UNIVERSITY OF LJUBLJANA
SCHOOL OF ECONOMICS AND BUSINESS

MASTER’S THESIS

THE RISE OF THE SPACETECH ECONOMY: EVOLUTION AND STRATEGIC OUTLOOK OF THE EUROPEAN SPACE SECTOR AND STARTUP ECOSYSTEM

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ABSTRACT

The SpaceTech economy has undergone a profound transformation, shifting from a domain dominated by national governments and large aerospace contractors to a dynamic, commercially-driven ecosystem. This master's thesis provides a comprehensive analysis of this paradigm shift, commonly known as "New Space". The study first examines the historical evolution of the European space sector and identifies the key drivers behind the emergence of a vibrant startup ecosystem. An empirical analysis is then conducted using two distinct regression models on a unique dataset of venture capital investments in European SpaceTech startups. The first model investigates the relationship between venture capital syndication and startup success, while the second explores the role of cross-border investment and its impact on the sector's growth. The findings highlight the critical role of these investment dynamics in fostering innovation and scaling New Space ventures, offering a strategic outlook for policymakers, investors, and entrepreneurs aiming to further develop Europe's position in the global space economy.

KEY WORDS: SpaceTech, New Space, Venture Capital, European Space Sector, Syndication, Cross-border Investment

SUSTAINABLE DEVELOPMENT GOALS

POVZETEK

Vzpon industrije vesoljskih tehnologij je doživelo globoko preobrazbo, saj se je premaknilo iz domene, kjer so prevladovale nacionalne vlade in veliki pogodbeniki v letalsko-vesoljski industriji, v dinamičen ekosistem, ki ga poganja komerciala. To magistrsko delo ponuja celovito analizo te paradigme, splošno znane kot "New Space". Študija najprej preučuje zgodovinski razvoj evropskega vesoljskega sektorja in opredeli ključne dejavnike za nastanek živahnega startup ekosistema. Nato je izvedena empirična analiza z uporabo dveh različnih regresijskih modelov na edinstvenem naboru podatkov o naložbah tveganega kapitala v evropske startupe SpaceTech. Prvi model raziskuje razmerje med sindiciranjem tveganega kapitala in uspehom startupov, medtem ko drugi raziskuje vlogo čezmejnih naložb in njihov vpliv na rast sektorja. Ugotovitve poudarjajo ključno vlogo teh naložbenih dinamik pri spodbujanju inovacij in širjenju podjetij New Space, kar ponuja strateški pogled za oblikovalce politik, vlagatelje in podjetnike, ki si prizadevajo za nadaljnji razvoj položaja Evrope v svetovnem vesoljskem gospodarstvu.

KLJUČNE BESEDE: SpaceTech, New Space, Tvegani kapital, Evropski vesoljski sektor, Sindikacija, Čezmejne naložbe

CILJI TRAJNOSTNEGA RAZVOJA

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sl. – Slovene

ARTES – (sl. Napredne raziskave v telekomunikacijskih sistemih); Advanced Research in Telecommunications Systems

ASI – (sl. Italijanska vesoljska agencija); Agenzia Spaziale Italiana

B2C – (sl. Podjetje–potrošnik); business-to-consumer

BIC – (sl. Podjetniški inkubacijski center); Business Incubation Centre

CAGR – (sl. Povprečna letna stopnja rasti); compound annual growth rate

CSA – (sl. Kanadska vesoljska agencija); Canadian Space Agency

DVSS – (sl. Strateški vizijski dokument za vesolje); Documento di Visione Strategica dello

Spazio

EDRS – (sl. Evropski sistem prenosa podatkov); European Data Relay System

EO – (sl. Opazovanje Zemlje); Earth Observation

ESA – (sl. Evropska vesoljska agencija); European Space Agency

EU – (sl. Evropska unija); European Union

EUSPA – (sl. Agencija Evropske unije za vesoljski program); European Union Agency for the Space Programme

FAO – (sl. Organizacija Združenih narodov za prehrano in kmetijstvo); Food and Agriculture Organization

GDP – (sl. Bruto domači proizvod); Gross Domestic Product

GNSS – (sl. Globalni navigacijski satelitski sistemi); Global Navigation Satellite Systems

GSTP – (sl. Splošni program za podporo tehnologijam); General Support Technology Programme

HAPS – (sl. Visokoleteče platforme); High Altitude Platform Stations

IPO – (sl. Prva javna ponudba delnic); Initial Public Offering

ISS – (sl. Mednarodna vesoljska postaja); International Space Station

IoT – (sl. Internet stvari); Internet of Things

JAXA – (sl. Japonska agencija za vesoljsko raziskovanje); Japan Aerospace Exploration Agency

LEO – (sl. Nizka zemeljska orbita); Low Earth Orbit

M2M – (sl. Stroj–stroj); machine-to-machine

MVP – (sl. Minimalno izvedljiv izdelek); Minimum Viable Product

NASA – (sl. Nacionalna uprava za aeronavtiko in vesolje); National Aeronautics and Space Administration

OECD – (sl. Organizacija za gospodarsko sodelovanje in razvoj); Organisation for Economic Co-operation and Development

SD – (sl. Standardni odklon); Standard deviation

SMEs – (sl. Mala in srednje velika podjetja); small and medium-sized enterprises

SSA – (sl. Spremljanje vesoljskih objektov); Space Situational Awareness

STM – (sl. Upravljanje vesoljskega prometa); Space Traffic Management

SATCOM – (sl. Satelitske komunikacije); satellite communications

TDE – (sl. Element razvoja tehnologije); Technology Development Element

TRL – (sl. Stopnja pripravljenosti tehnologije); Technology Readiness Level

U.K. – (sl. Združeno kraljestvo); United Kingdom

U.S. – (sl. Združene države Amerike); United States

VC – (sl. Tvegan kapital); Venture capital

1 INTRODUCTION

1.1 Motivation for the thesis

The global space sector is undergoing a profound transformation, evolving from a state-led, monopolistic environment into a dynamic, commercially driven ecosystem known as the "New Space Economy". This shift has opened the market to private actors and startups, reshaping competition, investment strategies, and industrial structures. Understanding these dynamics is critical for Europe, where traditional public institutions such as the European Space Agency coexist with an emerging generation of SpaceTech entrepreneurs and investors.

This thesis is motivated by the need to analyse how Europe can strengthen its position within this rapidly evolving sector. The research focuses particularly on the financial mechanisms, venture capital, syndication, and cross-border investment, that drive innovation and competitiveness. The topic is also relevant in the national context: Slovenia's accession as a full partner of the European Space Agency in 2025 provides both an opportunity and a strategic imperative to understand the structure and evolution of the European SpaceTech market. The work aims to provide analytical insights that can support policymakers and investors in shaping Slovenia's and Europe's role in the global space economy.

1.2 Research questions and objectives

The central research question guiding this thesis is: "How do venture capital strategies, specifically syndication and cross-border investment, affect the growth and valuation of startups within the European SpaceTech ecosystem, and what are the implications for Europe's competitiveness?"

To address this question, the study investigates three sub-questions:

I. What is the relationship between venture capital syndication and startup valuation in the European SpaceTech sector?

II. How do cross-border investments influence startup valuation compared with domestic investments and macroeconomic factors?

The aim is to contribute a structured analysis of the financial and strategic mechanisms underpinning Europe's New Space economy, offering policy-oriented insights for fostering innovation and global competitiveness.

1.3 Methodology

The research adopts a two-stage methodological approach. The first stage establishes a conceptual foundation through an extensive review of the academic and institutional literature on the New Space paradigm and the role of venture capital in high-technology and capital-intensive industries. This theoretical groundwork informs the development of the empirical framework and the formulation of testable hypotheses.

The second stage consists of an empirical investigation based on a unique dataset of venture capital investments in European SpaceTech startups. The analysis begins with a clustering procedure designed to identify underlying structures within the dataset, such as investor typologies, investment patterns, and startup characteristics. This exploratory step provides a clearer understanding of the ecosystem's composition and guides the specification of the econometric model, which examines the joint influence of venture capital syndication and cross-border investment, together with other conventional determinants of startup valuation, to assess the relative significance of these two focal factors;

1.4 Key findings and contribution

The analysis reveals that both syndication and cross-border investment have a statistically significant positive effect on startup valuations. Syndicated investments help mitigate risk and attract additional capital, while cross-border investments introduce new expertise and global visibility, often exerting a stronger influence than broader economic variables.

This thesis contributes to the field by offering quantitative evidence on the financial dynamics of Europe's emerging SpaceTech ecosystem, an area where academic research remains limited. It provides actionable insights for policymakers and investors seeking to enhance Europe's position in the global market and offers a framework for understanding how smaller nations such as Slovenia can integrate effectively into this evolving landscape.

1.5 Limitations and opportunities for further research

Despite its contributions, the thesis faces several limitations that open avenues for future study. The primary constraint lies in data availability: the SpaceTech investment sector remains young, and comprehensive datasets, especially for European startups, are scarce. Expanding the dataset temporally and geographically could strengthen the robustness and generalizability of the findings. Additionally, the study focuses narrowly on syndication and cross-border investment, leaving out other relevant factors such as dual-use technologies (civil–military applications) and the role of defence-related funding. These dimensions are increasingly important in the contemporary space economy and warrant dedicated investigation. Finally, future research could explore the heterogeneity of investors in greater depth, distinguishing, for instance, between corporate venture capital, private equity, and government-backed funds.

2 AN OVERVIEW OF THE SPACE ECONOMY

The Space Economy can be broadly defined, following the OECD (2012), as "the full range of activities and the use of resources that create value and benefits to human beings in the course of exploring, researching, understanding, managing, and utilising space". It comprises an extended value chain encompassing research, infrastructure development, and the creation of products and services derived from space-based technologies. These include satellite telecommunications, Earth observation (EO), navigation, meteorology, and numerous downstream applications across sectors such as agriculture, energy, logistics (OECD, 2022).

Historically, space activities were almost entirely dominated by governmental institutions and financed through public programs. However, from the early 2000s onwards, advances in digital technologies and the progressive reduction of launch and satellite costs enabled a shift toward commercialization and private-sector participation. This evolution transformed space from a closed, state-led domain into a dynamic, innovation-driven ecosystem, a transition that set the foundation for what is now referred to as the New Space Economy, discussed in the following section (Anderson, 2023).

2.1 The New Space Economy

According to the report *Harnessing "New Space" for Sustainable Growth of the Space Economy* by the OECD (2023), it can be defined as a global trend encompassing an emerging investment philosophy and a series of technological advances that are leading to the development of a private space industry driven largely by commercial motivations. Unlike the traditional paradigm, dominated by government agencies and institutional programs, the New Space Economy is based on the opening of the space market to private actors, the democratization of access to space, and the creation of scalable business models enabled by technological innovation. This new phase is shaping up as a dynamic and competitive ecosystem, in which startups, investors, large industrial groups, and public actors collaborate, or compete, to develop high-value-added solutions focused primarily on terrestrial applications (Di Pippo, 2022).

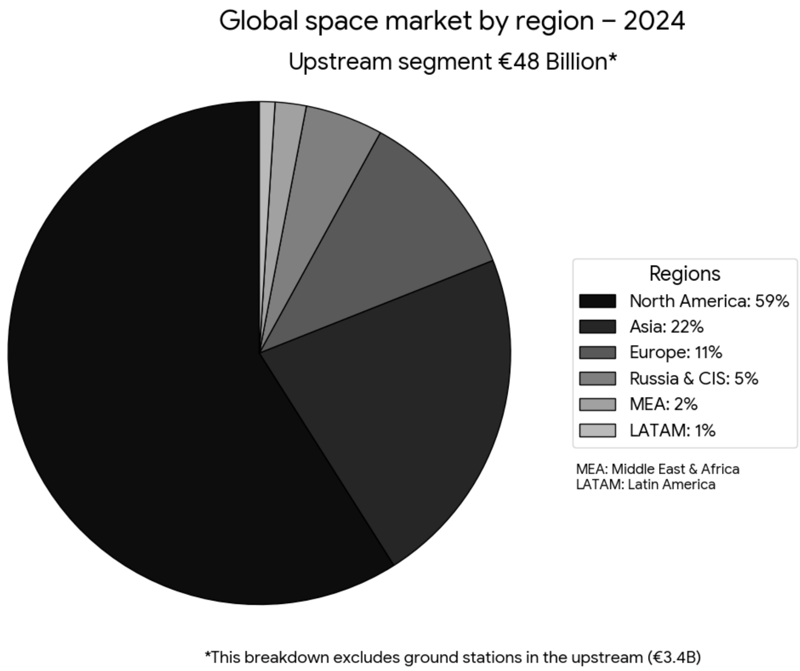
A defining feature of this transition is the sharp reduction in launch costs, driven by reusable vehicles, low-cost components, and agile engineering practices which have made it increasingly feasible for non-traditional players to enter the space sector. At the same time, there has been a broad diversification in the range of services, now including not only telecommunications and EO, but also in-orbit logistics, microgravity manufacturing, space tourism, and space debris management. From an economic and financial perspective, the New Space Economy is characterized by an increase in return opportunities and, consequently, a greater capacity to attract private investment, particularly from Venture Capital (VC) and technology investment funds (Spagnulo, 2023)

However, it remains difficult to precisely estimate the actual scope of the New Space Economy. Many of its effects are indirect or cross-sectoral, as seen, for example, in the digital transformation of businesses: through data collected by satellite infrastructures, such as for environmental monitoring, geolocation, or predictive analytics, many economic sectors are creating new services and accelerating their digital growth (Hertzfeld, 2013).

To better understand the complexity of the Space Economy and assess its impact, the OECD (2022) has proposed a structural breakdown of the space sector value chain into three main segments:

- *Upstream segment*: covers the development of space infrastructure and technology, forming the engineering backbone of the industry. This includes R&D, satellite and component design, launch systems, orbital platforms, and ground infrastructure such as mission control centres and receiving stations, essentially, everything required to enable space missions;
- *Downstream segment*: refers to applications and services that use upstream technologies and data, such as telecommunications, navigation, environmental monitoring, weather forecasting, and analytics. These services create high-value solutions for sectors like precision agriculture, logistics, emergency management, security, and intelligent mobility;
- *Space spin-offs*: technologies and products originally developed for space that have found applications in other sectors. Their direct connection to space may be partial, but they demonstrate the broader economic and social impact of space innovation.

Figure 1: Global upstream space market breakdown by geographies in 2024

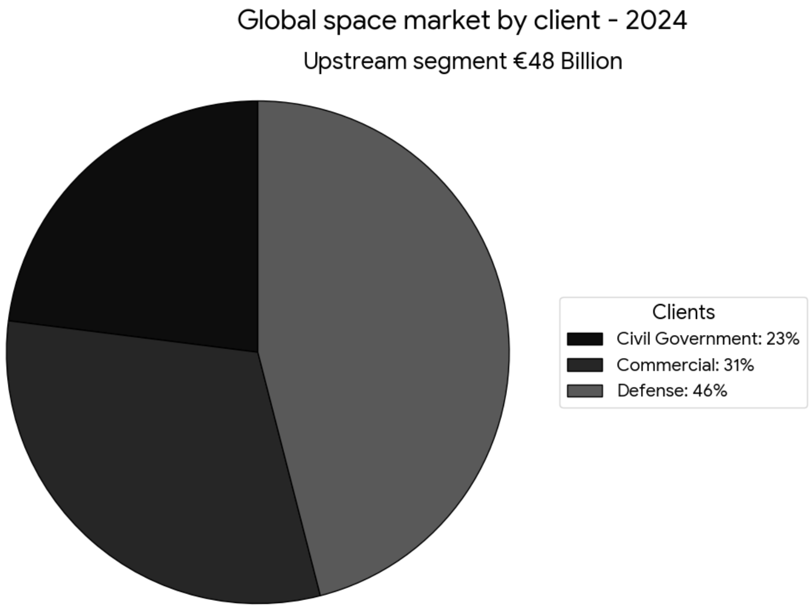


Source: Own work based on Novaspace (2025).

The primary upstream industry players, see Figure 1, are concentrated in North America, Asia, and Europe, where they benefit from stable domestic institutional demand and mature markets. These regions also show growing interest in commercially procured services, an approach pioneered in the U.S. and now increasingly in Europe and China (Novaspace, 2025).

As shown in Figure 2, defence remains the main driver of market value within the upstream segment. Although accounting for a limited number of missions, defence programmes are highly complex and costly, making them the dominant economic force.

Figure 2: Global upstream space market breakdown by client type in 2024



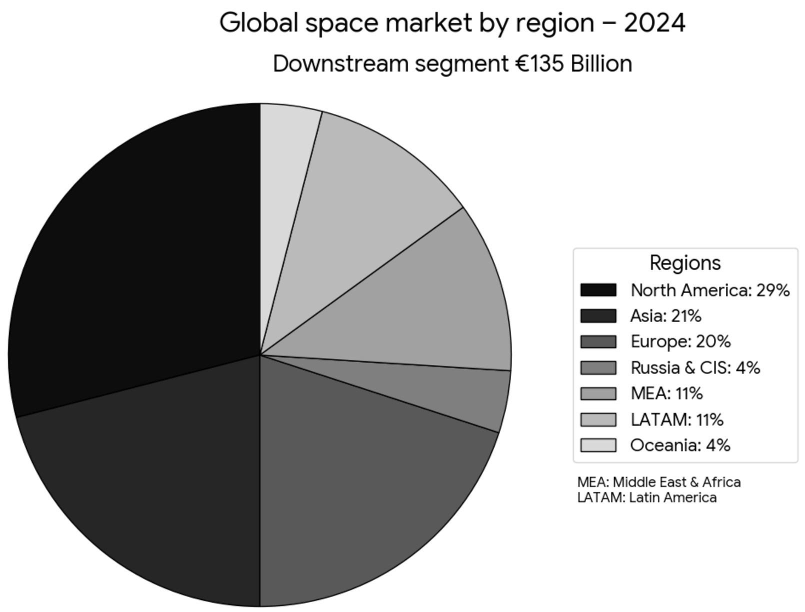
Source: Own work based on Novaspace (2025).

This trend is particularly evident in the U.S., where significant investments aim to sustain technological leadership and global security. Although Ministries of Defence traditionally manage proprietary assets, there is a growing inclination to outsource specific capabilities to private providers, accelerating the integration between public and private players (Novaspace, 2025).

Commercial clients have gained substantial ground through the deployment of large satellite constellations enabled by lower costs and faster production cycles. This has allowed private actors to emerge as key demand sources, especially for missions targeting connectivity, EO, and other data services. Civil governments, while less prominent in terms of total market share, continue to play a strategic role. Their involvement often centres on fewer, high-end missions, focused on scientific research, national security, and the procurement of satellite systems for public services such as environmental monitoring or free-access EO platforms stimulating downstream innovation (PwC, 2024).

The downstream segment benefits from a more diversified and accessible market than upstream activities. This is largely due to its closer proximity to end users and lower entry costs and more stable revenues, reducing dependence on government funding. Its growth is driven by mass-market applications and further supported by rising living standards, supporting demand for services such as connectivity and navigation. Public initiatives, such as the U.S. Rural Digital Opportunity Fund (RDOF) and similar programs in other countries, play a key role in expanding broadband adoption, often supporting large-scale projects such as Non-Geostationary Satellite Orbit (NGSO) constellations to close the digital divide (Novaspace, 2025).

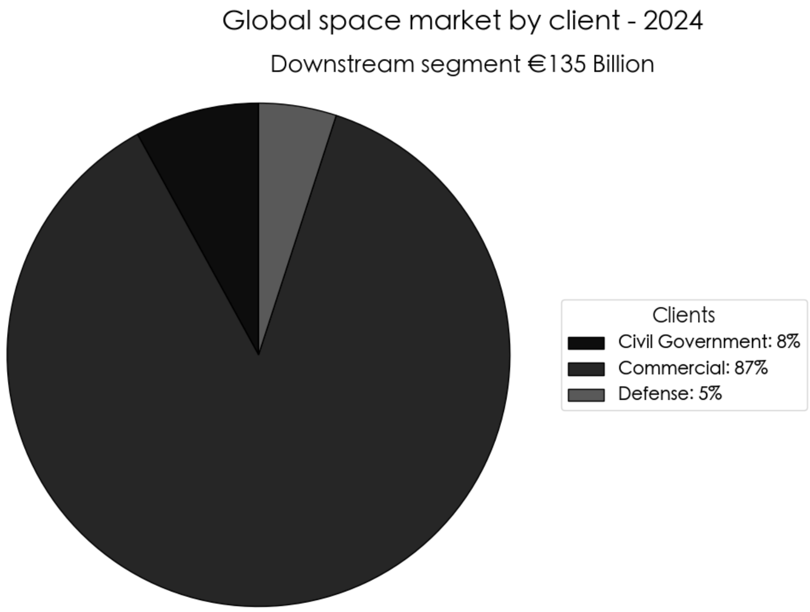
Figure 3: Global downstream space market breakdown by geographies in 2024



Source: Own work based on Novaspace (2025).

As shown in Figure 4, commercial activities dominate the downstream segment. This reflects the segment's strong business-to-consumer (B2C) orientation, particularly in satellite navigation and telecommunications (Novaspace, 2025). Governments and defence actors participate to a lesser extent, mainly for security applications, EO systems, or specific services such as satellite imagery.

Figure 4: Global downstream space market breakdown by client type in 2024



Source*: Own work based on Novaspace (2025).*

Industry experts tend to adopt a macroeconomic approach to measure the evolution of this market; however, it is important to understand that the evaluation is particularly complex because space activities are not yet classified under a standardized industrial classification system globally. One of the most critical challenges is defining the boundary between "space" and "non-space" activities, especially considering the wide range of terrestrial applications that utilize space technologies or data. This ambiguity significantly affects the overall estimation of the space economy. Consequently, market analyses conducted by leading consulting firms often differ in their segmentation criteria, making it difficult to directly compare the various available estimates (PwC, 2024). The following table 1 presents a summary of the main estimates made by some of the most prominent consulting companies.

Table 1 accurately reflects the previously mentioned challenges: the estimates, in fact, differ by tens of billions of dollars. Nevertheless, there is unanimous agreement in considering the sector as one that is growing, both in terms of investment and strategic relevance on a global scale.

Table 1: Estimated value of the Space Economy for 2023 and market forecasts from major consulting firms (2022)

Company	Value of space economy in 2023	Company	Space economy reaching 1 trillion $
BryceTech	$384B	Bank of America	2030
Euroconsult	$424B	McKinsey & Company	2035
PwC	$410B	Morgan Stanley	2040
Space Foundation	$596B	UBS	2040

Source: Own work based on PwC (2024).

2.2 The primary sectors within the SpaceTech industry

As noted in Section 2.1, accurately assessing the impact of the space industry is particularly complex. This complexity arises from the cross-sectoral nature of space technologies, increasingly integrated into non-space industries. Consequently, delineating boundaries between space and non-space activities is challenging, complicating assessment of the space economy's scope. The issue is particularly pronounced downstream, where distinguishing contributions to end users is difficult (PwC, 2024). Following the definitions provided by the OECD in the Handbook on Measuring the Space Economy (2022), the main categories of space activities can be classified as follows:

- *Satellite communications*: the development and/or use of satellites and related subsystems to transmit signals to Earth for the purpose of fixed or mobile telecommunications services (voice, data, Internet, and multimedia) and broadcasting services;
- *Positioning, navigation and timing*: the development and/or use of satellites and related subsystems for localisation, positioning, and timing services. Navigation is employed in transport, tracking, and for global positioning and timing standards (GNSS);
- *Earth observation*: the development and/or use of satellites and related subsystems to measure and monitor the Earth, including its climate, environment, and human activity;
- *Space transportation*: the development and/or use of launch vehicles and associated subsystems. This includes launch services, governmental and commercial spaceports, tourism, and in-orbit logistics;
- *Space exploration*: the development and/or use of crewed and uncrewed spacecraft (including space stations, rovers, and probes) for the exploration of the universe beyond Earth's atmosphere (the Moon, other planets, and asteroids), including the International Space Station and astronaut missions;

- *Science*: This category includes a wide range of scientific endeavours, encompassing space sciences, such as astrophysics, planetary science, space life sciences, and space debris tracking, as well as space-based Earth sciences for studying the Earth's atmosphere, climate, and physical and chemical composition;
- *Space technologies*: this includes specific technologies designed for space systems used in various missions, such as space nuclear systems (power, propulsion), solar electric propulsion, and others;
- *Generic technologies or components that may enable space capabilities*: some of these are not originally intended for use in a specific space system or application but may later contribute to the development of new space-related products and services, plus early-stage research, off-the-shelf components, or enabling tools such as AI and data analytics.

2.3 Key trends shaping the SpaceTech industry

PwC (2024) identifies several emerging trends in the most commercially developed SpaceTech segments:

- Earth Observation;
- Satellite Navigation;
- Satellite Telecommunications;
- Access to Space;
- Space Situational Awareness (SSA);
- Space Traffic Management (STM);
- Space Exploration.

