond the 99%, with a maximum value of $953M. The other cohorts (between 2002 and 2019) behave similarly: lower values below the 99% percentile, few big outliers over. To go more in depth, the biggest outliers among *DealSize* value, are now analyzed.To begin with, the 2007 cohort presents a 99% boundary determined by a deal of $635M but also presents some deals over $1B. First of all, Lyft gathered a $1B investment from DSCN Capital on 01/02/2016. Lyft offers a social ridesharing community platform online and was funded in San Francisco (CA) (Lyft website). The second relevant investment of 2007 time cohort was still gained on 14/03/2018 by Lyft. It was funded by AllianceBernstein. Finally, the third relevant deal of this cohort was gathered by Securonix, funded in Addison (TX) on 28/04/2022; this investment, of the value of $1.172,1M was done by Eight Roads, operating as a Corporate Venture Capitalist.

Going more in depth, into deals with sizes over $1B, we find the following.

The 2012 cohort presents other 6 significant deals. Four of these deals have a $1B value. The first $1B investment was allocated to ByteDance, founded in Beijing, China, and Operating content platforms (ByteDance website). The other three fundings of $1B value were allocated respectively, the first to Checkout.com, founded in London (UK) and the other two to Yuanfundao, founded in Beijing. Checkout.com operates in the payment elaboration business; Yuanfundao is an educational technology company, offering an app for tutoring and education (Checkout.com, website) (Yuanfundao, website).

Checkout gathered the funding from TeleSoft Partners while Yuanfundao gathered its first $1B trance by DC Capital and the second $1b trance by Tencent, operating as a CVC.

Following, LeSports, providing a platform for sports content, obtained a $1.233,58M funding (LeSports, website). Finally, JD Digits, offering a cloud computing platform that aims to offer specialized financial services and digitally enhanced industrial solutions thanks to its data technology, AI, IoT capabilities that develop tailored financial models for clients, gathered a $1.877,157M funding (JD Digits, website). Both LeSports and JD Digits were founded in Beijing.

Thirdly, in 2013, Databricks gathered two investments respectively of $1B and $1.6B value. Databricks, founded in San Francisco, is a cloud-based lakehouse platform; “it combines AI and lakehouse to enable its Data Intelligence Engine to interpret data”, consequently enabling customers to better gather insights and optimize their businesses.

The 2014 cohort sees SenseTime as its main character. The venture concluded a deal of $1,6B with Huaxinghe Investement, Corporate Venture Capital. SenseTime is a Chinese artificial intelligence pioneer, founded in Hong Kong. The venture is an “AI software company aiming to grow the research-AI’s state of the art, developing AI software platforms to improve the future of people, cities and the whole society”. The venture offers algorithms, AI infrastructure, platforms and improved expertise and technical capabilities, to lead the change (SenseTime, website).

Finally, the 2015 cohort presents four big deals. Two of them occurred between OpenAI and Microsoft. Microsoft, operating as a CVC allocated $1B in 2019 and $10B in 2023 on OpenAI. Additionally, OpenAI received $1B investment as a Grant, in 2015. Finally, Lacework, which is and AI-security platform founded in Mountain View (CA), gathered $1.3B by GV, Corporate Venture Capital.

To conclude, looking at the aggregated *DealSize’s* for all cohorts and observations, it presents a mean equal to $18.5M and a median equal to $1.75M. Few bigger values inflates the aggregated mean’s result.

The standard deviation is equal to 83.592, showing a wide data dispersion around the mean. The outliers, notably the ones above analyzed, boost the overall *DealSize’s* result.

Additionally, running a summarized description of *DealSize* for *CVC,* it is possible to observe that CVC-backed AI startups do not only tend to gather higher *TotalRaised* but even bigger single deals, on average, compared to non-CVC-backed. CVC-backed AI startups have a mean, regarding the *DealSize* variable, equal to 25.289; on the other hand, non-CVC-backed startups have a mean of gathered deals’ size equal to 18.418. These values result into a final aggregated mean equal to 18.5M, because the higher amount of observations registered for non-CVC-backed startups is driving down the final mean value. CVC-backed startups additionally have higher dispersion around the mean (228.179 vs 77.877).