EO continues to grow steadily, driven by demand from sectors like agriculture, urban development, and finance. With over 400 large commercial satellites and more than 1,200 small satellites expected to launch over the next decade the market for EO services is expanding rapidly. Vertical integration, cloud-based Big Data applications, and broader access to tools are accelerating downstream services. Radar sensors and complementary airborne systems enable continuous monitoring, supporting environmental and geopolitical applications (Denis et al., 2017).

The satellite navigation sector is evolving quickly, with advancements in multi-constellation and multi-frequency receivers enhancing precision and resilience (Denis et al., 2017). Europe's Galileo programme and global augmentation systems strengthen the navigation ecosystem, driving growth in commercial EO data, projected to reach $3 billion by 2025, with a 6% CAGR from 2015–2025 (Denis et al., 2017).

The satellite telecommunications market is highly competitive and expanding, driven by demand from mobility, IoT, and M2M applications. LEO constellations, such as SpaceX's Starlink and OneWeb, are lowering costs and increasing efficiency through vertically integrated models. Growing needs for low-latency, high-throughput connectivity are also accelerating satellite-enabled 5G adoption, with implications for sectors like maritime safety and intelligent mobility (Iqbal et al., 2024).

In the access-to-space segment, cost reduction is the main driver of innovation. Modular launch systems and reusable technologies, such as Falcon Heavy, Ariane 6, and Vega-C, are central to these efforts. The rise of micro-launchers for small satellites, often supported by national agencies, facilitates entry for new actors (Motta et al., 2024).

The rapid growth of satellites and orbital debris has made SSA and STM strategic priorities for safe and sustainable space operations. Approximately 35,000 debris fragments larger than 10 cm exist in orbit, with around 28,000 tracked daily, and the expansion of LEO constellations increases collision risks. Advanced tracking systems and debris mitigation strategies, including real-time orbital monitoring and AI-based collision-avoidance manoeuvres developed by institutions like ESA, are essential. Public and private actors are also investing in active debris removal technologies, such as RemoveDebris, experimental deorbiting tethers, and laser-based systems, although these remain in development (Brettle et al., 2019).

Space exploration is entering a dynamic phase, marked by collaboration between public institutions and private companies. Programs such as NASA's Artemis mission and planned Mars missions are driving the development of advanced interplanetary transport systems by companies like SpaceX and Blue Origin. Space Resource Utilization (SRU) is emerging as a strategic area, focusing on in-situ exploitation of extraterrestrial resources to support sustained off-Earth activities. Celestial bodies, such as the Moon, asteroids, and Mars, contain valuable materials scarce on Earth, including metals and water, which can also support life-support systems and spacecraft propellant. Start-ups like iSpace are investing in SRU technologies, though the sector faces regulatory and technological challenges, including legal frameworks and technological readiness (Dallas et al., 2020). Additionally, Space tourism is attracting growing private investment, with companies like Virgin Galactic and Blue Origin developing suborbital and orbital commercial flights. While significant technological and regulatory challenges remain, these activities are expected to create new commercial and recreational opportunities in the coming decades (Link et al., 2023).

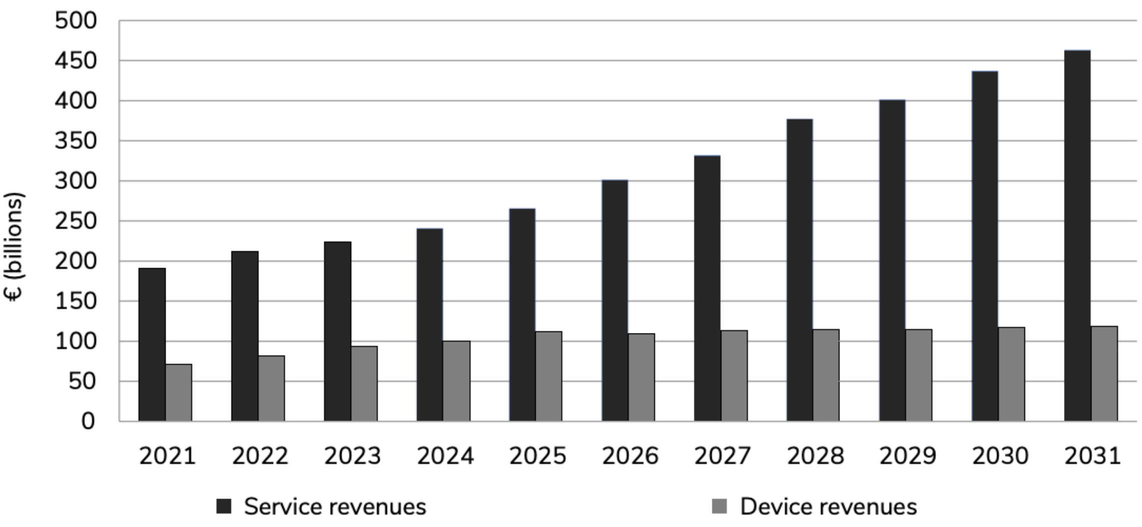
2.4 The main industries leveraging space-based technologies

Space-based technologies have become increasingly pervasive across a wide range of economic and industrial sectors, enabling innovative applications that go far beyond traditional aerospace missions. Their integration into terrestrial systems is driving transformation in key areas by improving efficiency, safety, and sustainability.

2.4.1 Transport and logistics

The transport and mobility sector has long represented a fundamental pillar for economic development and social well-being, as it enables the efficient movement of people, goods, and information, thereby ensuring adequate levels of accessibility and quality of life. Space technologies, such as Satellite navigation services, commonly referred to as GNSS, along with satellite communications and EO systems, are synergistically contributing to the digitalization and optimization of both public and private mobility systems (Jin et al., 2024).

Figure 5: Revenue from GNSS devices sales and services through time (2021-2031)



Source: EUSPA (2024).

Among these technological domains, the GNSS downstream market, which includes the sale of GNSS-based devices and services, is emerging as one of the segments with the highest growth potential. According to estimates from the European Union Agency for the Space Programme (EUSPA) EO and GNSS Market Report (2024), global revenues for this segment are expected to increase from approximately €260 billion in 2023 to €580 billion in 2033, reflecting a CAGR of over 8%. This expansion will be driven primarily by the growth of value-added services, which are projected to account for nearly 80% of total market revenues by 2033, amounting to approximately €460 billion.

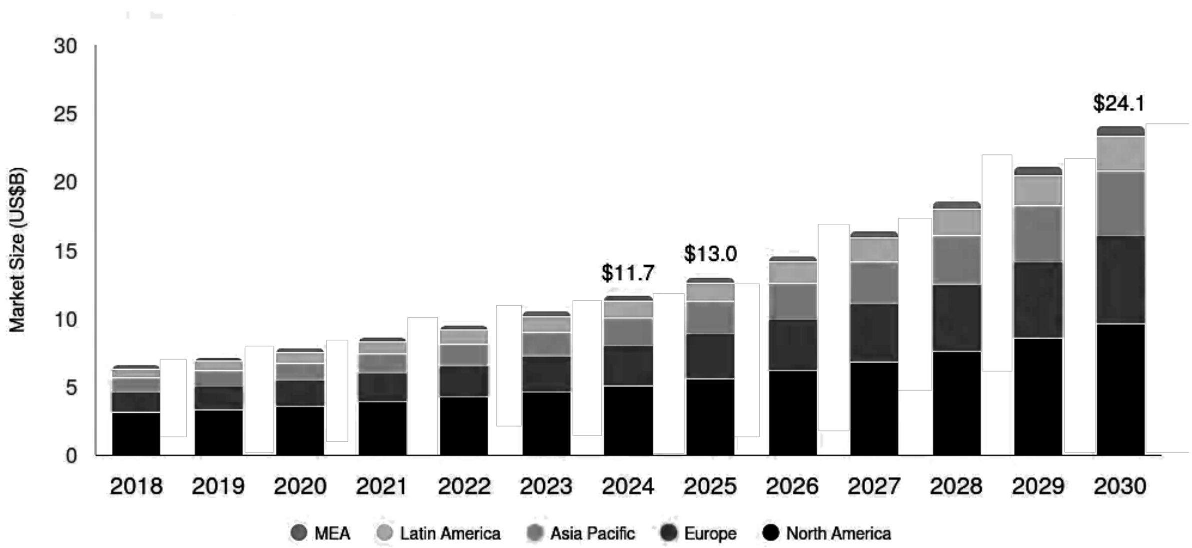
2.4.2 Agriculture and precision farming

The agri-food sector is facing crucial challenges, primarily related to the rapid growth of the global population and the scarcity of new land available for agriculture and grazing. According to the 2025 report, a collaboration between the OECD and FAO, global consumption of agricultural and fish products is projected to grow by 13% by 2034, with most of this growth concentrated in low- and middle-income countries. Specifically, in low-income nations, the increase is primarily driven by population growth, while in middle-income countries, it is partly attributed to a rise in per capita consumption, fueled by growing disposable incomes and urbanization. These changes also drive a shift in dietary patterns, with a growing demand for more nutritious and diversified foods, such as animal-source products and fish, whose caloric contribution to the global diet is projected to increase by 6% by 2034 (OECD/FAO, 2025).

This situation poses a complex challenge for governments, exacerbated by progressive desertification and the urbanization of existing agricultural areas, which are reducing the availability of arable land. Furthermore, the agricultural sector contributes significantly to greenhouse gas emissions, approximately 22%, and utilizes about 70% of the world's water resources. The indiscriminate use of pesticides also threatens the survival of many key insect species vital for the ecosystem, such as pollinating bees and butterflies, as well as natural predators like ladybugs, thereby increasing the risk to crops (OECD/FAO, 2025).

To address these challenges, the adoption of space technologies offers a significant contribution, particularly in the field of precision agriculture. The latter is based on decision-making systems that enable the real-time monitoring of agricultural land conditions, thereby optimizing resource use and reducing environmental impact. Increasing access to high-resolution satellite imagery, combined with AI and machine learning techniques, allows for the analysis of large quantities of data to precisely assess the water requirements of crops, which significantly reduces water waste. Additionally, these tools enable the estimation of soil fertility and the identification of the most suitable crops for specific areas, thus improving productive efficiency (Getahun et al., 2024). The global precision agriculture market was valued at approximately €10.02 billion in 2024 and is projected to reach a total value of €20.68 billion by 2030, with a CAGR of 13.1% during the 2025–2030 period (Grand View Research, 2024).

Figure 6: Precision farming market size by region (2018-2030)



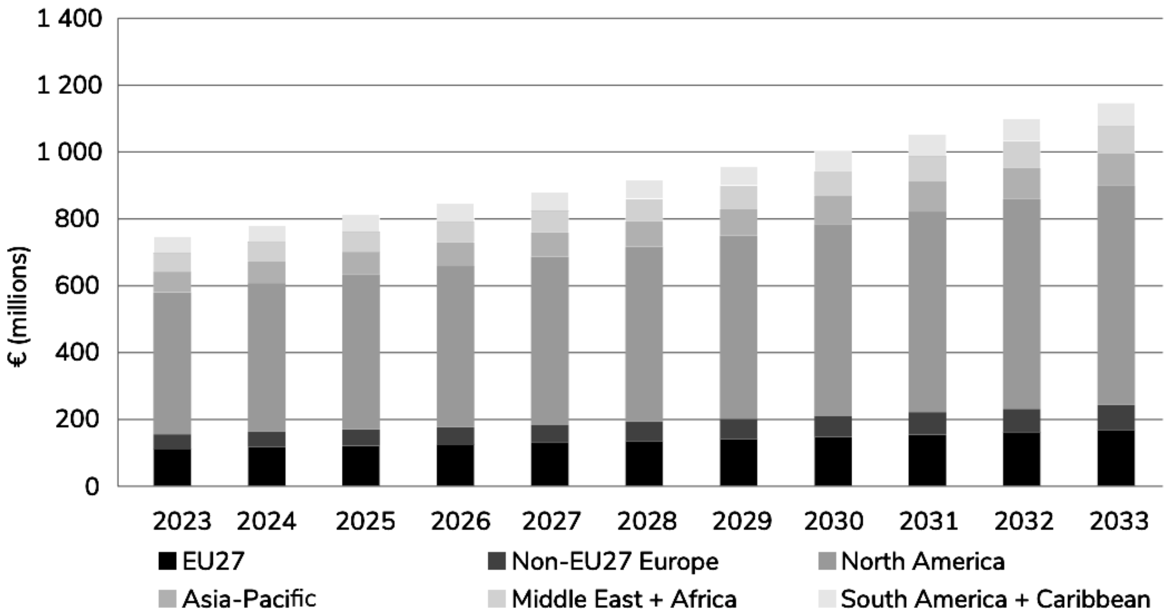
Source: Grand View Research (2024).

2.4.3 Environment management and infrastructure

At the same time, the increasingly extensive use of satellite technologies for monitoring the atmosphere and the environmental impacts of human activities is also profoundly transforming the fields of environmental management and infrastructure. In a context where sustainable development is a strategic priority, satellites offer a decisive advantage over ground-based systems, which provide only limited coverage. Satellites, by contrast, enable the observation of vast areas in a short amount of time, with continuously improving precision thanks to technological advances and the decreasing cost of satellite launches (Spacetech, 2022).

A data point supporting this trend can be found in the report published by EUSPA (2024), which states that revenues from the sale of EO data and services in the Climate, Environment and Biodiversity segment are expected to exceed €1 billion by 2031 (see Figure 7). The projected CAGR is over 4%, remaining consistent across time and geographic regions. North America is expected to remain the dominant market player due to its well-established position, while the fastest-growing regions include Asia-Pacific and non-EU27 Europe. This expansion is driven by global initiatives such as the Paris Agreement, the Global Environment Facility, and the Sustainable Development Goals, which are generating increasing demand for environmental and climate monitoring applications among both institutions and private companies worldwide (EUSPA, 2024).

Figure 7: Revenue from EO data and services sales by region (2023-2033)



Source: EUSPA (2024).

2.5 The strategic importance of Space agencies

Despite the increasing dominance of private actors in the global space ecosystem, national and international space agencies continue to play a critical role in the advancement of space technologies. This is especially evident in the upstream segment, where technologies typically require long development cycles and extensive testing to reach high levels on the Technology Readiness Level (TRL) scale. The extreme environmental conditions of space demand high-reliability systems, making public agencies indispensable as long-term coordinators of innovation and investment (Heitor et al., 2024).

The ESA established in 1975, is the core of European public involvement in space. This independent intergovernmental organization has 22 member states, including non-EU countries like Switzerland, Norway, and the U.K. Though separate from the EU, ESA works closely with it on flagship programs such as Galileo (satellite navigation) and Copernicus (Earth Observation), which are vital for Europe’s strategic autonomy in space (Canton, 2021).

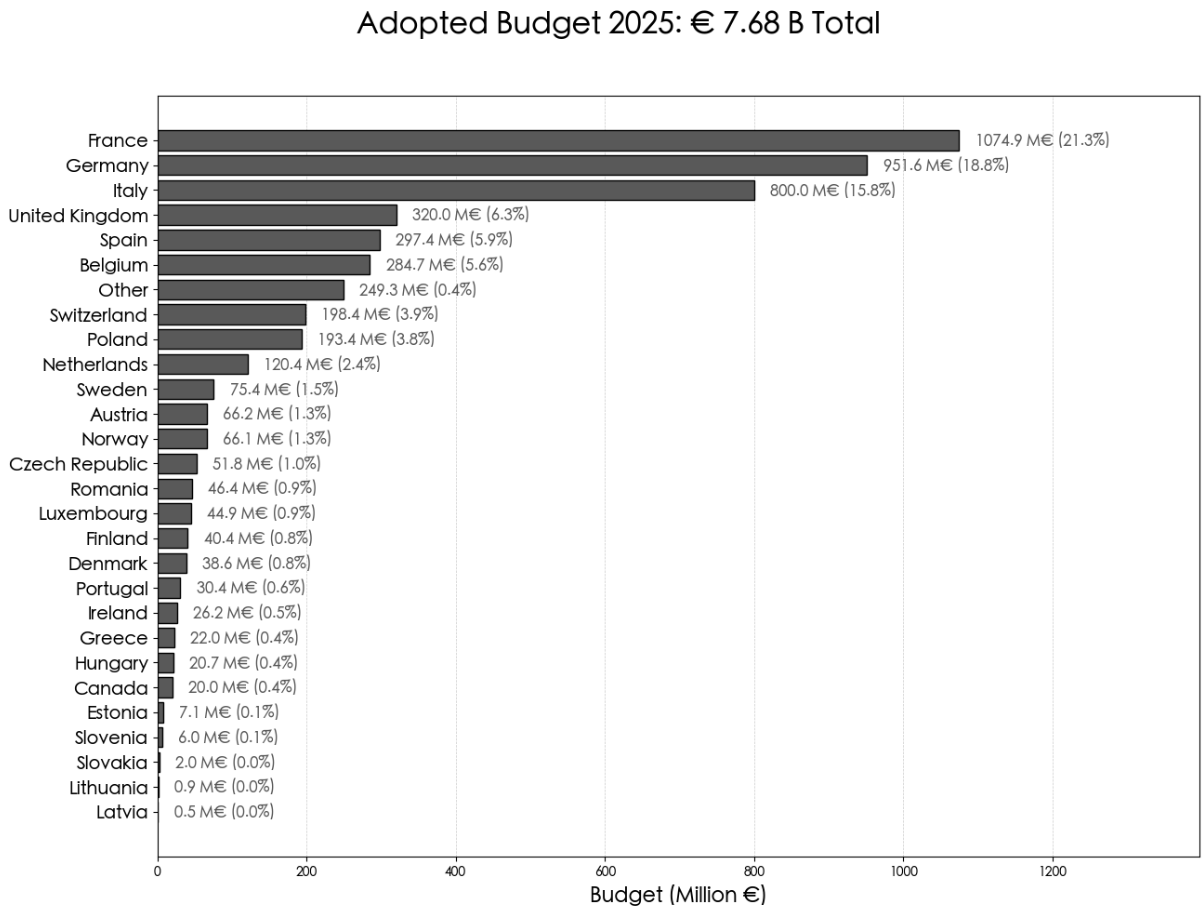
ESA's influence comes from its ability to coordinate technology development and strategically distribute investments using two funding mechanisms (ESA, 2025):

- Mandatory programs, which cover general scientific activities and core agency services. All member states contribute to these programs based on their GDP;
- Optional programs, which allow member states to voluntarily support projects aligned with their national interests.

The geographical return principle is key to ESA's structure, ensuring that industrial contracts are distributed to member states in proportion to their financial contribution. This makes ESA a major public investor in the EU space industry, with France, Germany, and Italy being the top beneficiaries and accounting for approximately 55.9% of the total ESA budget (ESA, 2025). ESA’s total budget has seen steady growth over the past decade, increasing from approximately €4.3 billion in 2013 to €7.68 billion in 2025, represented in Figure 8, with a Compound Annual Growth Rate (CAGR) of over 5%. This funding is allocated across key strategic domains such as space transportation, human spaceflight, navigation, EO, and telecommunications. Although the share dedicated to launch capabilities has slightly decreased in recent years, these sectors remain ESA’s core investment priorities (ESA, 2025).

Beyond its institutional role, ESA also provides a stable testing ground for emerging technologies, bridging the critical gap between R&D and commercialization. Its missions often serve as validation platforms for new solutions that would otherwise struggle to reach TRL-9, the threshold required for market deployment (Olechowski et al., 2020).

Figure 8: Breakdown of ESA budget by Member State contributions in 2025



Source: Own work based on ESA (2025).

2.5.1 ESA support schemes for entrepreneurship

The ESA has developed research and innovation programmes to support SMEs and startups in turning technological or business ideas into viable solutions, providing seed funding, technical assistance, networking, and help in securing external financing.

- *ARTES (Advanced Research in Telecommunications Systems)*

The *ARTES Programme* fosters innovation in the satellite communications (SATCOM) sector by providing financial and operational support to industrial projects in ESA Member Statesđ, through three main branches (ESA, n.d.-a):

- *ARTES Business Applications*: applies SATCOM technologies to new terrestrial markets and services;
- *ARTES Core Competitiveness*: funds early-stage R&D up to 100% and projects with strong commercial potential up to 80%;
- *Partnership Projects*: co-funds high-risk ventures with partners, enabling large-scale developments like the European Data Relay System and the Next Generation Platform.

- *Boost!*

The *Commercial Space Transportation Services and Support programme* aims to stimulate private-sector innovation in commercial space transport through co-funding and development support. It has two main components (ESA, n.d.):

- *Commercial Space Transportation Services*: invites startups, SMEs, and established companies to propose innovative concepts eligible for ESA backing;
- *Support to Participating States*: assists ESA Member States in advancing national goals, including the development of spaceports and related infrastructure.

- *Future EO (Future Earth Observation Programme)*

The *Future EO Programme* is ESA's main research and innovation framework for advancing the European Earth Observation (EO) sector, covering infrastructure to downstream applications. Its core component, EO Science for Society, supports EO-based solutions addressing global challenges such as climate change, environmental monitoring, resource management, and disaster resilience. The programme fosters integration of EO data with technologies like AI and big data analytics, while other components focus on mission design, small-scale science missions, and enhanced data access. Future EO employs a flexible funding model that maintains continuity with systems like Copernicus while promoting disruptive innovation across Europe's EO ecosystem (ESA, n.d.).

- *FLPP (Future Launchers Preparatory Programme)*

The *Future Launchers Preparatory Programme* is an optional ESA initiative aimed at fostering the development of enabling technologies for next-generation space missions. ESA's strategic plan for space launch focuses on supporting emerging technological projects that enhance the performance and reliability of current launch vehicles while simultaneously reducing operational costs and time-to-market. This approach is intended to facilitate easier and more cost-effective access to space (ESA, n.d.).

- *GSTP (General Support Technology Programme)*

The *General Support Technology Programme* aims to advance promising space technologies and prototypes into fully developed products ready for upcoming missions. Covering all space-related technological fields except telecommunications (under ARTES), GSTP has attracted participation from multiple member states despite its voluntary nature. ESA estimates that every euro invested generates a commercial return of approximately €3.5 (ESA, n.d.). The programme's activities are organized into three main components (PwC, 2024):

- *Develop*: advancing new technologies from early development to mission readiness, forming the basis for future innovations (see Table 2 for frameworks);

Table 2: Framework descriptions of the "Develop" element of the GSTP programme

Framework	Duration	Funding	Activities
De-Risk	9 months	≤ € 250000	Focus on evaluating the risks related to the development of a new technology
Advanced Manufacturing	≤ 12 months	≤ € 250000	Focus on the potential impact of advanced manufacturing techniques on products
Building Blocks	≤ 18 months	≤ € 1 million	Focus on the coordination and integration of national technological advancements

Source: Own work based on PwC (2024).

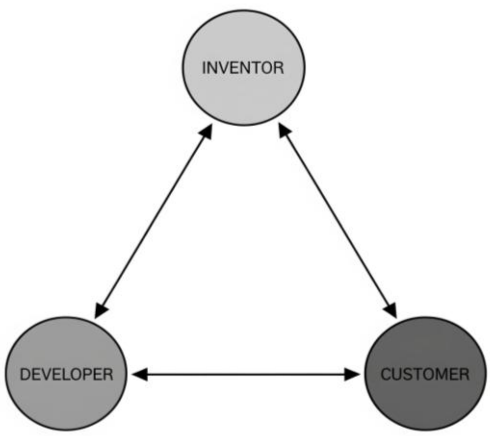
- *Make*: This component supports innovative proposals. ESA offers co-funding ranging from 50% to 75%, depending on the development stage and the nature of the companies involved;
- *Fly*: This component involves all activities related to the in-orbit testing and validation of new technologies to ensure their operational performance.

- *TDE (Technology Development Element)*

The *Technology Development Element* primary focus is on the preliminary development of new technologies, assessing the feasibility of concepts and their appropriateness for space use. It operates under ESA's Innovation Triangle Initiative framework, with three principal participants (van Burg et al., 2017):

- *Inventor*: responsible for originating the new technological concept;
- *Developer*: physically realizes the concept with space industry standards and demonstrates its viability and practical application;
- *Customer*: co-finances the project and commits to utilizing the developed technology.

Figure 9: Schematic representation of the Innovation Triangle Initiative framework



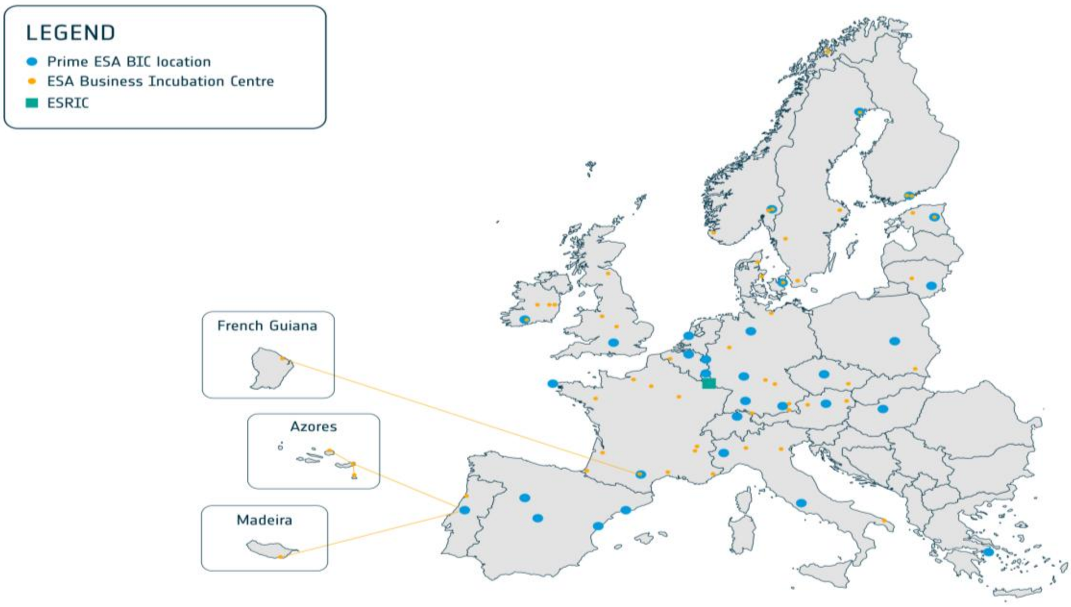
Source: Own work based on ESA (2007).

2.5.2 ESA Business Incubation Centres

Since its establishment in 2003, the ESA Business Incubation Centre (BIC) network has evolved into a Europe-wide framework supporting startups and SMEs in transforming space-related innovations into viable commercial ventures. Operating through partnerships with institutional, academic, and industrial actors, the network has supported over 1,800 startups, generating significant employment and contributing to economic growth across Europe (Eldering & Hulsink, 2021). Between 2020 and 2023, ESA BICs facilitated more than €1.25 billion in private investment and the filing of over 590 patents (Montanari, 2024).

As illustrated in Figure 10, the network currently comprises 33 hubs across 22 Participating States, encompassing more than 100 incubation sites. Each centre is managed locally by organisations with strong regional ties to academia, industry, and finance, ensuring tailored support aligned with local innovation ecosystems. ESA BICs pursue a dual objective: to foster upstream innovation in space infrastructure and to stimulate downstream applications of space technologies in non-space sectors (ESA, n.d.-b).

Figure 10: Geographical distribution of ESA BICs in 2024



Source: ESA (2024).

Startups selected for incubation undergo a two-year support programme, receiving up to €80,000 in funding, technical and business development assistance, access to ESA expertise, and legal and financial advisory services. This framework mitigates early-stage risks and enables entrepreneurs to focus on innovation and commercialisation (ESA, n.d.-b). The most recent addition to the network, ESA BIC Latvia, was inaugurated in November 2024 at Riga Technical University. Its establishment marks Latvia's integration into the ESA BIC network as an ESA Associate Member State and aligns with the objectives of the Latvian Space Strategy. Over the next five years, ESA BIC Latvia aims to support at least 12 startups, fostering technology transfer, job creation, and regional economic development within the national space ecosystem (Latvian Space Agency, 2025).

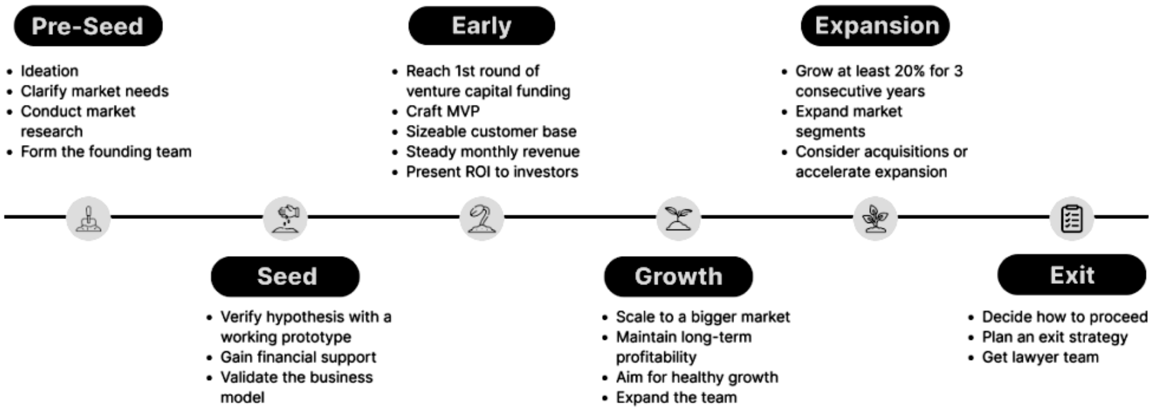
3 THE ROLE OF START-UPS IN THE NEW SPACE ECONOMY

In its most general definition, a start-up is a newly established enterprise, typically operating for less than five years. Unlike traditional firms, which rely on established processes and accumulated experience, start-ups aim to achieve rapid market penetration by leveraging innovative business models or offering products that are more disruptive or profitable than those of incumbent companies (Ries, 2011). Within the SpaceTech sector, start-ups introduce various forms of innovation, which can be grouped into three main categories:

- *Product innovation* refers to the creation of new goods or services, or significant improvements to existing ones, aimed at meeting evolving consumer needs or creating new markets. This directly contributes to market share growth and customer satisfaction, critical for start-ups in competitive sectors (Gunday et al., 2011);
- *Process innovation* involves optimizing how a product or service is designed, delivered, and supported. Enhancing operational processes helps start-ups reduce waste, increase productivity, and improve profitability, while supporting efficient resource allocation and sustainable growth. Its effects are often internal and less visible to end users (Damanpour & Aravind, 2012);
- *Business model innovation* entails restructuring how an organization creates, delivers, and captures value. It enables start-ups to gain competitive advantages and unique market positions, potentially transforming entire sectors (Chesbrough, 2010). Examples include Uber and Airbnb, which leveraged technology to offer previously unavailable value propositions.

To facilitate the understanding of the following sections of this paper, it is useful to provide a concise overview of the main phases that characterize the life cycle of a start-up. Generally, six distinct phases are recognized: pre-seed, seed, early stage, growth, expansion, and exit, illustrated in Figure 11.

Figure 11: Six stages of the startup lifecycle



Source: Enosta (2023).

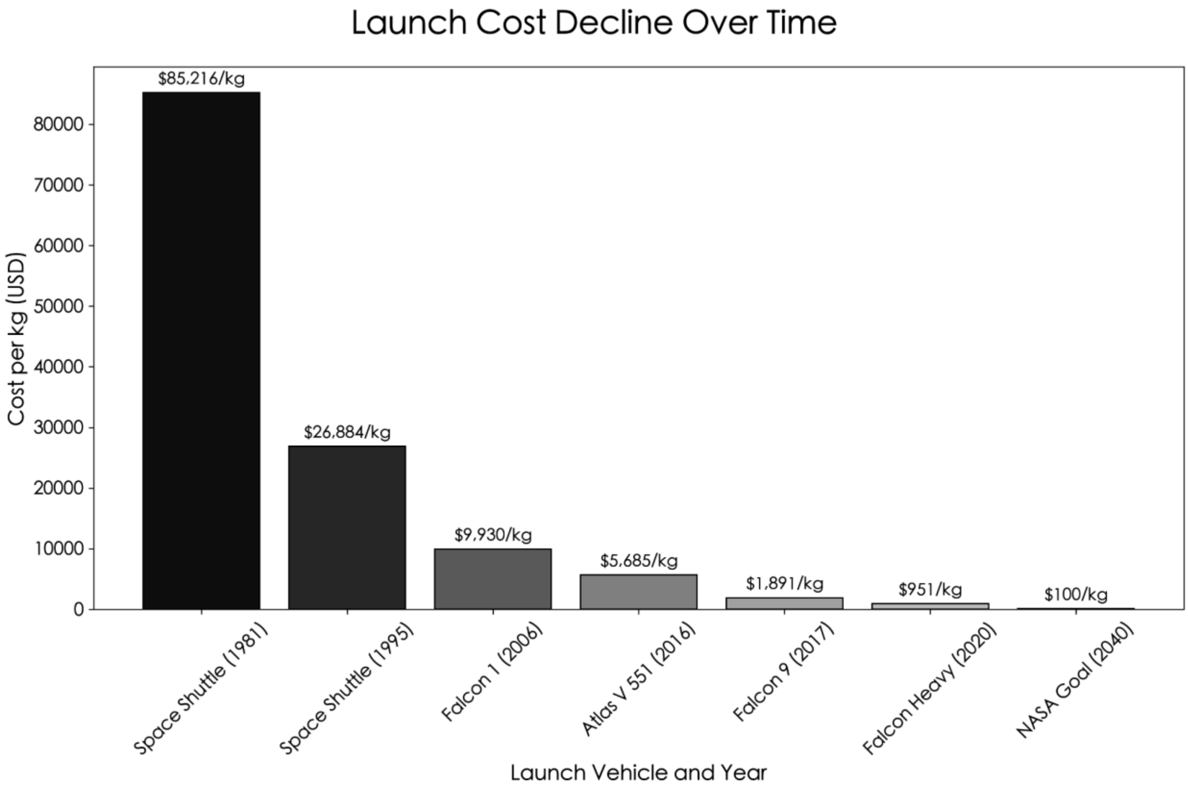
The pre-seed phase focuses on market and consumer analysis to assess idea viability, alongside defining the start-up's vision, mission, and milestones. Funding is usually limited, relying on bootstrapping or informal investors (family, friends, FFF). The seed phase aims to validate the business model by developing a first prototype and gathering initial user feedback. External investors, particularly business angels, often provide capital and entrepreneurial support. During the early stage, the prototype evolves into a Minimum Viable Product (MVP), an initial version of the product that is not yet fully complete and lacks some features. The MVP is launched on the market to help the founders understand whether the client needs identified in previous market research have been met (Enosta, 2023). At this point, personal funding is usually insufficient, requiring external investments from business angels and venture capitalists. The growth stage is considered one of the most challenging phases, where the start-up aims to rapidly increase its customer base and revenues. Professional management figures, often introduced through VC networks, play a central role in supporting this expansion. In the expansion phase, the start-up seeks to further grow by entering international markets or new segments (Enosta, 2023). Access to financing becomes easier due to the company's increased stability, attracting a wider range of investors, including private equity funds, banks, and large corporations, the latter often investing for strategic purposes such as gaining early access to innovative technologies developed by the start-up. Finally, the exit phase marks the moment when investors seek to realize returns on their investment through various options, including (Enosta, 2023):

- IPO (Initial Public Offering), the start-up transitions from a private to a publicly traded company by listing on the stock exchange;
- Secondary sale, shares of the start-up are sold to a third party in a private market transaction;
- Acquisition, the start-up is purchased by a larger company;
- Buyback, the founder repurchases shares previously ceded to investors during earlier development stages.

3.1 Transition from the traditional Space Economy to the New Space Economy

As briefly mentioned in section 2.1, Recent years have witnessed a shift from the traditional space economy, dominated by government programs and large corporations such as Boeing and Leonardo, with top-down structures and thousands of employees, towards the New Space economy. This emerging paradigm is marked by increased private funding and a focus on developing commercially viable space technologies. A central driver of this transition has been the reduction in launch costs, largely achieved through reusable launch vehicles such as SpaceX's Falcon 9 and Starship, and Blue Origin's New Shepard and New Glenn (FutureTimeline, 2018). This ongoing trend is expected to continue, as illustrated in Figure 12.

Figure 12: Launch costs to LEO (1980-2040)



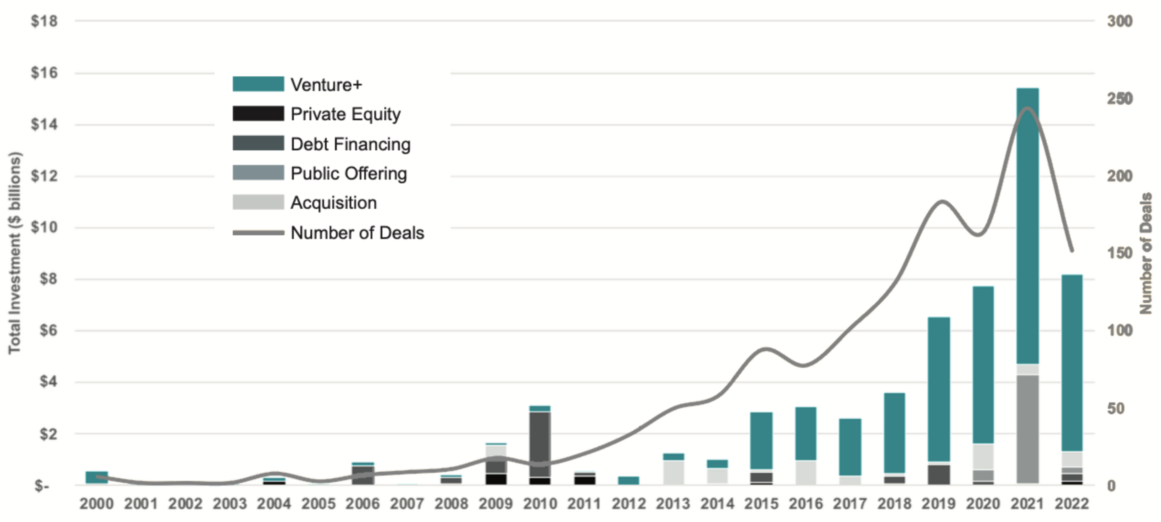
Source: Own work based on FutureTimeline (2018).

Furthermore, another significant aspect contributing to lower space access costs is the rising trend of deploying constellations composed of SmallSats and CubeSats. These smaller satellites reduce production costs per unit and enable the creation of novel business models that are highly attractive to private investors (Logue & Pelton, 2019).

The rise of the New Space economy is also supported by the establishment of new space agencies in emerging countries, creating opportunities for international collaboration and technological innovation. Recent national and international regulations further promote commercial space development and its integration with sectors such as telecommunications, agriculture, and infrastructure. For example, the European Copernicus program has made a large portion of satellite data publicly accessible since 2013, facilitating both commercial and non-commercial applications (Robinson & Mazzuccato, 2019).

The combined influence of these factors has led to the emergence of numerous start-ups that, through their innovative business models and advanced technological developments, are attempting to revolutionize the aerospace industry and secure their market share alongside other established international competitors. The graph extracted from BryceTech's Start-up Space report (2023) highlights a significant increase in investments in aerospace start-ups beginning in the latter half of the 2010s. Examining the past decade in detail, between 2015 and 2024, over 56 billion euros in funding was raised.

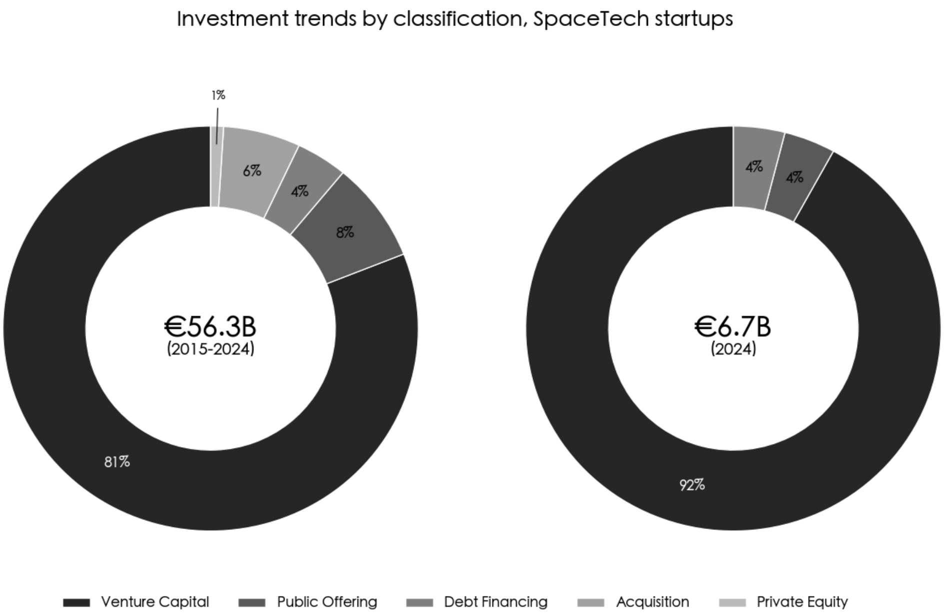
Figure 13: Evolution of SpaceTech startup investments (2000 – 2022)



Source: BryceTech (2023).

Notably, in 2024 alone, investments amounted to €6.7 billion, marking the third-highest value ever recorded, following €13.2 billion in 2021 and €6.9 billion in 2022. The decline after the 2021 peak is mainly attributed to interest rate hikes by institutions such as the Federal Reserve and European Central Bank, which constrained public offering financing opportunities and affected not only the aerospace sector but the broader economy (BryceTech, 2023).

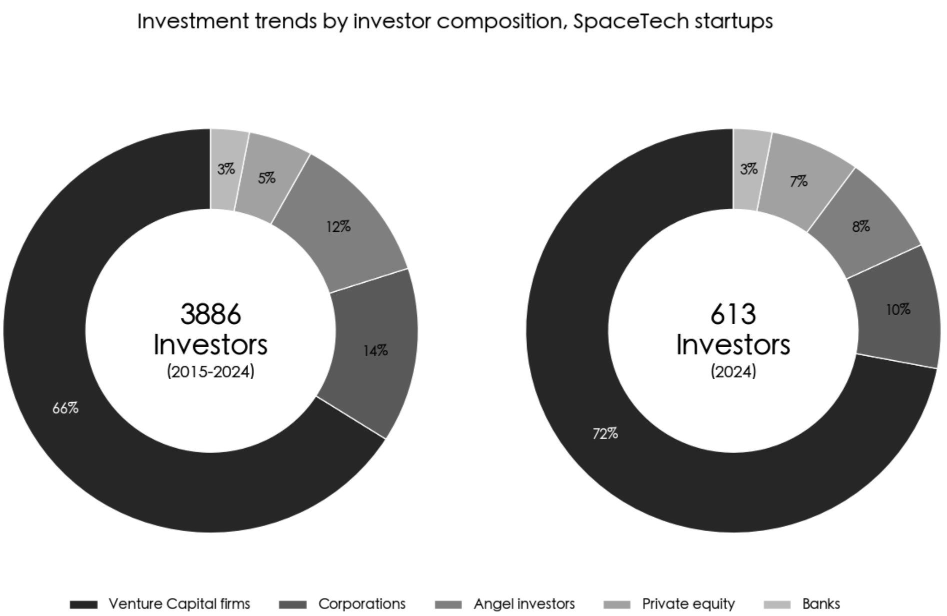
Figure 14: SpaceTech startup investment trends by classification (2015 – 2024)



Source: Own work based on BryceTech (2025).

Over the past decade, see Figure 15, VC has been the most active investor in the aerospace start-up sector. Between 2015 and 2024, VC firms accounted for 66% of the 3,886 investors making at least one investment, rising to 72% of 613 investors in 2024, the highest share ever recorded. Large corporations ranked second, representing 14% of investors over the period, typically investing strategically to gain early access to start-up innovations.

Figure 15: SpaceTech startup investment trends by investor composition (2015 – 2024)



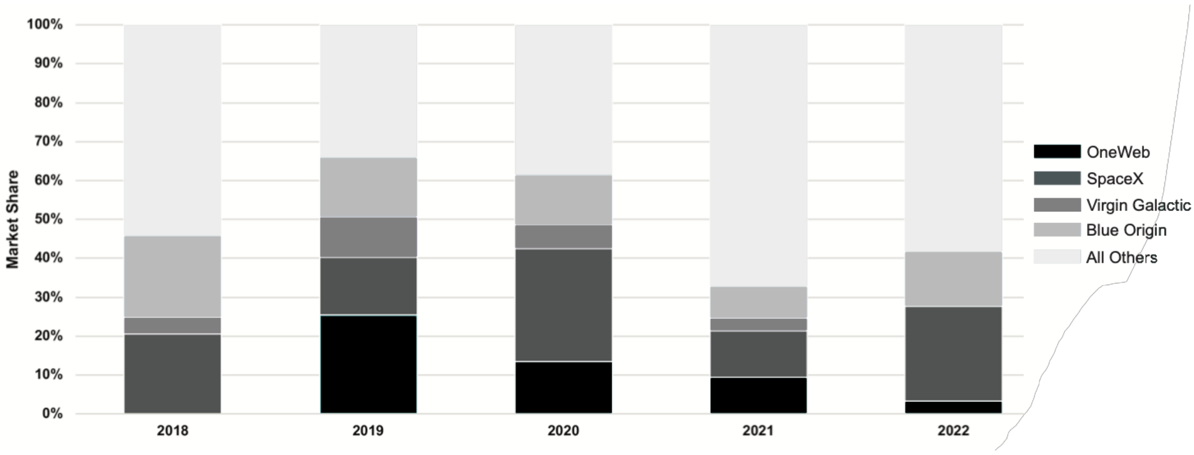
Source: Own work based on BryceTech (2025).

Given these figures, it is essential to examine the functioning and strategic role of VC funds, the predominant investor type, to better understand their investment logic and potential influence on the future trajectory of the New Space Economy.

3.2 The impact of major players in New Space ventures

Based on Dealroom data, SpaceX, OneWeb, Virgin Galactic, and Blue Origin raised approximately €18.69 billion between 2018 and 2023. This concentration of capital divides the competitive landscape into two categories: a few large "new space" ventures backed by prominent investors, and numerous smaller start-ups receiving comparatively modest funding. Figure 16 highlights this concentration: in 2019, the four companies accounted for 66% of total investment, while in 2021 early-stage companies captured a larger share, reducing the top four's portion to 33%. By 2022, SpaceX, Blue Origin, and OneWeb represented 42% of total investment, with SpaceX alone receiving an estimated €1.9 billion (Bryce Tech, 2023).

Figure 16: Concentration of startup space investments in major recipients (2018 – 2022)



Source: Own work based on BryceTech (2023).

Several trends emerge from Figure 16 and historical data (Bergan, 2022):

- Prior to 2010, VC investment in new space ventures was negligible, with SpaceX capturing nearly all funding;
- 2011–2014 saw the emergence of VC investment, approaching $200 million annually;
- 2015 marked a surge driven by Google's $1 billion in SpaceX and SoftBank's $500 million in OneWeb, doubling net VC funding from $200 million (2014) to $400 million;
- While SpaceX and OneWeb have attracted roughly 50% of total committed funds to date, VC funding for other startups grew significantly, with key increases in 2015 (+100% relative to 2014, reaching $400 million) and 2017 (+300% relative to 2016, $1.2 billion);
- Net VC investments reached $1.6 billion and $1.7 billion in 2018 and 2019, establishing new benchmarks.

Figure 16 suggests that the top four companies dominate funding, but these ventures have also catalysed sector-wide growth by validating technologies and attracting investor attention. This catalytic effect, combined with the anticipated rise of new start-ups, is expected to stimulate entrepreneurship in the sector and expand the pool of ventures accessing capital (Bergan, 2022).

4 ANALYSIS OF THE SYNDICATION PHENOMENON AND CROSS-BORDER INVESTMENTS IN THE VENTURE CAPITAL SECTOR

VC funds represent a specific category of private equity funds that specialize in financing high-growth companies, typically start-ups, with the objective of generating substantial returns over the medium to long term. These returns, often averaging between 25% and 35% annually, exceed market norms due to the elevated risk and uncertainty intrinsic to this type of investment (Cumming et al., 2007). Beyond providing financial resources, VC firms play a pivotal role in supporting portfolio companies strategically and operationally, offering managerial and technological expertise as well as access to their commercial networks (Ceccagnoli et al., 2018).

Within the VC sector, a widely observed practice is syndication, a co-investment arrangement in which two or more VC funds participate jointly in the same investment round. In contexts of high uncertainty, particularly where assets are highly specific and potential losses from failure are substantial, VC investors face an increased likelihood of unforeseen contingencies. To mitigate these risks, they collaborate with additional VC partners who contribute complementary expertise, thereby enhancing opportunity sourcing and investment selection (Lutz & Nörthemann, 2025). Furthermore, syndication promotes broader risk diversification: the involvement of multiple investors reduces each fund's capital exposure, enabling VC firms to allocate resources across a greater number of portfolio companies (Hopp & Rieder, 2011).

According to a study by Lockett and Wright (2001), the motivations driving VC funds to engage in syndication can be examined from three main perspectives:

- A financial perspective related to risk sharing;
- A resource-based perspective aimed at risk reduction;
- A market access perspective concerning the expansion of deal flow.

From a financial standpoint, syndication distributes investment risk among several investors, reducing overall portfolio exposure (Bygrave, 1987). This is particularly significant given the inherent challenges VC funds face in achieving diversification compared to investors in public markets. As Lockett and Wright (2001) note, a VC fund attempting to diversify by holding numerous small equity stakes would lack the capacity to provide the close monitoring and mentoring fundamental to venture investing. Furthermore, excessive portfolio fragmentation would raise transaction costs, as each investment requires ongoing bilateral negotiations between the fund and its portfolio companies.