All in all, regarding *DealSize,* we observe no clear time cohorts’ paths, mainly due to the presence of outliers in each cohort. Compared to the cumulative *TotalRasied, DealSize* seems less impacted by time, but some influences seem to still occur: on average cohorts between 2000 and 2011 also includes means’ values over $20M; cohorts between 2011 and 2019 only includes average value below (around $15M and $18M).

Despite the fact that these statistics do not allow us to derive causal conclusions, looking to the results in the light of previous literature, the following can be derived.

Time seems to impact *ExitSuccess*; the younger the cohort, the lower percentage of *exiting* startups it holds. On the other hand, beyond time effect, the more innovative the technological context of a specific cohort is, the more startups' births the cohort hosts.
Secondly, *TotalRaised* and *DealSize* seem to be impacted by time too: no clear paths across all cohorts exits, mainly because of outliers, however, on average, younger startups have gathered, lower deals and capital compared to older startups. Time impacts on capital and investments raised by startups but is not the only relevant factor to affect them.
On the other hand, CVC-backed AI startups gather bigger deals, and more capital in general, compared to non-CVC-backed.
The in depth conclusions, both leaning on descriptive statistics' results and on previous literature, are clearly presented in subsection 7.3, Descriptive statistics.

Stata Code

```
import excel "/Users/ariannaspagnolo/Desktop/CLSBE/Tesi DD/MergedD.xlsx", firstrow clear

destring TotalRaised Employees LastFinancingSize GII_byCountry DealSize, replace
*Time cohorts based on YearFounded
generate cohort = YearFounded
* Dummy variables for Successful exit and CVC
gen ExitSuccess = 0
replace ExitSuccess = 1 if LastFinancingDealType == "Merger/Acquisition" |
LastFinancingDealType == "IPO" | LastFinancingDealType == "Buyout/LBO"
gen CVC = 0
replace CVC = 1 if PrimaryInvestorType == "Corporate Venture Capital"
*Descriptive statistics by cohort
egen count_startups = count(CompanyID), by(cohort)
bysort cohort: egen success_exit_rate = mean(ExitSuccess)
bysort cohort: egen median_success_exit = median(ExitSuccess)
bysort cohort: egen std_success_exit = sd(ExitSuccess)
bysort cohort: egen tot_raised_mean = mean(TotalRaised)
bysort cohort: egen median_tot_raised = median(TotalRaised)
bysort cohort: egen std_tot_raised= sd(TotalRaised)
bysort cohort: egen mean_deal_size = mean(DealSize)
bysort cohort: egen std_deal_size = sd(DealSize)
```

```
bysort cohort: egen median_deal_size = median(DealSize)
*tables to visualize descriptive statistics' sum up
tabstat ExitSuccess, statistics(mean median sd)
tabstat TotalRaised, statistics(mean median sd)
tabstat DealSize, statistics(mean median sd)
table CVC, statistic(mean TotalRaised) statistic(sd TotalRaised)
table CVC, statistic(mean DealSize) statistic(sd DealSize)
sort DealID
* Logit Regressions: with CVC, with GII_byCountry, with both, moderation analysis
logit ExitSuccess CVC TotalRaised Employees i.YearFounded
logit ExitSuccess GII_byCountry TotalRaised Employees i.YearFounded
logit ExitSuccess GII_byCountry CVC TotalRaised Employees i.YearFounded
summarize GII_byCountry
generate GII_centered = GII_byCountry - r(mean)
gen interaction_GII_CVC= CVC*GIIcentered
logit ExitSuccess GII_centered TotalRaised Employees CVC interaction_GII_CVC
i.YearFounded
*Frequencies by Cities, Countries, CVC by Country, Successful exits by Country
bysort HQLocation: gen freq = _N
bysort HQLocation: keep if _n == 1
gsort -freq
list HQLocation freq in 1/10
bysort Country: gen freq2 = _N
bysort Country: keep if _n == 1
gsort -freq2
list Country freq2 in 1/10
bysort Country: egen cvc_freq = total(CVC)
bysort Country (cvc_freq): keep if _n == 1
gsort -cvc_freq
list Country cvc_freq in 1/10
bysort Country: egen exit_freq = total(ExitSuccess)
bysort Country (exit_freq): keep if _n == 1
gsort -exit_freq
list Country exit_freq in 1/10
```