A further financial rationale for syndication lies in the intrinsic illiquidity of VC investments compared to institutional holdings in publicly traded firms. This illiquidity makes it more difficult to exit underperforming investments whose costs exceed initial projections. Syndication thus functions as a mechanism for risk sharing while simultaneously expanding the pool of viable investment opportunities (Cumming et al., 2005). Lerner (2022) also identifies an additional financial motivation. Drawing on evidence from privately held biotechnology firms, he argues that VC funds may engage in syndication to enhance their ability to raise capital for future funds. The capacity to attract new investors is closely tied to a fund's performance relative to its peers.

However, because VC investing is inherently hands-on, requiring close involvement in start-up management and development, each additional portfolio company increases management costs, partially offsetting the diversification benefits. Effective portfolio construction therefore requires a careful balance between risk mitigation and operational efficiency (Maula et al., 2009).

From a resource-based perspective, the availability and quality of resources play a crucial role in mitigating firm-specific risks, both in the investment selection phase (ex-ante) and in the management phase (ex-post). During the selection phase, syndication reduces the risk of adverse selection, as each investment must be validated by multiple parties (Lockett & Wright, 2001). Pooling the analytical capabilities of several partners enhances decision quality, a value-added effect highlighted by Brander et al. (2002), who demonstrate that jointly approved investments tend to be more efficient than those decided unilaterally within hierarchical structures.

The choice of syndication partners is strongly influenced by reputation. VC funds with stronger track records occupy a privileged position and are more likely to be invited into early investment rounds, while later stages often include less experienced funds (Lerner, 2022). This evidence indicates that syndication improves the information available to VC firms, thereby enhancing the quality of investment decisions.

Syndication also facilitates the leveraging of complementary resources during the management phase. Partners with specialized expertise, whether in specific industries or in certain stages of the business life cycle, are particularly valued. Specialization, as opposed to diversification alone, provides a more effective form of risk management, enabling funds to operate with greater confidence and accept lower expected returns relative to generalist investors. However, specialization may also introduce informational asymmetries among partners. In such cases, reputation again serves a critical function, legitimizing managerial actions and aligning the interests of all participants (Tykvová, 2007).

Finally, a third rationale for engaging in syndication concerns the expansion of deal flow, made possible through the ongoing exchange of investment opportunities within a VC fund's professional network. This exchange may occur in an outbound form, when a fund invites other

VCs to join an investment rather than pursuing it independently, or in an inbound form, when it is invited to participate in a deal initiated by others. This mechanism becomes particularly relevant during periods of economic expansion, when competition for attractive deals intensifies and capital availability is high. In such contexts, syndication enables VC funds to cultivate collaborative relationships with other investors, thereby gaining access to additional resources and capabilities (Hopp, 2010).

4.1 The structural drivers of efficiency and valuation in VC syndication

Building on the theoretical foundations discussed in the previous section, which examined the main motivations driving venture capital funds to engage in syndication, this section explores how the structural and relational configurations of syndicates influence the performance and valuation of start-ups. Rather than focusing solely on organizational design, the analysis highlights the efficiency effects associated with syndication mechanisms such as governance structure, control and trust dynamics, and syndicate size. These elements determine not only how effectively syndicate members coordinate their actions but also how value is created and distributed within the portfolio company.

Within a syndication, two primary roles are identified: the lead investor and the non-lead investors (also referred to as co-investors). The lead investor acts as the coordinator of the entire syndication process, overseeing preliminary due diligence of the target company, negotiating contractual terms with the start-up entrepreneur, and securing a position on the company's board of directors. In this capacity, the lead investor performs mentoring and monitoring functions to ensure adherence to the agreed business plan.
The reputation and expertise of the lead investor provide a strong credibility signal to the financed start-up and to external stakeholders, enhancing the firm's ability to attract additional investors and often correlating with higher valuation outcomes and improved exit performance (Hopp, 2010).

Non-lead investors, by contrast, play a more marginal role within the syndication, conducting a less extensive due diligence than the lead investor and often not obtaining a seat on the company's board. Nevertheless, they can contribute significant complementary expertise or access to specialized industry networks, thereby reinforcing the start-up's resource base and improving its performance potential.

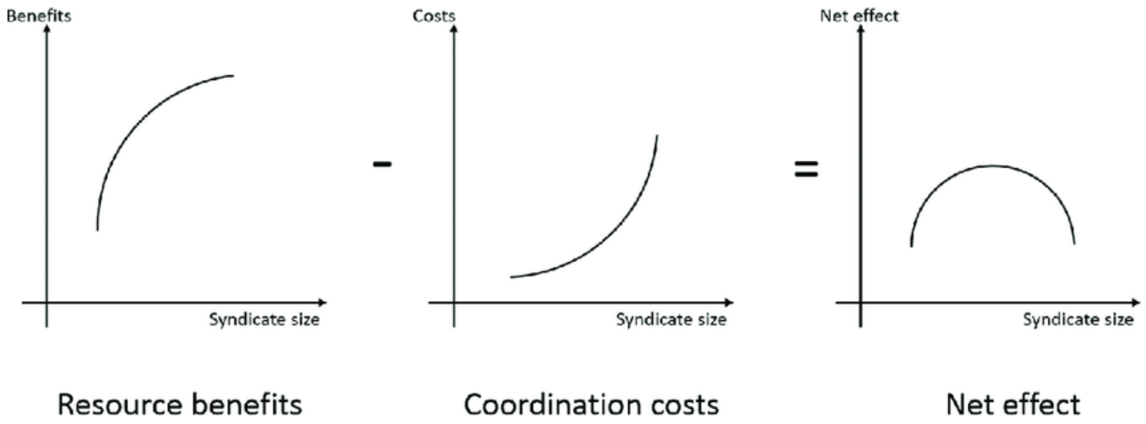
To ensure the effectiveness of collaboration and mitigate potential conflicts, syndicates employ both control mechanisms and trust mechanisms, which function as complementary tools to align investor interests. Control mechanisms are designed to guarantee that VC partners act consistently with shared objectives and that decisions are made to minimize undesirable outcomes. These can be divided into ownership control and managerial control (Wright & Lockett, 2003). Ownership control relates to residual decision rights derived from majority equity stakes, enabling investors to make decisions not specified in contractual agreements.

Managerial control, in contrast, governs how strategic and operational decisions are made within the start-up and is typically formalized in syndication agreements that specify who decides on particular matters and under what procedures (Lin et al., 2017). Effective governance structures that balance ownership and managerial control tend to enhance monitoring efficiency, reduce information asymmetries, and support better performance outcomes, thereby positively influencing firm valuation.

Trust mechanisms, on the other hand, are not based on formal agreements but rest on the expectation that VC partners will behave fairly and predictably toward all parties involved, even when such behaviour has not been explicitly stipulated. Trust thus represents not an absence of control, but a complementary governance mechanism that reduces transaction costs and increases adaptive capacity in uncertain environments. Empirical studies highlight that an optimal combination of formal control and relational trust fosters better coordination, faster decision-making, and stronger investor confidence, which collectively contribute to improved start-up performance and valuation (Rousseau et al., 1998).

Another important determinant of syndicate efficiency is the number of VC partners involved in the investment. Kim and Park (2021) demonstrate the existence of an inverted U-shaped relationship between syndication size and the performance of the target firm (see Figure 17). The positive effects stem from the diversity and complementarity of resources and expertise that multiple VCs bring, which can generate synergy effects and enhance the start-up's likelihood of success. However, as the number of investors increases, coordination and communication costs also rise, and the marginal benefits of additional partners diminish due to resource duplication or conflicting objectives. The negative effects become pronounced when divergent risk profiles or exit strategies create delays in decision-making, reducing efficiency and the start-up's valuation potential. Hence, there exists an optimal syndicate size at which resource complementarity is maximized and coordination costs remain manageable, beyond this point, performance tends to decline.

Figure 17: The effect of VC syndication size on start-up performance



Source: Kim & Park (2021).

Although most decisions within a syndication are made through the consensus of all involved parties, exceptional circumstances may require rapid managerial intervention in the target firm, such as financial restructuring during distress or responding to an unexpected acquisition offer. In these cases, unilateral actions by the lead investor, who typically holds a larger equity stake and thus greater residual control power, are often perceived by co-investors not as overreach but as a necessary efficiency mechanism that protects the collective investment (Busenitz et al., 2005).

4.2 Role of cross-border investments in the VC sector and dynamics between local and international VC firms

In recent years, VC funds have shown a marked upward trend in allocating capital to markets outside their domestic boundaries. Global data confirm this evolution: between 2023 and 2024, the total volume of cross-border investments increased by 18% (Elad, 2025). This expansion is particularly noteworthy given the additional challenges that VC firms encounter when operating abroad compared to those investing domestically. Such challenges are encapsulated in the concept of the "liability of foreignness", which describes the disadvantages faced by foreign entities due to limited local knowledge, potential bias from domestic stakeholders, and the managerial complexities of operating in unfamiliar institutional environments.

Moreover, the concept of distance plays a crucial role and can be understood from different perspectives. For instance, geographical distance limits the ability of VC funds to closely monitor their portfolio companies, which is typically important for providing added value. Additionally, institutional distance between the VC fund's home country and the start-up's country can affect investment decisions.

From an institutional distance perspective, two primary dimensions can be identified: formal and informal. The formal dimension is captured by three sub-dimensions:

- Regulatory efficiency;
- Country governance;
- Financial development.

Regulatory efficiency distance pertains to a country's regulatory conditions, including business, labour, and monetary freedom. Disparities in this dimension can increase entry costs and strategic adaptation challenges for firms expanding abroad. Country governance distance refers to the overall quality of governance, such as the government's effectiveness in policy formulation and implementation, as well as political stability. Differences in this area can heighten perceived uncertainty and risk, as politically unstable countries may have less predictable policies and regulations. Financial development distance concerns the efficiency and stability of a country's financial system. Less developed financial markets, such as those in emerging economies, can pose a barrier to internationalization due to higher volatility and potential information asymmetry, which increases monitoring costs.

Interestingly, empirical evidence offers a nuanced view of these effects. Depperu, Galavotti, and Baraldi (2024) found that while greater regulatory efficiency and financial development distance tend to discourage cross-border acquisitions, governance distance did not have a statistically significant effect. Even more intriguingly, their study revealed that informal institutional distance, particularly cultural distance, as measured by the GLOBE Project's nine dimensions, can be positively associated with cross-border investments into emerging markets.

This seemingly paradoxical result can be explained by the concept of context experience, which refers to a firm's accumulated experience in operating within institutionally similar markets. Context experience mitigates the negative effects of formal institutional differences and, in some cases, transforms cultural distance into an advantage. With sufficient international experience, VC firms may not only navigate formal barriers more effectively but also perceive cultural diversity as an opportunity, especially when pursuing global growth strategies.

Given the multiple risks associated with cross-border investments, a widely adopted strategy among international VC funds is to form syndicates with local partners. Typically, international VC funds possess greater expertise than local funds, particularly in emerging markets, both in selecting start-ups and in providing value-added support during the post-investment phase (Chemmanur et al., 2021). During the selection phase, international VCs leverage their accumulated knowledge and experience to conduct rigorous due diligence, particularly for early-stage start-ups with uncertain profitability. Their experience also enhances their ability to negotiate favourable contractual terms tailored to the start-up's maturity and risk profile. In the management phase, international VC funds draw upon their global networks of strategic suppliers, clients, and investors to accelerate the start-up's scaling process. They also often seek representation on the company's board to provide strategic and operational guidance throughout the firm's growth trajectory.

Empirical research strongly supports the superior performance of start-ups financed through international–local syndication structures. Bertoni and Groh (2014) found that international VC participation in foreign start-ups significantly increases the likelihood of successful exit via acquisition, primarily due to access to a broader network of strategic buyers in the investors' home markets. A similar, though less robust, effect was observed for IPO exits. Chemmanur et al. (2021) further confirm that firms backed by both local and international VC funds exhibit stronger post-IPO performance than those financed solely by one type of investor. Moreover, Bertoni and Groh (2014) note that international VC funds tend to liquidate underperforming start-ups more rapidly, reflecting a lower degree of emotional attachment compared to local investors and promoting a more efficient reallocation of capital.

Despite these advantages, Harvey et al. (2014) question the practical feasibility of cross-border syndication, emphasizing the challenges international VCs face in identifying suitable local partners amid the inherent uncertainty of foreign markets. Two distinct types of uncertainty are particularly relevant: firm-level and country-level uncertainty.

Firm-level uncertainty concerns the unpredictability of a target start-up's future performance, which is especially acute in early stages when limited historical data impede reliable projections. In such cases, access to local information networks, often through partnerships with domestic VCs, becomes critical to mitigate informational disadvantages. However, as international funds accumulate foreign market experience, the informational benefits of local partnerships tend to diminish (Harvey et al., 2014).

Country-level uncertainty encompasses factors such as weak legal institutions, political instability, corruption, macroeconomic volatility, and low market transparency—all of which complicate foreign operations. Partnering with local VC funds can help international investors navigate these risks by leveraging local expertise in regulation and business practices. Nonetheless, in countries with high institutional uncertainty, the reliability of local partners may itself be questioned due to difficulties in contract enforcement and governance opacity. As with firm-level uncertainty, accumulated experience can reduce dependence on local intermediaries, as international funds become more adept at managing country-specific risks independently (Liu & Maula, 2016).

However, Liu and Maula (2016) also emphasize that country-specific operational experience enhances an international VC's ability to identify trustworthy local partners, facilitating the formation of effective co-investment agreements that mitigate uncertainty and improve performance outcomes.

5 OBSERVING SPACE INNOVATION: EMPIRICAL ANALYSIS

The following chapter presents the empirical component of this research, focused on quantitatively analysing the dynamics of the European SpaceTech ecosystem. Specifically, it aims to identify and measure the key factors that contribute to higher startup valuations within this emerging sector. Building on the qualitative overview of industry trends and investment behaviours discussed in the previous chapters, this analysis adopts a data-driven approach, integrating descriptive statistics with rigorous regression modelling to uncover the underlying drivers of innovation in SpaceTech startups.

5.1 Methodology

The empirical analysis is based on a dataset of 337 European startups operating in the SpaceTech sector, specifically compiled using data from Dealroom's database developed in collaboration with the ESA (spacetech.dealroom.co). Dealroom is a leading international platform for startup and VC intelligence, partnering with governmental agencies, investment funds, and other innovation ecosystem stakeholders to provide accurate, up-to-date insights.

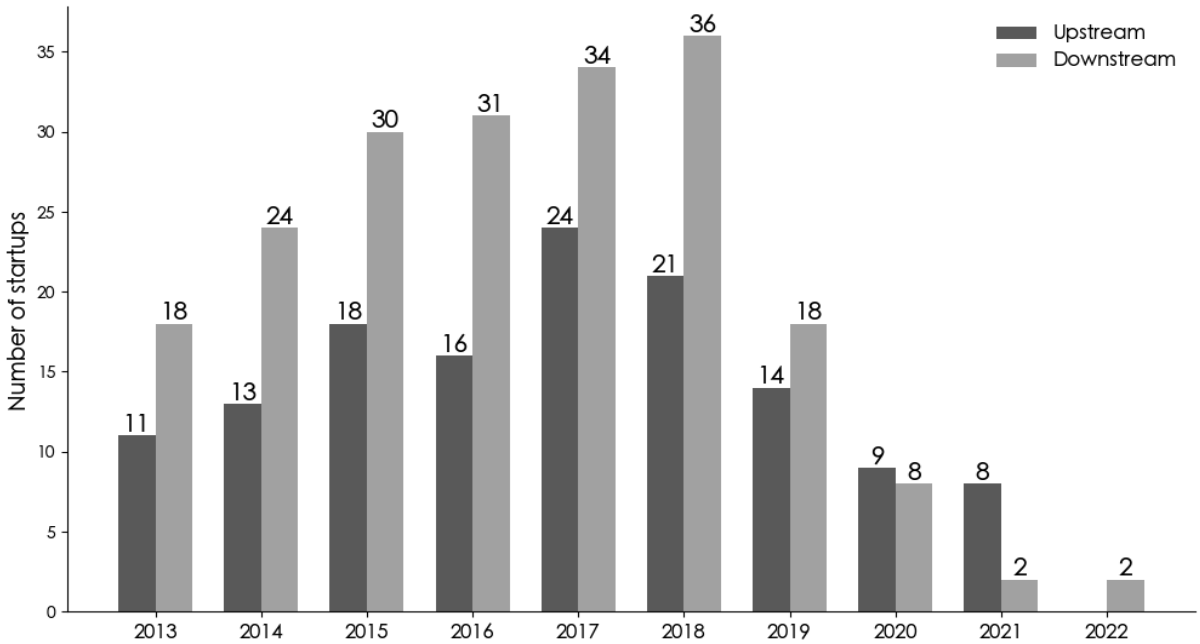
Notably, in 2022, Dealroom launched a dedicated platform for the space industry together with ESA and the E. Amaldi Foundation, aiming to improve transparency and traceability of capital flows within the sector.

The observation period covers startups founded between 2013 and 2022, a decade characterized by the accelerated growth of the commercial space sector and marked by an increasing availability of VC for innovative initiatives, the first validations of business models in emerging markets such as reusable launchers, miniaturized satellites, EO, and satellite telecommunications and the progressive expansion of cross-border investments, enabled by both European and international VC funds. Inclusion in the dataset was based on specific selection criteria: at least €1 million raised across one or more funding rounds and founding year between 2013 and 2022, to avoid both very recent startups (with fragmented or less reliable funding data) and older firms established before the current wave of interest in the New Space Economy.

5.1.1 Descriptive analysis of the dataset

The following graphs provide an overview of the collected dataset. Figure 18 illustrates the number of startups founded during the observation period, distinguishing between the upstream and downstream segments.

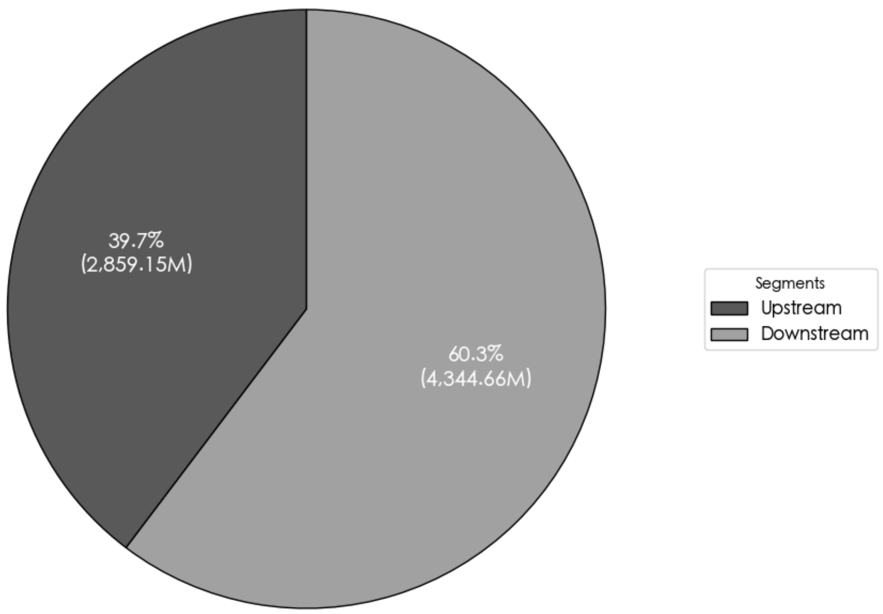
Figure 18: Number of startups per segment in the dataset (2013-2022)



Source: Own work.

Specifically, the data show that, on average, 13.5 startups per year were established in the upstream segment, whereas the downstream segment registered an annual average of 20.3 new startups. Overall, the startups included in the analysis have collectively raised approximately €7,203.81 million across various funding rounds, in Figure 19 the total is divided between the two main segments. This corresponds to an average of €53.76 million per startup operating in the upstream segment and €35.49 million per startup in the downstream segment. The higher average funding for upstream startups is consistent with the characteristics of this segment, where market entry barriers and initial operational costs tend to be significantly higher compared to those faced by downstream ventures.

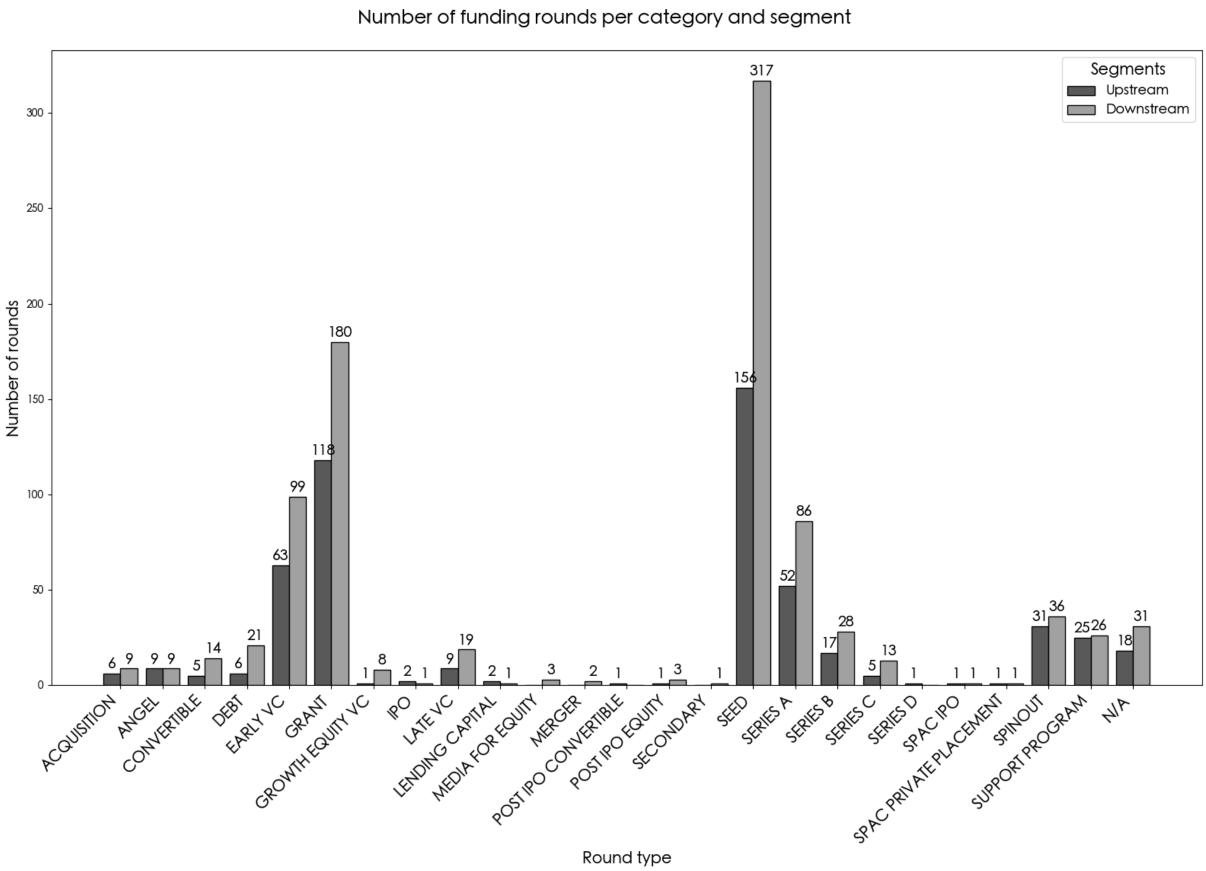
Figure 19: Total funding rounds amount per segment in the dataset



Source: Own work.

Among the various investment rounds recorded in the dataset, see Figure 20, the most frequent is the Seed round, with a total of 473 transactions. This stage typically represents the first significant injection of external capital into a startup, aimed at validating its product and business model. The second most common category is Grants (298), which are non-repayable financial contributions provided mainly by governmental entities or EU–linked organizations, such as the European Innovation Council. These are generally awarded to early-stage startups whose technology has not yet reached a maturity level that would attract private investors. Next in frequency are Early VC rounds (162), a Dealroom classification for funding events in the approximate range of €2–20 million when the exact round type is not disclosed publicly. Following these are Series A rounds (138), typically targeting startups that have validated their market fit and require capital to expand operations, enhance their product, and grow their customer base. In fifth place comes the Support Program category (51), which usually refers to initiatives offering financial resources, mentorship, and networks to help startups refine their business model or enter new markets. The sixth most common is Spinout (67), indicating cases where the startup's core technology originated within a university or research institution, often with the parent organization retaining some form of equity or royalty rights. Finally, Series B rounds (45) rank seventh, targeting companies that have proven their market traction and are ready to accelerate growth, enter new regions, or diversify their product offerings.

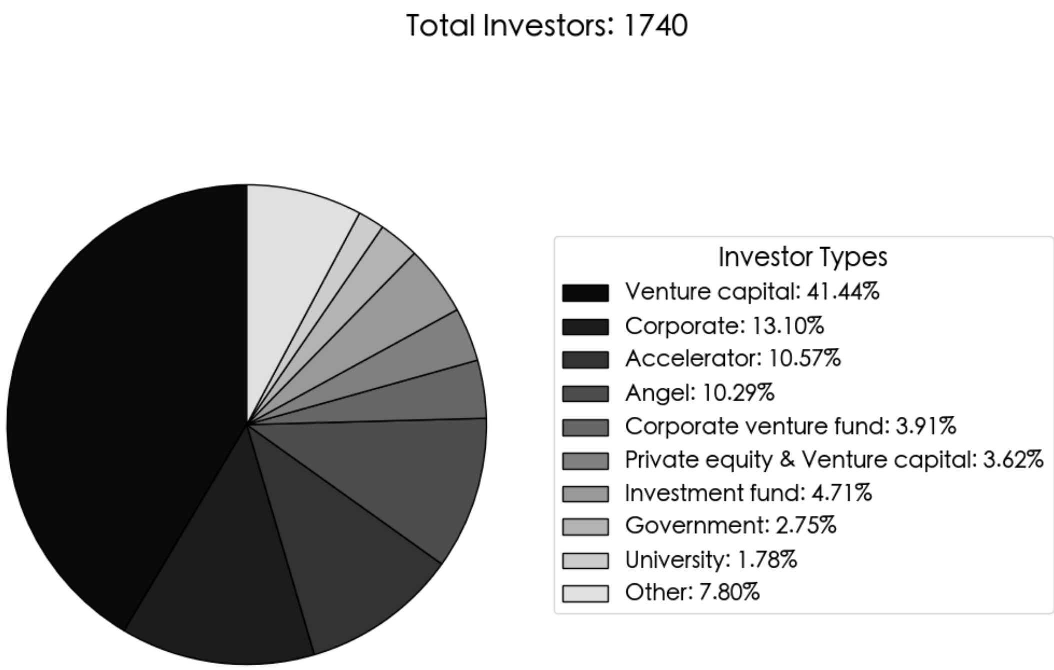
Figure 20: Number of funding rounds per category and segment in the dataset



Source: Own work.

In total, 1,740 investors have contributed funding to the startups included in the dataset. The most prominent category is VC funds, representing 41.44% of all investors. This category plays a crucial role in early and growth-stage financing, providing substantial financial resources and strategic guidance. Corporations constitute the second largest group, accounting for 13.10% of investors, often pursuing strategic investments that complement their innovation pipelines. Accelerators follow closely at 10.57%, offering early-stage startups mentorship, networking opportunities, and operational support through structured programs. Angel investors, representing 10.29% of the sample, frequently provide both capital and managerial expertise, contributing significantly to the startup ecosystem. Corporate venture funds make up 3.91%, acting as vehicles through which large corporations channel investments in innovative ventures. Hybrid private equity and VC funds account for 3.62%, typically engaging in later-stage funding rounds. Investment funds represent 4.71% of investors, focusing on diversified portfolios across different stages. Government entities and non-profit organizations combined constitute 2.75%, generally intervening to stimulate economic growth in riskier phases rather than seeking immediate financial returns. Universities contribute 1.78%, often investing when the underlying technology originates from academic research supported by institutional resources. The remaining 7.80% falls under the “Other” category, which aggregates family offices, angel funds, pure private equity funds, and other less frequent investor types, reflecting the diverse landscape of startup financing.

Figure 21: Investor type distribution in the dataset



Source: Own work.

To provide an initial overview of syndication patterns in the dataset, the analysis focuses on Seed, Series A, Series B, and Series C funding rounds, as these stages contain the most complete and reliable investor information in Dealroom. Concentrating on these categories allows for a consistent comparison across startup development phases and enables the identification of broad syndication trends, while more detailed, stage-specific analyses are addressed later through regression models.

Table 3 shows that among the 473 Seed rounds considered, syndicated investments occur in 42.28% of cases, while single-investor rounds account for 57.72%. This indicates a moderate level of collaboration at the earliest financing stage, reflecting the typically smaller funding requirements and simpler investment structures. In the 138 Series A rounds, the syndication rate rises substantially to 76.81%, signifying a growing tendency among investors to share financial risk as startups progress to more capital-intensive development phases. The 45 Series B rounds exhibit an even higher syndication incidence of 84.44%, consistent with the larger funding amounts generally required at this stage and the corresponding need for diversified investment to mitigate risk exposure. Similarly, the 18 Series C rounds show a syndication rate of 77.78%, in line with the trends observed in Series A and B rounds, although the smaller sample size reflects the relatively limited number of startups reaching this advanced stage.

Table 3: Summary of syndication rates across selected funding rounds in the dataset

EACH ROUND TYPE	TOTAL	SYNDICATION	NO SYNDICATION
Seed	473	42.28%	57.72%
Series A	138	76.81%	23.19%
Series B	45	84.44%	15.56%
Series C	18	77.78%	22.22%

Source: Own work.

Crucially, examining the dataset from a temporal perspective and including all round types reveals an increasing syndication trend in the SpaceTech industry over the past decade. The syndication index, representing the proportion of rounds with multiple investors, rose markedly from 28.57% in 2013 to 64.10% in 2023. This upward trajectory highlights an evolving preference for collaborative investment strategies, likely driven by escalating capital demands and greater risk aversion in startup financing markets.

5.1.2 Data preparation

The original dataset was sourced from the Dealroom's SpaceTech comprehensive database previously mentioned, containing detailed information on startups, their funding rounds, valuations, investors, and related macroeconomic indicators. The data was initially provided in a wide format (Table 4 provides an illustrative example of the concept, using three selected variables for demonstration purposes) with aggregated startup-level variables and multiple rounds of financing embedded in concatenated strings within single columns.

Table 4: Initial dataset structure and key variables

NAME	EACH ROUND AMOUNT	EACH ROUND TYPE
3bee	5;0.1;1;N/A;0.05	SERIES A;SEED; GRANT; SEED;GRANT
9T Labs	17;4.3;1.02;0.26;0.2;N/A	SERIES A;SEED;SEED; SEED;SEED;SPINOUT
Abelio	1	SEED

Source: Own work.

To facilitate rigorous econometric analyses, particularly panel regressions and event-based models focusing on funding rounds, it was essential to reshape the dataset into a long format. This restructuring involved "unpacking" the multiple financing rounds per startup into individual observations, each corresponding to a single funding event with associated variables such as amount raised, round type, date, and participating investors.

Table 5: Dataset structure following conversion to long format

NAME	EACH ROUND AMOUNT	EACH ROUND TYPE
3bee	5.00	SERIES A
3bee	0.10	SEED
3bee	1.00	GRANT
3bee	NA	SEED
3bee	0.05	GRANT
9T Labs	17.00	SERIES A

Source: Own work.

This transformation is critical because it allows the modelling of temporal dynamics and heterogeneity across financing rounds within startups, rather than limiting the analysis to cross-sectional or aggregated summaries. By converting to long format, see Table 5, time-varying covariates such as round-specific investment amounts, syndication status, and international investor participation could be accurately aligned with corresponding macroeconomic indicators at the year level. Moreover, currency conversions were applied to harmonize funding amounts into a common denomination (EUR), and key derived variables such as log-transformed funding and valuation were computed to account for skewness in financial measures.

Additional data cleaning and integration steps included the extraction and transformation of dates, calculation of startup age and stage at each round, as well as the construction of binary indicators for syndication and cross-border investment involvement. This structured and enriched long-format dataset enables detailed temporal and cross-sectional econometric modelling to explore determinants of startup valuation, syndication patterns, and the influence of international investor networks.

5.2 Clustering

In the study of innovative startups, a mere description of variables, such as the number of employees, funding received, or patents, is often insufficient to capture the complexity of the dynamics characterizing these ecosystems. To explore the latent structure of the dataset and identify relevant patterns, a clustering technique was employed, specifically k-means clustering, with the aim of segmenting startups into homogeneous groups based on key characteristics.

This technique allows us to overcome the limitations of univariate or descriptive analyses by highlighting groups of firms that share similar profiles in terms of growth, internationalization, and fundraising capabilities. Prior to the analysis, the dataset underwent careful cleaning, including the removal of outliers that could have distorted the results, thus ensuring a more robust and representative segmentation.

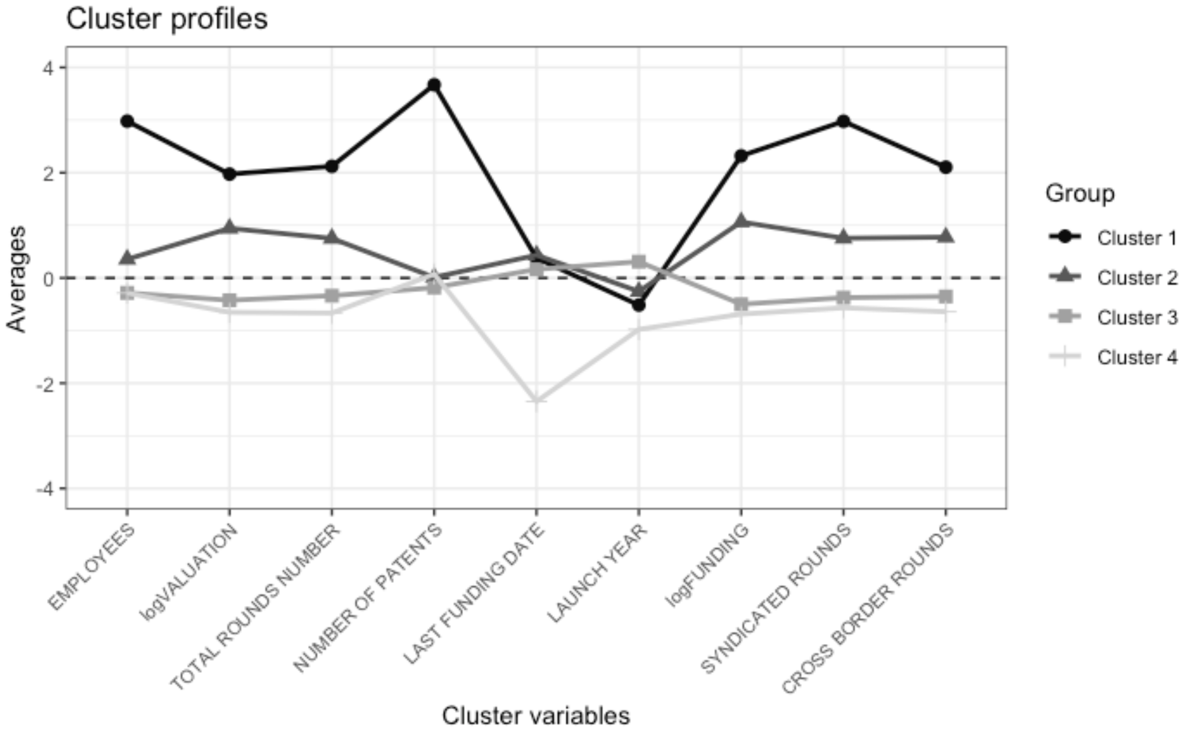
The final dataset includes variables related to firm size (number of employees), technological capacity (number of patents), fundraising activity (number and type of rounds, most recent funding date), and internationalization (syndicated and cross-border rounds). This selection of variables enabled the construction of multidimensional profiles for each startup, which are essential for understanding their competitive positioning in the global market.

The clustering analysis serves two purposes: it provides a structured overview of the composition of European SpaceTech startups, highlighting differences in maturity, fundraising capacity, and internationalization and justifies the inclusion of key explanatory variables, such as syndication and cross-border investment, in the econometric model. By showing how these characteristics co-occur with different levels of startup valuation, clustering identifies the patterns that later regressions aim to test quantitatively.

5.2.1 Cluster description

The analysis led to the identification of four distinct clusters, each characterized by specific features reflecting different stages of maturity and varying capacities to attract capital and international networks. The cluster means are graphically illustrated in Figure 22.

Figure 22: Cluster profiles in the dataset



Source: Own work.

- *Cluster 1: "International excellences"*

This group comprises large and highly developed startups, with an average of 2.98 standardized employees and a high mean valuation of 1.97 (z-score). The average number of patents (approximately 2.12) and elevated values for syndicated (2.97) and cross-border rounds (2.10) indicate strong technological expertise and excellent capacity for international networking. It is therefore unsurprising that this cluster contains the highest concentration of startups participating in Series C funding rounds, indicative of a high level of financial maturity and global market attractiveness.

- *Cluster 2: "The rising next generation"*

The second cluster is characterized by intermediate values for employees (0.35) and valuation (0.94), with fundraising activity in a growth phase. Syndicated and cross-border round averages are lower than in Cluster 1 but remain positive (0.75 and 0.77, respectively). Startups in this cluster exhibit scalability potential and progressive internationalization, as reflected by the predominance of seed, Series A, and Series B rounds. This group thus represents a crucial segment for the future of the innovative market.

- *Cluster 3: "Market reactives"*

Cluster 3 includes startups with moderately negative values for size and valuation and with more limited fundraising activity, predominantly seed funding, signalling that many firms are still in early stages or awaiting clearer market signals. With slightly negative averages for syndicated and cross-border rounds (approximately -0.37 and -0.35), these startups appear to adopt a wait-and-see or adaptive strategy, positioning themselves as "followers" in the market.

- *Cluster 4: "Forgotten/niche players"*

This cluster is distinguished by markedly negative values for the date of the last funding (-0.98), suggesting stagnation or absence of recent investments. Average size (-0.29) and number of patents (-2.34) are among the lowest, and international networking activity is limited (syndicated and cross-border rounds around -0.57 and -0.64). Sector data indicate greater involvement in niches such as real estate, kids, and entertainment, which are less attractive to large investors. These startups thus appear "forgotten" by the market or active in areas yet to be fully developed.

To validate and further investigate the segmentation, additional criteria such as funding type and industry affiliation were employed, integrating the results with statistical tests based on standardized residuals.

Residual analysis highlights that Series C rounds are strongly associated with Cluster 1 (standardized residual 3.31), confirming their role as mature, internationalized "excellences". Cluster 2 exhibits a high concentration of Series B rounds (residual 3.97), consistent with its characterization as the "next generation". Cluster 3 shows a surplus of seed funding (3.42), reflecting its nature as an early-stage or reactive group. Cluster 4, in contrast, is marked by a lack of advanced funding rounds and stagnant financial activity. Although the industrial distribution is not statistically significant, the analysis of standardized residuals suggests interesting differences: Cluster 1 favours high-tech sectors such as space (1.44) and semiconductors (1.68), while Cluster 4 is associated with less "hot" niches such as kids (2.86), real estate (1.17), and home living (1.29). These findings indicate that more mature startups are concentrated in high value-added sectors, whereas less dynamic startups operate in niche or underexplored markets. Classification by growth stage further underscores that Cluster 1 is dominated by late growth startups (residual 3.09), while Cluster 2 presents very high values for late growth (5.84), confirming its expansion phase. Cluster 3 shows a surplus of early growth startups (2.54), whereas Cluster 4 is characterized by a notable presence of seed-stage firms (2.26), indicative of growth stagnation. Finally, the distinction between upstream and downstream activities, although not statistically significant, shows a slight tendency for upstream startups to receive higher funding, in line with literature emphasizing the need for initial support in capital-intensive sectors.

The clustering results provide clear empirical evidence of heterogeneity within the European SpaceTech ecosystem, particularly in relation to syndication and cross-border investment patterns. This exploratory analysis serves as a critical precursor to the regression modelling by highlighting how startups with higher levels of syndication and internationalization, represented by Clusters 1 and 2, tend to exhibit higher valuations. Conversely, Clusters 3 and 4, characterized by limited syndication and cross-border activity, offer a natural point of comparison, illustrating the contrast between more and less mature, internationally connected ventures. Moreover, the clustering confirms the relevance of other key covariates, including firm size, segment, growth stage, industry, and funding round type, as important determinants of startup valuation. By systematically identifying these distinct startup profiles, clustering provides a data-driven foundation that contextualizes the subsequent regression analysis. In particular, it clarifies why variables such as syndication and cross-border participation are expected to exert a positive influence on valuations, ensuring that the regression model is firmly grounded in empirically observed patterns rather than purely theoretical assumptions.

5.3 Regression analysis

The empirical analysis in this study focuses on a single, micro-level regression model designed to capture the key determinants of startup valuation within the European SpaceTech ecosystem. This model directly addresses the central research question of the thesis: *"How do venture capital strategies, specifically syndication and cross-border investment, affect the growth and valuation of startups within the European SpaceTech ecosystem?"* By integrating firm-level characteristics with indicators of collaborative and internationalized financing, the model provides a comprehensive framework for understanding the financial and strategic mechanisms driving startup performance.

Specifically, the dependent variable is the logarithm of startup valuation, observed at the level of individual funding rounds. Independent variables include firm-specific attributes such as the number of employees, age, and growth stage, as well as strategic positioning variables, including segment focus (upstream vs. downstream), industry sector, and the geographical location of headquarters. Most importantly, the model incorporates proxies for syndication (presence of multiple lead investors) and cross-border investment, capturing the ability of startups to attract diversified, risk-sharing capital from domestic and international venture capital sources. These variables are central to testing the hypotheses formulated in the research sub-questions, providing empirical evidence on whether collaborative and international financing strategies are associated with higher startup valuations.

The regression is specified as follows:

$$log(Valuation_{it}) = \beta_0 + \beta_1 Syndication_i + \beta_2\, CrossBorder_i + \beta_3\, Employees_i + \beta_4\, Segment_i + \beta_5\, Age_i + \beta_6\, GrowthStage_i + \beta_7\, Industry_i + \beta_8\, RoundType_i + \beta_9\, HQCountry_i + \varepsilon_i \quad (1)$$

This formulation allows for the identification of the relative contributions of syndication and cross-border investment to startup valuation, while controlling for other firm-specific determinants commonly recognized in the literature. By grounding the model in the descriptive and clustering analyses presented in the previous sections, the regression is informed by empirically observed patterns rather than purely theoretical assumptions. For instance, the clustering analysis revealed that startups with higher syndication and internationalization (Clusters 1 and 2) tend to achieve higher valuations, providing a strong rationale for including these variables as key predictors. Similarly, the descriptive analysis highlighted the importance of firm size, growth stage, and segment, supporting their inclusion as controls in the model.

Overall, this micro-level regression provides a rigorous, quantitative assessment of how venture capital structures and international networks shape the financial performance of European SpaceTech startups. The results offer actionable insights for investors and policymakers, clarifying the mechanisms through which syndication and cross-border investment contribute to value creation and supporting evidence-based strategies for fostering innovation and competitiveness in the New Space economy.

5.3.1 Sample description

The micro-level regression analysis is based on a carefully prepared dataset of startup-level funding events, refined through a series of preprocessing steps to ensure consistency across variables and alignment with the theoretical framework discussed in previous chapters. Extreme outliers were removed using residual analysis and Cook's distance thresholds to avoid distortion in coefficient estimation and enhance model fit.

The dependent variable, log(ValuationYear), represents the natural logarithm of each startup's reported valuation in the observation year. This transformation addresses skewness in the original distribution and allows estimated coefficients to be interpreted as semi-elasticities, providing an intuitive measure of proportional effects on valuation.

Key explanatory variables capture relational investment dynamics, namely:

- *Syndication*: a binary indicator equal to 1 if the latest funding round involved more than one lead investor, serving as a proxy for collaborative investment and risk-sharing behaviour;
- *CrossBorder*: a binary indicator equal to one if at least one foreign investor participated in the latest funding round, capturing the openness of the startup to international capital flows.

Firm-level controls account for structural characteristics and operational capacity:

- *Employees*: number of employees, representing organizational scale and capacity;
- *Age*: years since foundation, reflecting lifecycle effects on valuation;
- *Segment*: categorical variable distinguishing between upstream and downstream segments of the space value chain;
- *GrowthStage*: ordinal variable categorizing the maturity of the company at the time of funding (early growth, late growth);
- *Industry*: binary factor differentiating space-focused ventures from adjacent sectors;
- *RoundType*: categorical variable classifying the latest funding round into one of the main investment stages (Seed, Early VC, Grant, Series A–C, Other);
- *Country*: binary grouping identifying whether the company's headquarters are located in one of the five largest European economies with significant space sector GDP (France, Germany, Italy, U.K., Spain) or elsewhere.

Table 6: Variables used in the regression model and expected effects

VARIABLE	TYPE	DESCRIPTION	EXPECTED EFFECT
Syndication	Binary	1 if multiple lead investors participated in the round	Positive
CrossBorder	Binary	1 if at least one foreign investor participated	Positive
Employees	Continuous	Number of employees	Positive
Age	Continuous	Years since foundation	Positive
Segment	Categorical	Upstream vs Downstream	Upstream ↑
GrowthStage	Ordinal	Early growth vs late growth	Positive
Industry	Binary	Space-focused vs adjacent sectors	Positive
RoundType	Categorical	Seed, Early VC, Grant, Series A–C, Other	Positive
Country	Binary	HQ in top 5 EU space economies vs elsewhere	Positive

Source: Own work.

The resulting model thus integrates both structural characteristics and relational capital indicators, reflecting the premise that startup valuation in the New Space ecosystem is jointly determined by internal resources, stage of development, sector positioning, and the ability to access syndication networks and cross-border financing channels.

5.3.2 Descriptive statistics

In addition to continuous dependent and explanatory variables, several categorical variables are incorporated to capture key structural dimensions of startups and their funding rounds. Descriptive statistics for the continuous variables are reported in Table 7.

Table 7: Descriptive statistics of numerical variables in linear regression model

VARIABLE	N	MEAN	SD	MIN	MAX
log(ValuationYear)	748	2.96	1.43	0.1	8.1
Employees	748	39.91	68.98	0.0	883.0
Age	748	3.51	2.32	0.0	10.0

Source: Own work.

The dependent variable, *log(ValuationYear)*, representing the natural logarithm of startup valuation at the time of funding, has a mean of 2.96 and a standard deviation (SD) of 1.43, reflecting substantial heterogeneity in firm valuations, which range from a minimum of 0.1 to a maximum of 8.1. This wide dispersion aligns with the heterogeneous maturity levels and market positioning observed within the New Space ecosystem.

Among firm characteristics, the average number of employees is approximately 40, with a relatively high SD of 69, indicating the coexistence of both small, early-stage startups and more mature firms. The Age variable shows an average of 3.5 years, with moderate variability, consistent with the predominance of young ventures operating within this emerging industry.

The binary variable *Syndication*, shows an almost even split with 51.9% of startups having syndication and 48.1% not. This suggests a widespread adoption of syndication as a risk-sharing mechanism across the sample. Regarding geographic openness, cross-border funding is observed in 66.7% of cases, underscoring the international nature of investment flows in the New Space domain. The $Segment$ variable reveals a predominance of downstream startups (63.2%) compared to upstream (36.8%), reflecting the current market composition in the dataset. Startups are fairly evenly split between early growth (45.2%) and late growth (48.0%), with a small fraction still in the seed phase (6.8%). The majority of startups (86.9%) operate outside the core space industry segment, with only 13.1% explicitly classified as space ventures (*Industry*). Funding rounds are distributed, with Seed rounds representing the largest group (32.4%), followed by grants (15.1%), Early VC (11.9%), and Series A (14.6%).

Table 8: Descriptive statistics of categorical variables in linear regression model

VARIABLE	FACTOR	COUNT	%
Syndication	Yes	388	51.87
	No	360	48.13
CrossBorder	Yes	499	66.71
	No	249	33.29
Segment	upstream	275	36.76
	downstream	473	63.24
Growth Stage	seed	51	6.82
	early growth	338	45.19
	late growth	359	47.99
Industry	space	98	13.1
	Other	650	86.9
Round Type	SEED	242	32.35
	EARLY VC	89	11.9
	GRANT	113	15.11
	SERIES A	109	14.57
	SERIES B	41	5.48
	SERIES C	16	2.14
	Other	138	18.45
Country	Top5_SpaceEconomy	441	58.96
	Other	307	41.04

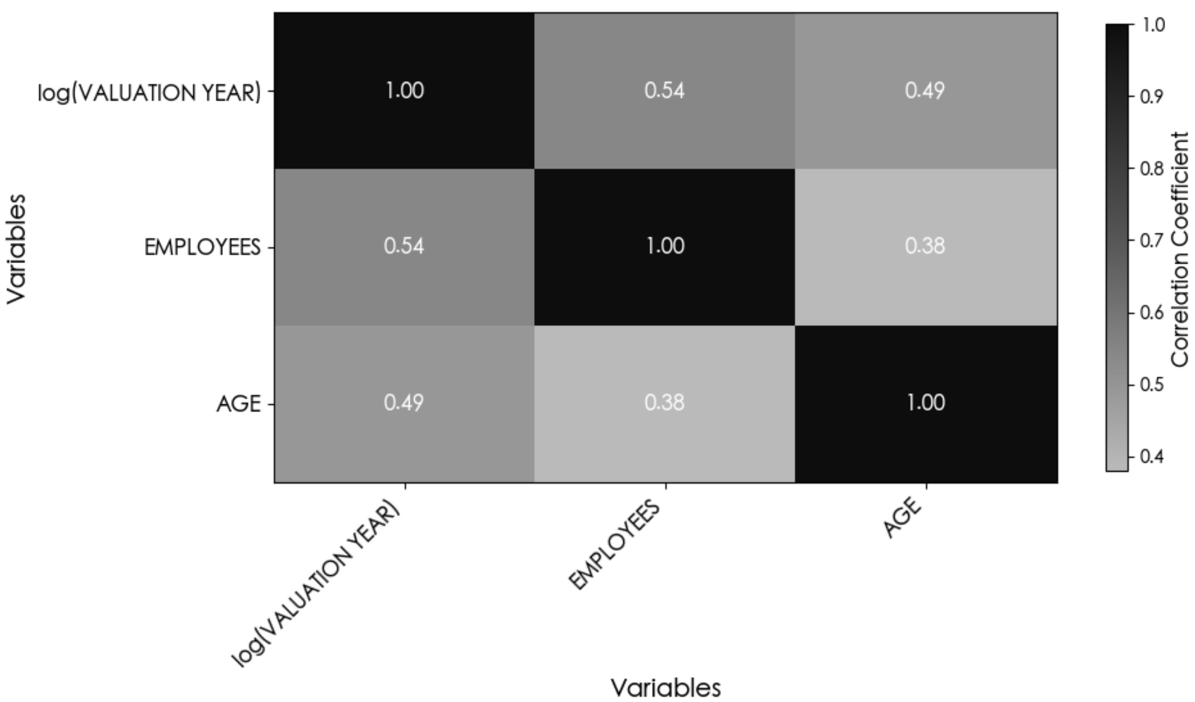
Source: Own work.

Later rounds (Series B and C) and other types account for smaller shares. Finally, the headquarters location variable ($Country$) shows that 59.0% of startups are based in one of the top five European space economies (France, Germany, Italy, U.K., Spain), while 41.0% are located elsewhere. Overall, these descriptive statistics reveal a heterogeneous and evolving sample of startups, characterized by diverse sizes, stages, and funding structures, consistent with a dynamic and rapidly developing New Space ecosystem.

5.3.3 Correlation analysis

Prior to estimating the regression model, a correlation analysis was conducted to explore potential linear relationships among the key continuous variables and the dependent variable, log(ValuationYear)**.** The resulting Pearson correlation coefficients are reported in Figure 23.

Figure 23: Correlation matrix heatmap – linear regression model



Source: Own work.

Overall, the results reveal moderate positive associations across all variable pairs. Notably, log(ValuationYear) displays a correlation of 0.54 with Employees, suggesting that startups with higher valuations generally maintain larger workforces. This finding is consistent with theoretical expectations, as firms with greater financial resources and maturity tend to expand their organizational capacity. Similarly, log(ValuationYear) correlates positively with Age (0.49), indicating that older ventures typically achieve higher valuations, reflecting both accumulated experience and increased market credibility over time. The Employees–Age correlation (0.38) further supports this interpretation, highlighting that older startups often exhibit larger operational scales.

These relationships imply that firm size and age are related yet distinct dimensions of startup development that jointly influence valuation outcomes. Importantly, none of the correlations approach levels indicative of multicollinearity, thereby supporting the inclusion of both variables in the regression model to capture different aspects of organizational and temporal growth.

5.3.4 Linear regression

The micro-level regression model investigates the determinants of startup valuations in the European SpaceTech ecosystem, incorporating both firm-specific characteristics and funding-related factors. The dependent variable is the logarithm of each startup's valuation in the year of observation. *log(ValuationYear)*, while explanatory variables include syndication participation, cross-border investment, firm size, age, segment focus, growth stage, industry, funding round type, and headquarters country group.

$$\begin{aligned} log(Valuation_{it}) = {} & \beta_0 + \beta_1 Syndication_i + \beta_2\, CrossBorder_i + \beta_3\, Employees_i + \\ & \beta_4\, Segment_i + \beta_5\, Age_i + \beta_6\, GrowthStage_i + \beta_7\, Industry_i + \\ & \beta_8\, RoundType_i + \beta_9\, HQCountry_i + \varepsilon_i \qquad (1) \end{aligned}$$

Equation 1 allows us to capture how variations in investment syndication, international participation, firm scale, maturity, and contextual factors affect startup valuations. Categorical variables were coded with the following baseline categories: non-syndicated, domestic, downstream, seed-stage, non-space startups headquartered outside the top five European space economies, and Seed funding rounds. Accordingly, the estimated coefficients for other categories indicate the valuation premium or relative effect compared to these reference conditions.

The results in Table 9 indicate that startups involved in syndicated funding rounds exhibit a valuation premium of approximately 30% relative to non-syndicated firms, highlighting the importance of risk-sharing and collaborative financing. Similarly, participation of at least one cross-border investor is associated with a 14.5% higher valuation compared to purely domestic funding rounds, reflecting the added value of international capital, networks, and expertise.

Firm characteristics also play a significant role. Each additional employee contributes roughly a 0.75% increase in valuation, and older startups tend to achieve higher valuations, reflecting accumulated experience and market traction. The segmentation of startups shows that upstream ventures are valued about 22% higher than downstream firms, consistent with the capital intensity and technological complexity of upstream activities. Growth stage exerts a pronounced influence: early and late growth firms experience significant valuation increments relative to seed-stage startups, demonstrating the natural value progression along the startup lifecycle. Space-focused ventures also benefit from a sector-specific premium of approximately 26%, confirming that technological specialization in the New Space economy is recognized and rewarded by investors. Funding round type influences valuations as well. Early VC, Series A, and Series B rounds show positive effects ranging from 58% to 120% relative to seed rounds, while Series C rounds are not significant in this model, possibly due to heterogeneity in later-stage financings or limited sample size. Finally, headquarters location is a relevant determinant: startups based in the top five European space economies enjoy a valuation premium of roughly 24% relative to firms headquartered elsewhere, emphasizing the competitive advantage conferred by proximity to established space clusters and supportive ecosystems.

Table 9: Linear regression model - results

Variable	Coefficient	Std. error	T value	Pr(>|t|)	Sig.
(Intercept)	0.569913	0.1396643	4.081	4.99e-05	***
SyndicationYes	0.299988	0.0764512	3.924	9.53e-05	***
CrossBorderYes	0.1452626	0.0711765	2.041	0.041621	*
Employees	0.0074943	0.0005824	12.868	< 2e-16	***
SegmentUpstream	0.2237121	0.0707407	3.162	0.001629	**
Age	0.1542287	0.0153584	10.042	< 2e-16	***
GrowthStageearly growth	0.4114623	0.1287069	3.197	0.001449	**
GrowthStagelate growth	1.0110459	0.1343653	7.525	1.55e-13	***
IndustrySpace	0.2625354	0.1016192	2.584	0.009972	**
RoundTypeEARLYVC	0.5846491	0.1097796	5.326	1.34e-07	***
RoundTypeGRANT	0.3273575	0.1072255	3.053	0.002348	**
RoundTypeSERIES A	0.8383827	0.1043387	8.035	3.74e-15	***
RoundTypeSERIES B	1.1960678	0.1537772	7.778	2.51e-14	***
RoundTypeSERIES C	-0.0485029	0.2494717	-0.194	0.845899	
RoundTypeOther	0.3437011	0.1008695	3.407	0.000692	***
CountryTop5_SpaceEconomy	0.2405093	0.0670565	3.587	0.000357	***

Source: Own work.

The model achieves an adjusted R^2 of 0.647, indicating substantial explanatory power given the cross-sectional heterogeneity typical of startup data. Residual diagnostics confirm a stable and reliable fit.

In summary, these results empirically demonstrate that startup valuations in the European SpaceTech ecosystem are jointly shaped by syndication, cross-border investment, firm size and maturity, segment, growth stage, sectoral focus, funding round, and geographic location. By explicitly referencing baseline categories, the model clarifies the relative contribution of each factor, offering actionable insights for investors and policymakers seeking to support high-value startups in this rapidly evolving sector.

Table 10: Linear regression model – statistics

REGRESSION STATISTICS	
Multiple R	0.8089
Multiple (R^2)	0.6543
Adjusted R^2	0.6472
Residual standard error	0.85
Observations	747

ANOVA					
Component	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Regression	15	1015.61	67.71	92.34	< 2.2e-16
Residuals	732	528.81	0.72		

Source: Own work.

5.4 Empirical analysis results and discussion

The combined findings from the clustering and regression analyses provide a nuanced understanding of the factors shaping the European New Space startup ecosystem. The model highlights that syndication plays a crucial role in mitigating the financial risks inherent in a capital-intensive sector such as space. By pooling resources across multiple investors, syndication not only spreads risk but also facilitates greater access to funding, increasing confidence among both investors and founders. This mechanism translates into higher valuations for startups that demonstrate strong growth potential and scalability. A larger syndicate serves as a powerful signal of credibility and collective due diligence, which is particularly valuable in a nascent and highly technical market.

The analysis also underscores the importance of cross-border investment in enhancing startup valuations. Startups that actively engage international investors tend to secure broader financial support and signal credibility in global markets. Regression results show that cross-border participation has a statistically significant positive effect on valuation, even when controlling for firm size, age, growth stage, and other structural characteristics. This finding suggests that international investors operate according to motivations that are partly independent from domestic trends, such as accessing unique European technologies, diversifying portfolios, and establishing strategic footholds in an emerging ecosystem.

The clustering results complement these insights by revealing heterogeneous startup profiles with distinct syndication and internationalization patterns. Clusters 1 ("International Excellences") and 2 ("The Rising Next Generation") exhibit high levels of syndicated and cross-border funding, larger size, and stronger technological capacity, correlating with elevated valuations. In contrast, Clusters 3 ("Market Reactives") and 4 ("Forgotten/Niche Players") show limited syndication and international engagement, smaller size, and lower technological output, providing a natural comparison that contextualizes the regression findings. Together, these results confirm that syndication and international investor involvement are central to shaping value creation in the European SpaceTech sector.

The structure of investment rounds, the composition of syndicates, and the involvement of leading startups act as additional signals influencing investor behaviour. Investors closely monitor prominent companies' successes and setbacks, such as high-profile launches, technological milestones, or project delays, as benchmarks for directing funds toward smaller, high-potential startups. This dynamic creates a virtuous cycle in which syndication attracts more investors, enabling startups to develop and validate innovative technologies, while strong valuations further reinforce investor confidence.

While these findings provide a comprehensive view of micro-level drivers of valuation, it is important to acknowledge limitations. The current dataset, although robust at the startup level, covers a relatively short period and may not capture long-term trends in syndication and cross-border investment. Extending the dataset temporally and incorporating additional investment rounds and international actors could provide more generalizable insights and further elucidate the motivations behind cross-border participation.

In conclusion, the empirical evidence demonstrates that syndication and cross-border investment are key mechanisms driving valuation in European SpaceTech startups, working alongside firm-specific factors such as size, age, segment, and technological focus. These findings provide actionable insights for investors, policymakers, and emerging startups seeking to navigate and strengthen Europe's position within the New Space economy.

6 CONCLUSION

The rapid rise of the global space economy has generated significant changes, producing advantages across multiple sectors. A growing list of services, enabled by the combination of space technology and digital tools, demonstrates strong growth potential driven by recent social and environmental changes. The energy sector, for instance, has been among the first to benefit from space-enabled solutions, using satellite data combined with machine learning models to monitor facilities and prevent adverse exogenous events. In recent years, other sectors, such as agriculture, urban planning, and insurance, have increasingly leveraged space data to optimize operations and outcomes.

These advancements have been possible largely due to public institutions providing critical support and resources to nascent space ventures. In Europe, agencies such as the ESA and various national space organizations have played a central role by offering incubation services, competitions, and funding programs that foster continuous innovation. Once this mechanism was established, private investors began to enter the market, recognizing the potential for substantial economic returns.

Venture capital has emerged as a key driver of this ecosystem. By providing financial resources and expertise, VCs support the growth and success of high-potential startups. However, the inherent risk of space investments can limit capital inflows. As this thesis demonstrates, syndication is a crucial strategy to mitigate these risks, spreading investment across multiple partners and generating a virtuous cycle in which more investors participate and more startups gain access to funding. This dynamic promotes the creation of new projects and accelerates the development of the European space economy.

Despite these advances, the European capital market for space ventures is still maturing. Targeted measures, such as tailored funding instruments and support programs, will allow both new and established companies to flourish. This, in turn, will build confidence among private investors and enhance fundraising capacity, facilitating the proliferation of innovation. The evidence and trends discussed indicate a transformation of the competitive landscape. Increased capital accessibility, favourable forecasts, and the growing prominence of major newcos are attracting innovative entrants, shaping a dynamic, fast-evolving industry. Major space newcos, such as SpaceX, Blue Origin, and Virgin Galactic, achieve impressive results by deploying innovative solutions in capital-intensive markets. While not strictly disruptive in the traditional sense due to their significant initial funding and market entry strategies, these companies influence the market by setting benchmarks and expectations.

Conversely, smaller entrants, such as emerging European startups, operate under tighter capital constraints, often targeting underserved or niche market segments. These companies may become truly disruptive, scaling upward over time and challenging both incumbents and major newcos. The European space market is thus experiencing a layered competitive environment: major players compete at the top while potentially disruptive startups gain traction at the margins. The main challenge remains whether these startups can overcome high capital requirements and long development cycles, or whether major newcos will internalize disruption, maintaining control over the commercialization of innovation.

This research, in its exploration of syndication and cross-border investment dynamics, provides new insights into effective venture capital strategies within the European SpaceTech ecosystem. The observed trends suggest that it is time to move beyond conventional investment frameworks, particularly given modern dynamics such as the increasing importance of dual-use technologies, the integration of both civilian and military applications, which was beyond the scope of this thesis but warrants significant future research.

Ultimately, the path for the European space sector is not about simply chasing the ambitions of big players who speak of conquering Mars or finding a new planet. While these grand visions are inspiring, Europe's true advantage lies in its international and collaborative structure. This thesis demonstrates that with proper strategic decisions and co-investment among expert VC funds, Europe can leverage its unique international makeup to stimulate valuations and drive innovation, thereby gaining a significant foothold in the field without lagging behind other major geographical players and new entrants. This strategic focus on collaboration and networked investment is more critical than simply riding the momentum created by large players' decisions.

Finally, while these findings reflect current trends in Europe, a larger and more temporally extended dataset would be necessary to confirm whether these patterns persist across different periods and regions. Nonetheless, the combination of public support, VC strategies, syndication, cross-border investment, and the activity of major newcos clearly defines a rapidly evolving ecosystem poised for growth, innovation, and eventual industry transformation.

REFERENCE LIST

1. Anderson, C. (2023). *The Space Economy: Capitalize on the Greatest Business Opportunity of Our Lifetime*. John Wiley & Sons.
2. Bergan, B. (2022). *Space race 2.0: SpaceX, Blue Origin, Virgin Galactic, NASA, and the Privatization of the Final Frontier*. Motorbooks International.
3. Bertoni, F., & Groh, A. P. (2014). Cross-Border Investments and Venture Capital Exits in Europe. *Corporate Governance: An International Review, 22*(2), 84-99.
4. Brander, J. A., Amit, R., & Antweiler, W. (2002). Venture-capital syndication: Improved venture selection vs. the value-added hypothesis. *Journal of Economics & Management Strategy, 11*(3), 423-452.
5. Brettle, H., Forshaw, J., Auburn, J., Blackerby, C., & Okada, N. (2019). Towards a future debris removal service: evolution of an ADR business model. In *70th International Astronautical Congress*.

6. BryceTech. (2023). *Start-Up Space 2023*. https://brycetech.com/reports/report-documents/Bryce_Start_Up_Space_2023.pdf
7. BryceTech. (2025). *Start-Up Space 2025*. https://brycetech.com/reports/report-documents/start_up_space_2025/BryceTech_Start_Up_Space_2025.pdf
8. Busenitz, L. W., Fiet, J. O., & Moesel, D. D. (2005). Signaling in venture capitalist—New venture team funding decisions: Does it indicate long–term venture outcomes?. *Entrepreneurship Theory and Practice, 29*(1), 1-12.
9. Bygrave, W. D. (1987). Syndicated investments by venture capital firms: A networking perspective. *Journal of Business Venturing*, *2*(2), 139-154.
10. Canton, H. (2021). European Space Agency—ESA. In *The Europa Directory of International Organizations 2021* (pp. 549-551). Routledge.
11. Ceccagnoli, M., Higgins, M. J., & Kang, H. D. (2018). Corporate venture capital as a real option in the markets for technology. *Strategic Management Journal*, *39*(13), 3355-3381.
12. Chemmanur, T. J., Hull, T. J., & Krishnan, K. (2021). Cross-border LBOs, human capital, and proximity: Value addition through monitoring in private equity investments. *Journal of Financial and Quantitative Analysis, 56*(3), 1023-1063.
13. Cumming, D., Fleming, G., & Schwienbacher, A. (2007). The structure of venture capital funds. In *Handbook of research on venture capital*. Edward Elgar Publishing.
14. Cumming, D., Fleming, G., & Schwienbacher, A. (2005). Liquidity risk and venture capital finance. *Financial Management*, *34*(4), 77-105.
15. Dallas, J. A., Raval, S., Gaitan, J. A., Saydam, S., & Dempster, A. G. (2020). Mining beyond earth for sustainable development: Will humanity benefit from resource extraction in outer space?. *Acta Astronautica, 167*, 181-188.
16. Denis, G., Claverie, A., Pasco, X., Darnis, J. P., de Maupeou, B., Lafaye, M., & Morel, E. (2017). Towards disruptions in Earth observation? New Earth Observation systems and markets evolution: Possible scenarios and impacts. *Acta Astronautica*, *137*, 415-433.
17. Depperu, D., Galavotti, I., & Baraldi, F. (2024). Institutional distance and cross-border acquisitions into emerging markets: the moderating effect of context experience. *International Journal of Emerging Markets, 19*(5), 1449-1472.
18. Di Pippo, S. (2022). *Space economy: la nuova frontiera dello sviluppo*. EGEA spa.
19. Elad, B. (2025). Venture Capital Industry Statistics 2025: Funding stages, deal sizes, and market indicators. CoinLaw. https://coinlaw.io/venture-capital-industry-statistics/
20. Eldering, C., & Hulsink, W. (2021). 9. Incubation with space-space for incubation: the European Space Agency's network of business. *Handbook of Research on Business and Technology Incubation and Acceleration: A Global Perspective*, 160.
21. Enosta. (2023). *The 6 stages of startups: Where are you? How to master each?* https://enosta.com/insights/startup-stages
22. ESA. (2025). *ESA budget 2025* [Photograph]. https://www.esa.int/ESA_Multimedia/Images/2025/01/ESA_budget_2025

23. ESA. (2024). *ESA Business Incubation Centres 2024* [Photograph]. https://www.esa.int/ESA_Multimedia/Images/2024/05/ESA_Business_Incubation_Centres_2024
24. ESA. (2020). *Technology transfer services*. https://www.esa.int/Enabling_Support/Space_Engineering_Technology/Technology_Transfer_services
25. ESA. (2007). *More opportunities to develop innovative technologies for space*. https://www.esa.int/About_Us/Business_with_ESA/More_opportunities_to_develop_innovative_technologies_for_space
26. ESA. (n.d.-a). *Applications*. European Space Agency. https://www.esa.int/Applications
27. ESA. (n.d.-b). *ESA Business Incubation Centres*. European Space Agency. https://commercialisation.esa.int/esa-business-incubation-centres/
28. EUSPA. (2024). *EO and GNSS Market Report* (Issue 2).
29. FutureTimeline. (2018). Launch costs to low Earth orbit, 1980-2100. https://www.futuretimeline.net/data-trends/6.htm
30. Getahun, S., Kefale, H., & Gelaye, Y. (2024). Application of precision agriculture technologies for sustainable crop production and environmental sustainability: A systematic review. *The Scientific World Journal, 2024*(1), 2126734.
31. Grand View Research. (2024). *Precision farming market size, share & trends analysis report by offering (hardware, software, services), by application (yield monitoring, field mapping, crop scouting), by region, and segment forecasts, 2025–2030*. https://www.grandviewresearch.com/industry-analysis/precision-farming-market
32. Harvey, R., Bolton, P., Wilse-Samson, L. H., An, L., & Samama, F. (2014). Barriers to long-term cross-border investing: A survey of institutional investor perceptions. *Rotman International Journal of Pension Management, 7*(2), 14-43.
33. Heitor, M., Cunha, M. P., Clegg, S., Sirage, E., & Oliveira, P. (2024). Beyond new space: Changing organizational forms, collaborative innovation and public and semi-public domains. *Space Policy, 68*, 101609.
34. Hertzfeld, H. R. (2013). The state of space economic analyses: real questions, questionable results. *New Space, 1*(1), 21-28.
35. Hopp, C. (2010). When do venture capitalists collaborate? Evidence on the driving forces of venture capital syndication. *Small Business Economics, 35*(4), 417-431.
36. Hopp, C., & Rieder, F. (2011). What drives venture capital syndication?. *Applied Economics, 43*(23), 3089-3102.
37. Iqbal, A., Shakeel, A., Rashid, A., & Kim, S. W. (2024). IoT and M2M Applications in Satellite Networks. In *Integrated Terrestrial and Non-Terrestrial Networks* (pp. 17-45). Cham: Springer Nature Switzerland.
38. Jin, S., Meng, X., Dardanelli, G., & Zhu, Y. (2024). Multi-Global Navigation Satellite System for Earth Observation: Recent Developments and New Progress. *Remote Sensing, 16*(24), 4800.

39. Kim, J. Y., & Park, H. D. (2021). The influence of venture capital syndicate size on venture performance. *Venture Capital*, *23*(2), 179-203.
40. Latvian Space Agency. (2025, October 30). *ESA BIC Latvia*. Latvian Space Agency. Retrieved November 3, 2025, from https://latviaspace.gov.lv/en/esa-bic-latvia/
41. Lerner, J. (2022). The syndication of venture capital investments. In *Venture capital* (pp. 207-218). Routledge.
42. Lin, Y. H., Chen, C. J., & Lin, B. W. (2017). The influence of strategic control and operational control on new venture performance. *Management Decision, 55*(5), 1042-1064.
43. Link, M., Martin, G., & Mousel, J. (2023). The economics of space resources: future markets and value chains. In *Handbook of Space Resources* (pp. 1023-1051). Cham: Springer International Publishing.
44. Liu, Y., & Maula, M. (2016). Local partnering in foreign ventures: Uncertainty, experiential learning, and syndication in cross-border venture capital investments. *Academy of Management Journal, 59*(4), 1407-1429.
45. Lockett, A., & Wright, M. (2001). The syndication of venture capital investments. *Omega, 29*(5), 375-390.
46. Logue, T. J., & Pelton, J. (2019). Overview of commercial small satellite systems in the "New Space" age. In *Handbook of Small Satellites: Technology, Design, Manufacture, Applications, Economics and Regulation* (pp. 1-18). Cham: Springer International Publishing.
47. Lutz, E., & Nörthemann, A. (2025). Venture Capital Syndication. In *The Palgrave Encyclopedia of Private Equity* (pp. 1286-1290). Cham: Springer Nature Switzerland.
48. Maula, M. V., Autio, E., & Murray, G. C. (2009). Corporate venture capital and the balance of risks and rewards for portfolio companies. *Journal of Business Venturing*, *24*(3), 274-286.
49. Montanari, Elias. (2024). *ESA's Business Incubation Centres' (ESA BICs) impact on small and medium-sized enterprises (SMEs)*. 10.31229/osf.io/2dzb4.
50. Morgan Stanley. (2017). *Space: Investment Implications of the Final Frontier*.
51. Motta, F., Pessoa Filho, J. B., & de Oliveira Moraes, A. (2024). Is there a market for micro-launch vehicles?. *Space Policy, 70*, 101629.
52. Novaspace. (2025). *Space Economy Report* (11th ed.). Novaspace.
53. OECD. (2012). *OECD Handbook on Measuring the Space Economy*. OECD Publishing. http://dx.doi.org/10.1787/9789264169166-en
54. OECD. (2022). *OECD Handbook on Measuring the Space Economy* (2nd ed.). OECD Publishing. https://doi.org/10.1787/8bfef437-en
55. OECD. (2023). *Harnessing "New Space" for Sustainable Growth of the Space Economy*. OECD Publishing. https://doi.org/10.1787/a67b1a1c-en
56. OECD/FAO. (2025). *OECD-FAO Agricultural Outlook 2025-2034*. OECD Publishing, Paris/FAO, Rome. https://doi.org/10.1787/601276cd-en

57. Olechowski, A. L., Eppinger, S. D., Joglekar, N., & Tomaschek, K. (2020). Technology readiness levels: Shortcomings and improvement opportunities. *Systems Engineering, 23*(4), 395-408.
58. PwC. (2024). *Main trends & challenges in the space sector* (4th ed.). PwC.
59. Ries, E. (2011). *The Lean Startup: How today's entrepreneurs use continuous innovation to create radically successful business*. Crown Business.
60. Robinson, D. K., & Mazzucato, M. (2019). The evolution of mission-oriented policies: Exploring changing market creating policies in the US and European space sector. *Research Policy, 48*(4), 936-948.
61. Rousseau, D. M., Sitkin, S. B., Burt, R. S., & Camerer, C. (1998). Not so different after all: A cross-discipline view of trust. *Academy of Management Review, 23*(3), 393-404.
62. Spacetech. (2022). *Intesa Sanpaolo Innovation Centre*.
63. Space Foundation. (2024). Global turnover of the space economy from 2009 to 2023 (in billion U.S. dollars). In *Statista*. https://www.statista.com/statistics/946341/space-economy-global-turnover/
64. Spagnulo, M. (2023). *Capitalismo stellare: Come la nuova corsa allo spazio cambia la Terra*. Rubbettino Editore.
65. Tykvová, T. (2007). Who chooses whom? Syndication, skills and reputation. *Review of Financial Economics, 16*(1), 5-28.
66. van Burg, E., Giannopapa, C., & Reymen, I. M. (2017). Open innovation in the European space sector: Existing practices, constraints and opportunities. *Acta astronautica*, *141*, 17-21.
67. Wright, M., & Lockett, A. (2003). The structure and management of alliances: syndication in the venture capital industry. *Journal of Management Studies, 40*(8), 2073-2102.

APPENDICES

Appendix 1: Data cleaning and transformation for analysis

```r
# Load necessary libraries
library(readxl)
library(dplyr)
library(stringr)
library(lubridate)
library(tidyr)
library(purrr)
```

```r
# ----------------------------
# 1. Load Raw Data
# ----------------------------
file <- "Downloads/Database_MasterThesis.xlsx"

db <- read_excel(file, sheet = "DATABASE_cleaned")
major <- read_excel(file, sheet = "MAJOR")
synd <- read_excel(file, sheet = "SYND INDEX")
cb <- read_excel(file, sheet = "CROSS BORDER INDEX")
gse <- read_excel(file, sheet = "GLOBAL SPACE ECONOMY")
vc <- read_excel(file, sheet = "VC TOT INVESTMENTS")
investors_data <- read_excel(file, sheet = "INVESTOR TYPE")
```

```r
# ----------------------------
# 2. Clean and Prepare Index Data
# ----------------------------

# Major index
major_clean <- major %>%
  select(YEAR = 1, Major = 7) %>%
  mutate(YEAR = as.numeric(YEAR))

# Syndication index
synd_clean <- synd %>%
  select(YEAR = 1, SYND_PERC = 4) %>%
  mutate(
    YEAR = as.numeric(YEAR),
    SyndIndex = as.numeric(str_replace(SYND_PERC, "%", ""))
  ) %>%
  select(YEAR, SyndIndex)

# Cross-border index
cb_clean <- cb %>%
  select(YEAR = 1, CROSSBORDER_PERC = 2) %>%
  mutate(
    YEAR = as.numeric(YEAR),
    CrossBorderIndex = as.numeric(str_replace(CROSSBORDER_PERC, "%",
""))
  ) %>%
  select(YEAR, CrossBorderIndex)

# Global Space Economy
gse_clean <- gse %>%
  select(YEAR = 1, SpaceEconomyValue = 3) %>%
  mutate(YEAR = as.numeric(YEAR))

# VC Funding
vc_clean <- vc %>%
  select(YEAR = 1, SpaceVCFunding = 3) %>%
  mutate(YEAR = as.numeric(YEAR))
```

```
# ----------------------------
# 3. Clean Database Table
# ----------------------------

db_clean <- db %>%
  mutate(
    `TOTAL FUNDING (EUR M)` = as.numeric(`TOTAL FUNDING (EUR M)`),
    logFUNDING = log1p(`TOTAL FUNDING (EUR M)`),

    VALUATION_RAW = `VALUATION (EUR)`,
    VALUATION_MIN = as.numeric(str_extract(VALUATION_RAW, "^[0-9]+")
),
    VALUATION_MAX = as.numeric(str_extract(VALUATION_RAW, "(?<=-)[0-
9]+")),
    VALUATION_EUR = ifelse(!is.na(VALUATION_MAX), (VALUATION_MIN + V
ALUATION_MAX)/2, VALUATION_MIN),
    logVALUATION = log1p(VALUATION_EUR),
    `VALUATION (EUR)` = VALUATION_EUR,

    INDUSTRY = str_split(INDUSTRIES, ";") %>% map_chr(~ str_trim(.x[
1]))
  ) %>%
  select(-`TOTAL FUNDING (USD M)`, -VALUATION_RAW, -VALUATION_MIN, -
VALUATION_MAX, -VALUATION_EUR, -INDUSTRIES)
```

```
# ----------------------------
# 4. Clean Valuation Dates
# ----------------------------
db_clean <- db_clean %>%
  mutate(
    VALUATION_DATE_CLEAN = tolower(`VALUATION DATE`),
    VALUATION_DATE = parse_date_time(VALUATION_DATE_CLEAN, orders =
"b/Y"),
    VALUATION_YEAR = year(VALUATION_DATE)
  ) %>%
  select(-VALUATION_DATE_CLEAN, -VALUATION_DATE, -`VALUATION DATE`)

head(db_clean %>% select(NAME, `HQ COUNTRY`, `LAUNCH YEAR`, `EACH RO
UND AMOUNT`))
```

NAME <chr>	HQ COUNTRY <chr>	LAUNCH YEAR <chr>	EACH ROUND AMOUNT <chr>
3bee	Italy	2017	5;0.1;1;n/a;0.05
9T Labs	Switzerland	2018	17;4.3;1.02;0.26;0.2;n/a
Abelio	France	2018	1

Accelercomm	UK	2016	21.5;5.8;2.5;n/a;n/a
AegiQ	UK	2019	n/a;1.4;1.8;n/a;1.4;n/a
Aerdron	Spain	2014	0.18;0.05;0.05;5;0.33;0.05;0.05

6 rows

```
# ----------------------------
# 5. Process Funding Rounds
# ----------------------------
rounds_long <- db %>%
  select(NAME, `EACH ROUND AMOUNT`, `EACH ROUND DATE`, `EACH ROUND TYPE`, `EACH ROUND CURRENCY`, `EACH ROUND INVESTORS`) %>%
  separate_rows(`EACH ROUND AMOUNT`, `EACH ROUND DATE`, `EACH ROUND TYPE`, `EACH ROUND CURRENCY`, `EACH ROUND INVESTORS`, sep = ";")

# Currency conversion table
conversion_table <- tibble(
  CURRENCY = c("EUR","USD","GBP","JPY","CHF","CAD","AUD","CNY","SEK","NZD","RUB","INR","PLN","CZK","DKK","HUF","RON","ISK","BGN"),
  TO_EUR = c(1,0.86,1.15,0.0059,1.07,0.63,0.56,0.12,0.089,0.51,0.011,0.0098,0.23,0.041,0.13,0.0025,0.20,0.0070,0.51)
)

# Clean rounds
rounds_clean <- rounds_long %>%
  mutate(
    `EACH ROUND AMOUNT` = na_if(`EACH ROUND AMOUNT`, "n/a"),
    `EACH ROUND AMOUNT` = as.numeric(str_replace_all(`EACH ROUND AMOUNT`, ",", ".")),
    ROUND_DATE = parse_date_time(str_trim(`EACH ROUND DATE`), orders = c("b/Y", "B/Y", "Y")),
    ROUND_YEAR = year(ROUND_DATE),
    CURRENCY = str_to_upper(str_trim(`EACH ROUND CURRENCY`))
  ) %>%
  left_join(conversion_table, by = "CURRENCY") %>%
  mutate(
    ROUND_AMOUNT_EUR = `EACH ROUND AMOUNT` * TO_EUR,
    log_amount = log1p(ROUND_AMOUNT_EUR),
    Investors = ifelse(is.na(`EACH ROUND INVESTORS`), 0, str_count(`EACH ROUND INVESTORS`, fixed("++")) + 1),
    Syndication = ifelse(Investors > 1, 1, 0),
    Syndication = factor(Syndication, levels = c(0,1), labels = c("No","Yes"))
  ) %>%
  select(-CURRENCY, -`EACH ROUND DATE`, -ROUND_DATE)
head(rounds_clean %>% select(NAME, ROUND_YEAR, ROUND_AMOUNT_EUR, log_amount, Investors, Syndication))
```

NAME	ROUND_...	ROUND_AMOUN...	log_amount	Investors	Sy
<chr>	<dbl>	<dbl>	<dbl>	<dbl>	<fc
3bee	2022	5.000	1.79175947	3	Ye
3bee	2022	0.086	0.08250122	1	No
3bee	2019	1.000	0.69314718	1	No
3bee	2018	NA	NA	1	No
3bee	2017	0.050	0.04879016	1	No
9T Labs	2022	14.620	2.74855214	4	Ye

6 rows

```
# ----------------------------
# 6. Merge with Indices and Valuations
# ----------------------------
dataset_round <- rounds_clean %>%
  left_join(major_clean, by = c("ROUND_YEAR" = "YEAR")) %>%
  left_join(synd_clean, by = c("ROUND_YEAR" = "YEAR")) %>%
  left_join(cb_clean, by = c("ROUND_YEAR" = "YEAR")) %>%
  left_join(gse_clean, by = c("ROUND_YEAR" = "YEAR")) %>%
  left_join(vc_clean, by = c("ROUND_YEAR" = "YEAR")) %>%
  left_join(db_clean %>% select(NAME, `VALUATION (EUR)`, logVALUATIO
N, VALUATION_YEAR), by = "NAME")
head(dataset_round %>% select(NAME, ROUND_YEAR, Major, SyndIndex, Cr
ossBorderIndex, SpaceEconomyValue, SpaceVCFunding))
```

NAME	ROUND_...	Major	SyndIndex	CrossBorderIndex	Space
<chr>	<dbl>	<dbl>	<dbl>	<dbl>	
3bee	2022	2773.5	0.6187050	0.8274	
3bee	2022	2773.5	0.6187050	0.8274	
3bee	2019	3182.0	0.4339623	0.7348	
3bee	2018	1075.0	0.4942529	0.6460	
3bee	2017	387.0	0.4210526	0.6809	
9T Labs	2022	2773.5	0.6187050	0.8274	

6 rows

```r
# ----------------------------
# 7. Cross-Border Identification
# ----------------------------
investors_data <- investors_data %>% mutate(Investor = str_trim(Inve
stor))

is_crossborder <- function(investor_string, startup_country) {
  if (is.na(investor_string) || is.na(startup_country)) return(NA)
  investor_list <- str_split(investor_string, pattern = "\\+\\+|;")[
[1]] %>% str_trim()
  investor_countries <- investors_data %>% filter(Investor %in% inve
stor_list) %>% pull(Country)
  if (length(investor_countries) == 0) return(NA)
  any(investor_countries != startup_country)
}

dataset_round <- dataset_round %>%
  left_join(db_clean %>% select(NAME, `HQ COUNTRY`), by = "NAME")

dataset_round$CrossBorder <- mapply(is_crossborder,
                                   dataset_round$`EACH ROUND INVESTO
RS`,
                                   dataset_round$`HQ COUNTRY`) %>% a
s.integer()
dataset_round$CrossBorder <- factor(dataset_round$CrossBorder, level
s = c(0,1), labels = c("No","Yes"))
```

```
# ----------------------------
# 8. Compute Age and Employees
# ----------------------------
dataset_round <- dataset_round %>%
  left_join(db_clean %>% select(NAME, `LAUNCH YEAR`), by = "NAME") %
>%
  mutate(
    `LAUNCH YEAR` = as.numeric(`LAUNCH YEAR`),
    Age = ROUND_YEAR - `LAUNCH YEAR`,
    Age = ifelse(is.na(Age) | Age < 0, NA, Age)
  )

# Employees data
employees_raw <- db %>%
  select(NAME, `EMPLOYEES (2016,2017,2018,2019,2020,2021,2022,2023)`
) %>%
  rename(EMPLOYEES = `EMPLOYEES (2016,2017,2018,2019,2020,2021,2022,
2023)`) %>%
  separate(EMPLOYEES, into = paste0("E_", 2016:2023), sep = ";", con
vert = FALSE)

employees_long <- employees_raw %>%
  pivot_longer(cols = starts_with("E_"), names_to = "year", values_t
o = "Employees") %>%
  mutate(year = as.numeric(sub("E_", "", year)), Employees = as.nume
ric(na_if(Employees, "n/a")))

dataset_round <- dataset_round %>%
  left_join(employees_long, by = c("NAME" = "NAME", "ROUND_YEAR" = "
year")) %>%
  arrange(NAME, ROUND_YEAR) %>%
  group_by(NAME) %>%
  mutate(
    first_non_na_year = suppressWarnings(min(ROUND_YEAR[!is.na(Emplo
yees)], na.rm = TRUE)),
    first_non_na_value = Employees[ROUND_YEAR == first_non_na_year][
1],
    Employees = ifelse(
      is.na(Employees) & ROUND_YEAR < first_non_na_year & is.finite(
first_non_na_year),
      floor(first_non_na_value / (2 ^ (first_non_na_year - ROUND_YEA
R))),
      Employees
    )
  ) %>%
  ungroup() %>%
  select(-first_non_na_year, -first_non_na_value)
```

```
# ----------------------------
# 9. Final Transformations
# ----------------------------
# Segment, Growth Stage, Industry
db_segment <- db_clean %>%
  select(NAME, UPSTREAM, DOWNSTREAM) %>%
  mutate(Segment = case_when(
    UPSTREAM == 1 ~ "Upstream",
    DOWNSTREAM == 1 ~ "Downstream",
    TRUE ~ NA_character_
  )) %>%
  select(NAME, Segment)

dataset_round <- dataset_round %>%
  left_join(db_segment, by = "NAME") %>%
  left_join(db_clean %>% select(NAME, `GROWTH STAGE`, INDUSTRY), by
= "NAME") %>%
  mutate(
    Segment = factor(Segment, levels = c("Downstream", "Upstream")),
    GrowthStage = factor(`GROWTH STAGE`, levels = c("seed", "early g
rowth", "late growth")),
    INDUSTRY = factor(INDUSTRY)
  )

head(dataset_round %>% select(NAME, Segment, GrowthStage, INDUSTRY,
Age, Employees))
```

NAME <chr>	Segment <fct>	GrowthStage <fct>	INDUST… <fct>	… <dbl>	Employees <dbl>
3bee	Downstream	late growth	food	0	1
3bee	Downstream	late growth	food	1	2
3bee	Downstream	late growth	food	2	4
3bee	Downstream	late growth	food	5	34
3bee	Downstream	late growth	food	5	34
9T Labs	Upstream	late growth	space	0	8

6 rows

Appendix 2: Clustering analysis

```
library(dplyr)
library(factoextra)
library(NbClust)
library(tidyr)
library(ggplot2)
library(lubridate)
library(effectsize)
```

```
# -------------------------------
# 1. Prepare data
# -------------------------------
db_clustering <- db_clean %>%
  mutate(
    Segment = case_when(
      UPSTREAM == 1 ~ "Upstream",
      DOWNSTREAM == 1 ~ "Downstream",
      TRUE ~ NA_character_
    ) %>% factor(),
    `HQ COUNTRY` = factor(`HQ COUNTRY`),
    `LAST ROUND` = factor(`LAST ROUND`),
    `LAST FUNDING` = as.numeric(`LAST FUNDING`),
    `LAST FUNDING DATE` = year(parse_date_time(`LAST FUNDING DATE`,
orders = "my")),
    `SEED YEAR` = as.numeric(`SEED YEAR`),
    `LAUNCH YEAR` = as.numeric(`LAUNCH YEAR`),
    INDUSTRY = factor(INDUSTRY),
    `GROWTH STAGE` = factor(`GROWTH STAGE`),
    EMPLOYEES = as.numeric(EMPLOYEES),
    `NUMBER OF PATENTS` = as.numeric(`NUMBER OF PATENTS`)
  ) %>%
  select(
    -UPSTREAM, -DOWNSTREAM, -INVESTORS, -`EACH INVESTOR TYPES`,
    -`FIRST FUNDING DATE`, -`EMPLOYEES (2016,2017,2018,2019,2020,202
1,2022,2023)`,
    -`HISTORICAL VALUATIONS - VALUES EUR M`,
    -LINKEDIN, -CRUNCHBASE, -`EACH ROUND TYPE`, -`EACH ROUND AMOUNT`
,
    -`EACH ROUND CURRENCY`, -`EACH ROUND DATE`, -`EACH ROUND INVESTO
RS`,
    -`COMPANY STATUS`, -VALUATION_YEAR
  )

# Count syndicated and cross-border rounds
rounds_summary <- dataset_round %>%
  group_by(NAME) %>%
  summarise(
    `SYNDICATED ROUNDS` = sum(Syndication == "Yes", na.rm = TRUE),
    `CROSS BORDER ROUNDS` = sum(CrossBorder == "Yes", na.rm = TRUE),
    .groups = "drop"
  )

db_clustering <- db_clustering %>%
  left_join(rounds_summary, by = "NAME") %>%
  mutate(
    `SYNDICATED ROUNDS` = replace_na(`SYNDICATED ROUNDS`, 0),
    `CROSS BORDER ROUNDS` = replace_na(`CROSS BORDER ROUNDS`, 0)
  )
```

```r
# ------------------------------
# 2. Select numeric variables
# ------------------------------
vars_num <- c(
  "EMPLOYEES", "logVALUATION", "TOTAL ROUNDS NUMBER",
  "NUMBER OF PATENTS", "LAST FUNDING DATE",
  "LAUNCH YEAR", "logFUNDING", "SYNDICATED ROUNDS",
  "CROSS BORDER ROUNDS"
)

complete_rows <- complete.cases(db_clustering[, vars_num])
db_clustering_clu <- db_clustering[complete_rows, c("NAME", vars_num
)]
```

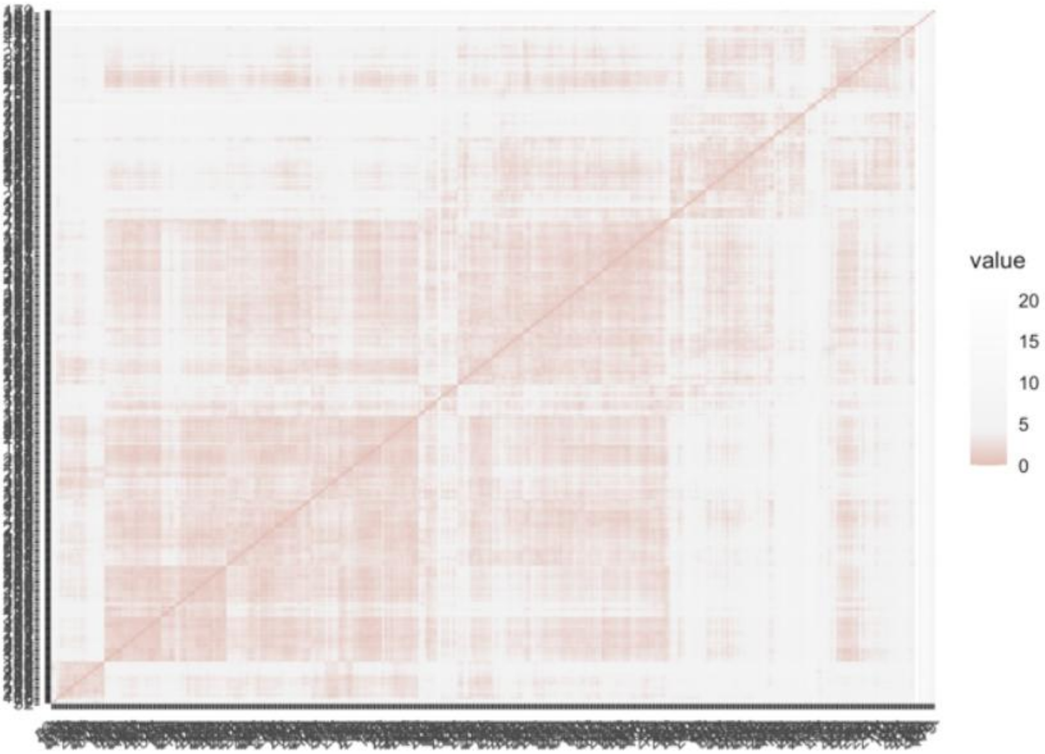
```r
# ------------------------------
# 3. Standardize numeric variables
# ------------------------------
scaled_vars <- scale(db_clustering_clu[, vars_num])
db_clustering_clu <- cbind(NAME = db_clustering_clu$NAME, as.data.fr
ame(scaled_vars))
```

```r
# ------------------------------
# 4. Compute dissimilarity (Euclidean norm)
# ------------------------------
db_clustering_clu$dissimilarity <- apply(db_clustering_clu[, -1], 1,
function(x) sqrt(sum(x^2)))
head(db_clustering_clu %>% arrange(desc(dissimilarity)) %>% select(N
AME, dissimilarity))
```

	NAME <chr>	dissimilarity <dbl>
1	Lilium	15.836515
2	What3words	10.609275
3	Paragraf	10.281970
4	ICEYE	9.429695
5	Isar Aerospace	7.859527
6	Blickfeld	7.184980

6 rows

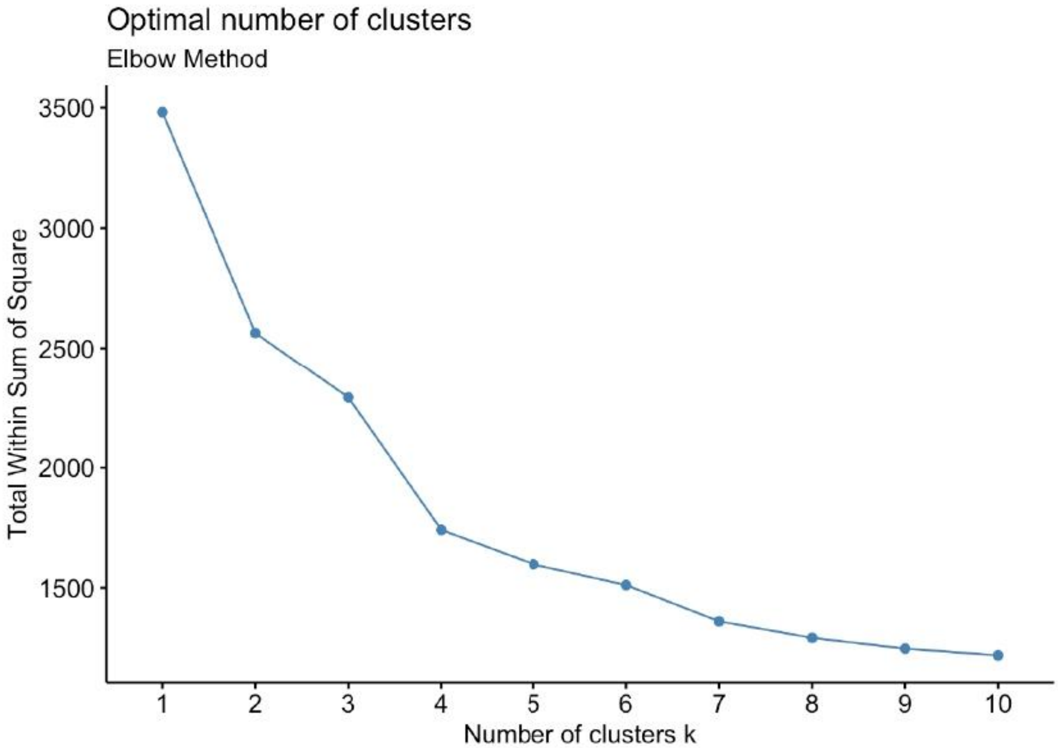
```
# -------------------------------
# 5. Distance matrix and heatmap
# -------------------------------
Distances <- get_dist(db_clustering_clu[, -1], method = "euclidean")
fviz_dist(Distances, gradient = list(low = "darkred", mid = "grey95"
, high = "white"))
```



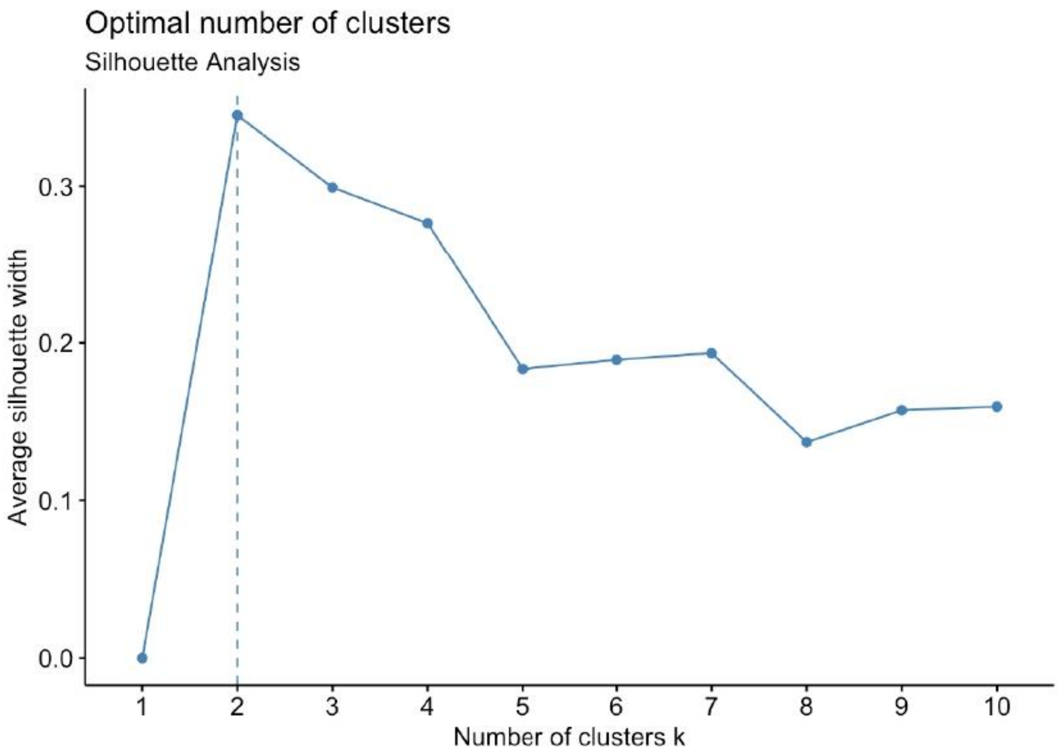

```
# -------------------------------
# 6. Clustering tendency (Hopkins)
# -------------------------------
get_clust_tendency(db_clustering_clu[, -1], n = nrow(db_clustering_c
lu) - 1, graph = FALSE)
```

```
## $hopkins_stat
## [1] 0.8621707
##
## $plot
## NULL
```

```
# -------------------------------
# 7. Optimal number of clusters (Elbow & Silhouette)
# -------------------------------
fviz_nbclust(db_clustering_clu[, -1], kmeans, method = "wss") + labs
(subtitle = "Elbow Method")
```



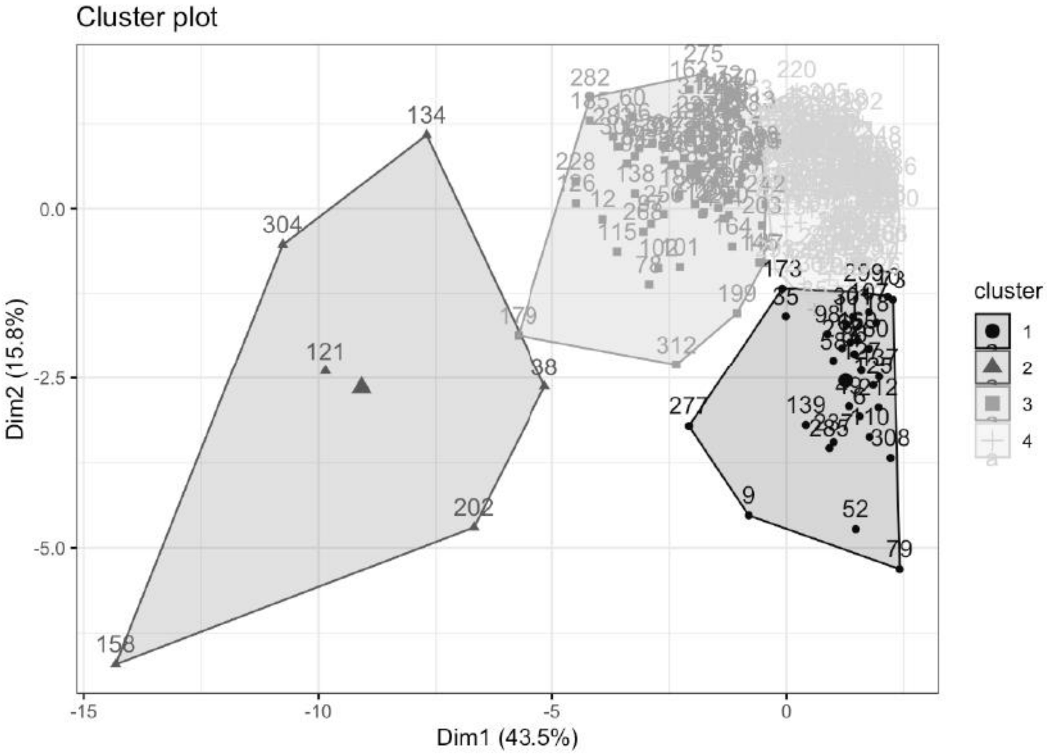

```
fviz_nbclust(db_clustering_clu[, -1], kmeans, method = "silhouette")
+ labs(subtitle = "Silhouette Analysis")
```



```
# ------------------------------
# 8. NbClust (multiple indices)
# ------------------------------
pdf(NULL)

output <- capture.output(
  nc <- NbClust(
    db_clustering_clu[, -1],
    distance = "euclidean",
    min.nc = 2,
    max.nc = 10,
    method = "kmeans",
    index = "all"
  )
)
summary_lines <- output[grepl("\\* Among all indices|\\* According t
o the majority rule|\\* [0-9]+ proposed", output)]
cat(paste(summary_lines, collapse = "\n"))
```

```
## * Among all indices:
## * 6 proposed 2 as the best number of clusters
## * 6 proposed 3 as the best number of clusters
## * 10 proposed 4 as the best number of clusters
## * 1 proposed 5 as the best number of clusters
## * 1 proposed 9 as the best number of clusters
## * According to the majority rule, the best number of clusters is
4
```

```
# ------------------------------
# 9. K-means clustering
# ------------------------------
Clustering <- kmeans(db_clustering_clu[, -1], centers = 4, nstart =
25)

my_colors <- c("#0d0d0d", "#595959", "#a1a1a1", "#d4d4d4")

fviz_cluster(
  Clustering,
  data = db_clustering_clu[, -1],
  repel = FALSE,
  ggtheme = theme_bw()
) +
  scale_color_manual(values = my_colors) +
  scale_fill_manual(values = my_colors)
```

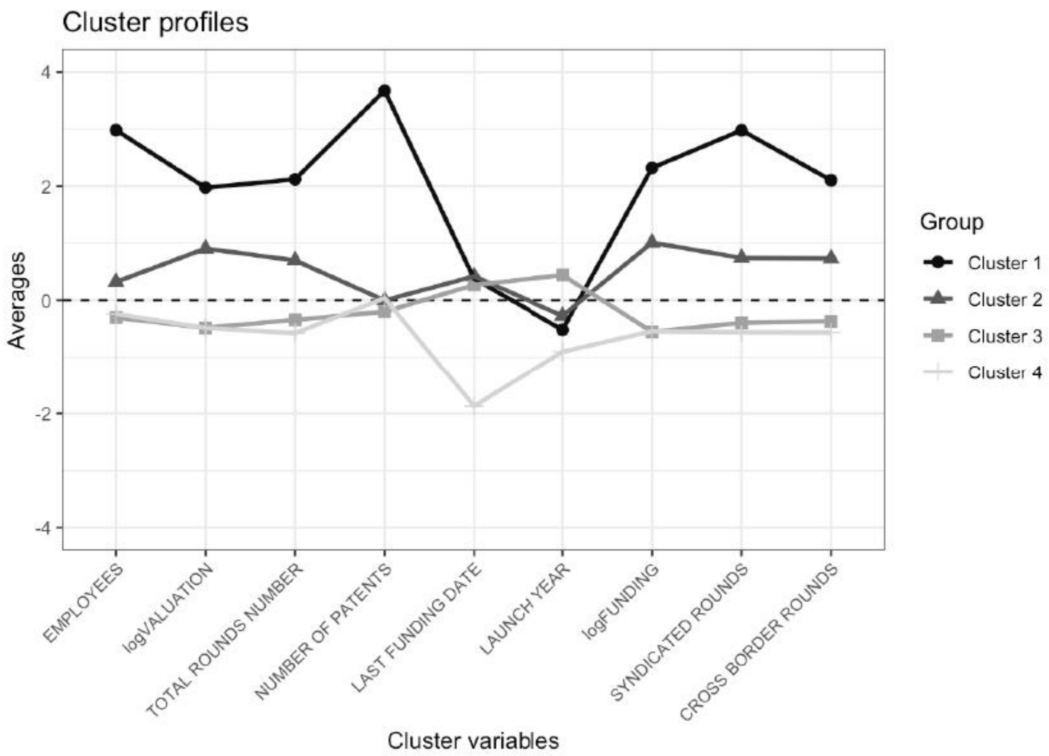



```
# ------------------------------
# 10. Remove outliers manually (ID58 = Lilium)
# ------------------------------
db_clustering_clu <- db_clustering_clu %>% filter(NAME != "Lilium")
vars_num <- setdiff(names(db_clustering_clu), "NAME")
db_clustering_clu_std <- as.data.frame(scale(db_clustering_clu[, var
s_num]))
```

```
# ------------------------------
# 11. Cluster centroids
# ------------------------------
options(width = 100)
vars_num_clean <- setdiff(colnames(db_clustering_clu), c("NAME", "di
ssimilarity"))
Clustering <- kmeans(
  db_clustering_clu[, vars_num_clean],
  centers = 4,
  nstart = 25
)

averages <- Clustering$centers
averages
```

```
##     EMPLOYEES logVALUATION TOTAL ROUNDS NUMBER NUMBER OF PATENTS L
AST FUNDING DATE LAUNCH YEAR
## 1  2.9795461    1.9729529          2.1208107       3.671152060
0.3778327  -0.5160821
## 2  0.3237657    0.9077943          0.7003819      -0.001258682
0.4234583  -0.2718669
## 3 -0.3031246   -0.4801171         -0.3417017      -0.199900316
0.2703466   0.4432790
## 4 -0.2376111   -0.4833529         -0.5739745       0.039894559
-1.8721073  -0.9001754
##    logFUNDING SYNDICATED ROUNDS CROSS BORDER ROUNDS
## 1  2.3196667          2.9760952           2.1044123
## 2  1.0110828          0.7432649           0.7347155
## 3 -0.5495028         -0.3931149          -0.3653312
## 4 -0.5412544         -0.5576190          -0.5627775
```

```
# ------------------------------
# 12. Prepare data for ggplot
# ------------------------------
figure <- as.data.frame(averages)
figure$ID <- 1:nrow(figure)
figure <- pivot_longer(figure, cols = all_of(vars_num_clean), names_
to = "variable", values_to = "value")
figure$Group <- factor(figure$ID, levels = 1:4, labels = paste("Clus
ter", 1:4))
figure$variable <- factor(figure$variable, levels = vars_num)

ggplot(figure, aes(x = variable, y = value, group = ID, color = Grou
p)) +
  geom_hline(yintercept = 0, linetype = "dashed") +
  geom_point(aes(shape = Group), size = 2.5) +
  geom_line(linewidth = 1) +
  scale_color_manual(values = c("#0d0d0d", "#595959", "#a1a1a1", "#d
4d4d4")) +
  theme_bw() +
  ylab("Averages") +
  xlab("Cluster variables") +
  ylim(-4, 4) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1, vjust = 1,
size = 8)) +
  ggtitle("Cluster profiles")
```




```
# ------------------------------
# 13. Add cluster labels to dataset
# ------------------------------
db_clustering_clu$Group <- Clustering$cluster
```

```
# ------------------------------
# 14. MANOVA for cluster differences
# ------------------------------
fit <- aov(cbind(EMPLOYEES, logVALUATION, `TOTAL ROUNDS NUMBER`,
                 `NUMBER OF PATENTS`, `LAST FUNDING DATE`, `LAUNCH
YEAR`,
                 logFUNDING, `SYNDICATED ROUNDS`, `CROSS BORDER ROU
NDS`) ~ Group,
           data = db_clustering_clu)
summary(fit)
```

```
##  Response EMPLOYEES :
##              Df  Sum Sq Mean Sq F value    Pr(>F)
## Group         1  41.555  41.555  95.403 < 2.2e-16 ***
## Residuals   310 135.028   0.436
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##  Response logVALUATION :
##              Df Sum Sq Mean Sq F value    Pr(>F)
## Group         1 115.67  115.67  186.41 < 2.2e-16 ***
## Residuals   310 192.35    0.62
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##  Response TOTAL ROUNDS NUMBER :
##              Df  Sum Sq Mean Sq F value    Pr(>F)
## Group          1  93.159  93.159  136.57 < 2.2e-16 ***
## Residuals    310 211.459   0.682
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##  Response NUMBER OF PATENTS :
##              Df  Sum Sq Mean Sq F value    Pr(>F)
## Group          1  12.359 12.3593  17.266 4.208e-05 ***
## Residuals    310 221.906  0.7158
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##  Response LAST FUNDING DATE :
##              Df Sum Sq Mean Sq F value    Pr(>F)
## Group          1 114.71 114.706  181.16 < 2.2e-16 ***
## Residuals    310 196.28   0.633
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##  Response LAUNCH YEAR :
##              Df  Sum Sq Mean Sq F value Pr(>F)
## Group          1   0.628 0.62811  0.6265 0.4293
## Residuals    310 310.807 1.00260
##
##  Response logFUNDING :
##              Df Sum Sq Mean Sq F value    Pr(>F)
## Group          1 147.28 147.279  307.53 < 2.2e-16 ***
## Residuals    310 148.46   0.479
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##  Response SYNDICATED ROUNDS :
##              Df Sum Sq Mean Sq F value    Pr(>F)
## Group          1 114.90 114.902  181.79 < 2.2e-16 ***
## Residuals    310 195.94   0.632
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##  Response CROSS BORDER ROUNDS :
##              Df Sum Sq Mean Sq F value    Pr(>F)
## Group          1  97.23  97.230  145.84 < 2.2e-16 ***
## Residuals    310 206.68   0.667
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
# ------------------------------
# 15. Criterion validity: categorical variables
# ------------------------------
vars_cat <- c("HQ COUNTRY", "LAST ROUND", "INDUSTRY", "GROWTH STAGE"
, "Segment")

db_clustering_clu <- db_clustering %>%
  filter(NAME %in% db_clustering_clu$NAME) %>%
  select(all_of(vars_num_clean), all_of(vars_cat), NAME) %>%
  mutate(Group = factor(Clustering$cluster))
```

```r
# --- HQ COUNTRY grouping ---
freq_country <- table(db_clustering_clu$`HQ COUNTRY`)
threshold_country <- 10

db_clustering_clu <- db_clustering_clu %>%
  mutate(
    HQ_COUNTRY_GROUPED = if_else(
      freq_country[`HQ COUNTRY`] >= threshold_country,
      as.character(`HQ COUNTRY`),
      "Other"
    ) %>% factor()
  )

chi_hq <- chisq.test(db_clustering_clu$HQ_COUNTRY_GROUPED, db_cluste
ring_clu$Group)
chi_hq
```

```
##
##  Pearson's Chi-squared test
##
## data:  db_clustering_clu$HQ_COUNTRY_GROUPED and db_clustering_clu
$Group
## X-squared = 37.316, df = 24, p-value = 0.04069
```

```r
chi_hq$residuals
```

```
##              db_clustering_clu$Group
##                        1           2           3           4
##   France      -1.16023870 -2.48622579  1.55927440  1.06400462
##   Germany      2.59807621  0.28867513 -0.30461683 -0.77356593
##   Italy       -0.51887452 -1.11187397  0.99313640 -0.07503928
##   Netherlands -0.43852901  0.52623481 -0.97316924  1.21691345
##   Other       -0.14322297 -0.10741723 -0.24043770  0.65245351
##   Portugal    -0.45993311 -0.75261781  0.93991349 -0.51042424
##   Spain       -0.48038446  0.16012815 -0.10752701  0.14303239
##   Switzerland -0.80860754  1.71234538 -0.65553624 -0.93754539
##   UK           0.73969345  1.81401013 -1.12294429 -0.76559800
```

```
cramers_v(db_clustering_clu$HQ_COUNTRY_GROUPED, db_clustering_clu$Gr
oup)
```

Cramers_v_adjusted <dbl>	CI <dbl>	CI_low <dbl>	CI_high <dbl>
0.1195048	0.95	0	1

1 row

```
# --- LAST ROUND grouping ---
db_clustering_clu <- db_clustering_clu %>%
  mutate(
    LAST_ROUND_GROUPED = case_when(
      `LAST ROUND` %in% c("ACQUISITION","ANGEL","CONVERTIBLE","DEBT"
,"GROWTH EQUITY VC",
                           "IPO","POST IPO CONVERTIBLE","POST IPO EQ
UITY","SERIES D") ~ "OTHER",
      TRUE ~ as.character(`LAST ROUND`)
    ) %>% factor()
  )

chi_last <- chisq.test(db_clustering_clu$LAST_ROUND_GROUPED, db_clus
tering_clu$Group)
chi_last
```

```
##
##  Pearson's Chi-squared test
##
## data:  db_clustering_clu$LAST_ROUND_GROUPED and db_clustering_clu
$Group
## X-squared = 140.04, df = 24, p-value < 2.2e-16
```

```
chi_last$residuals
```

```
##                     db_clustering_clu$Group
##                               1          2          3          4
##   EARLY VC        -1.0703416 -0.9319458 -1.4560446  4.4596582
##   GRANT            0.5469835  0.9512818 -0.7101998 -0.2205178
##   LATE VC          1.3132385  1.1407912 -1.0354374 -0.1559297
##   OTHER            3.4192014  2.0190286 -1.3891850 -1.5060577
##   SEED            -1.3653123 -4.8489238  4.2661928 -0.6060933
##   SERIES A        -0.9853293  1.9973212 -0.8519589 -0.8955788
##   SERIES B        -0.5213872  3.7510598 -1.9816012 -1.4436559
##   SERIES C         3.3094818  1.6165102 -1.4525950 -0.7716665
##   SUPPORT PROGRAM -0.5213872  0.8436748  0.2262646 -1.4436559
```

```
cramers_v(db_clustering_clu$LAST_ROUND_GROUPED, db_clustering_clu$Gr
oup)
```

Cramers_v_adjusted <dbl>	CI <dbl>	CI_low <dbl>	CI_high <dbl>
0.3554263	0.95	0.2522874	1

1 row

```
# --- INDUSTRY grouping ---
freq_industry <- table(db_clustering_clu$INDUSTRY)
threshold_industry <- 30

db_clustering_clu <- db_clustering_clu %>%
  mutate(
    INDUSTRY_GROUPED = if_else(
      freq_industry[INDUSTRY] >= threshold_industry,
      as.character(INDUSTRY),
      "Other"
    ) %>% factor()
  )

chi_industry <- chisq.test(db_clustering_clu$INDUSTRY_GROUPED, db_cl
ustering_clu$Group)
chi_industry
```

```
##
##  Pearson's Chi-squared test
##
## data:  db_clustering_clu$INDUSTRY_GROUPED and db_clustering_clu$G
roup
## X-squared = 21.595, df = 12, p-value = 0.04231
```

```
chi_industry$residuals
```

```
##                 db_clustering_clu$Group
##                            1           2           3           4
##   energy         -0.83250784 -0.29390358  0.20304679  0.35175856
##   Other          -1.18862394 -0.98816908  0.35240154  1.21156489
##   robotics        1.39705562  0.79280041 -0.49115964 -0.74462902
##   space           1.43814628  0.02485985  0.97136005 -2.37561873
##   transportation  0.36868204  1.51733950 -1.44070223  0.35175856
```

```
cramers_v(db_clustering_clu$INDUSTRY_GROUPED, db_clustering_clu$Grou
p)
```

Cramers_v_adjusted <dbl>	CI <dbl>	CI_low <dbl>	CI_high <dbl>
0.1030424	0.95	0	1

1 row

```
# --- SEGMENT grouping ---
freq_segment <- table(db_clustering_clu$Segment)
threshold_segment <- 30

db_clustering_clu <- db_clustering_clu %>%
  mutate(
    SEGMENT_GROUPED = if_else(
      freq_segment[Segment] >= threshold_segment,
      as.character(Segment),
      "Other"
    ) %>% factor()
  )

chi_segment <- chisq.test(db_clustering_clu$SEGMENT_GROUPED, db_clus
tering_clu$Group)
chi_segment
```

```
##
##  Pearson's Chi-squared test
##
## data:  db_clustering_clu$SEGMENT_GROUPED and db_clustering_clu$Gr
oup
## X-squared = 3.9764, df = 3, p-value = 0.264
```

```
chi_segment$residuals
```

```
##             db_clustering_clu$Group
##                      1          2          3          4
##   Downstream -0.3236454  0.4146706 -0.7283135  0.8793215
##   Upstream    0.3985084 -0.5105889  0.8967811 -1.0827191
```

```
cramers_v(db_clustering_clu$SEGMENT_GROUPED, db_clustering_clu$Group
)
```

Cramers_v_adjusted <dbl>	CI <dbl>	CI_low <dbl>	CI_high <dbl>
0.05575312	0.95	0	1

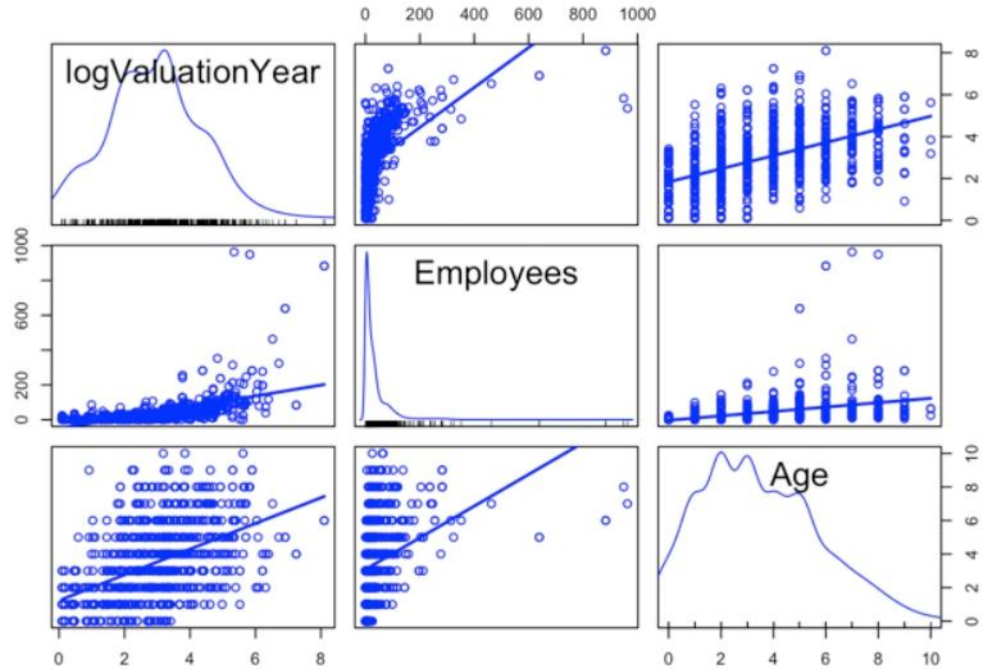
1 row

Appendix 3: Regression analysis

```
library(dplyr)
library(Hmisc)
library(car)
library(olsrr)
library(ggplot2)
```

```
# ------------------------------
# 1. Dataset Preparation
# ------------------------------

# Add ID column
dataset_round <- dataset_round %>%
  mutate(ID = row_number())

# HQ Country grouping
Top5_SpaceCountries <- c("France", "Germany", "Italy", "UK", "Spain"
)

dataset_round <- dataset_round %>%
  mutate(Country = if_else(`HQ COUNTRY` %in% Top5_SpaceCountries,
                           "Top5_SpaceEconomy", "Other")) %>%
  mutate(Country = factor(Country))

# Industry grouping
dataset_round <- dataset_round %>%
  mutate(Industry = if_else(INDUSTRY == "space", "space", "Other"))
%>%
  mutate(Industry = factor(Industry, levels = c("Other", "space")))

# Round Type grouping
keep_rounds <- c("SEED", "EARLY VC", "GRANT", "SERIES A", "SERIES B"
, "SERIES C")
dataset_round <- dataset_round %>%
  mutate(RoundType = if_else(`EACH ROUND TYPE` %in% keep_rounds,
                             as.character(`EACH ROUND TYPE`), "Other
")) %>%
  mutate(RoundType = factor(RoundType,
                            levels = c(keep_rounds, "Other")))
```

```
# -------------------------------
# 2. Exploratory Data Analysis
# -------------------------------
# Scatterplot matrix for numeric variables
scatterplotMatrix(dataset_round[, c("logValuationYear", "Employees",
"Age")], smooth = FALSE)
```




```
# Correlation matrix
num_vars <- data.matrix(dataset_round[, c("logValuationYear", "Emplo
yees", "Age")])
rcorr(num_vars)
```

```
##                   logValuationYear Employees  Age
## logValuationYear             1.00      0.54 0.49
## Employees                    0.54      1.00 0.38
## Age                          0.49      0.38 1.00
##
## n
##                   logValuationYear Employees  Age
## logValuationYear             1056       883 1054
## Employees                     883      1190 1171
## Age                          1054      1171 1419
##
## P
##                   logValuationYear Employees Age
## logValuationYear                    0         0
## Employees          0                          0
## Age                0                0
```

```
# ------------------------------
# 3. Linear regression model 1
# ------------------------------
# Full model
regression <- lm(logValuationYear ~ Syndication + CrossBorder + Empl
oyees + Segment + Age + GrowthStage +
                   Industry + RoundType + Country,
                 data = dataset_round)
vif(regression)
```

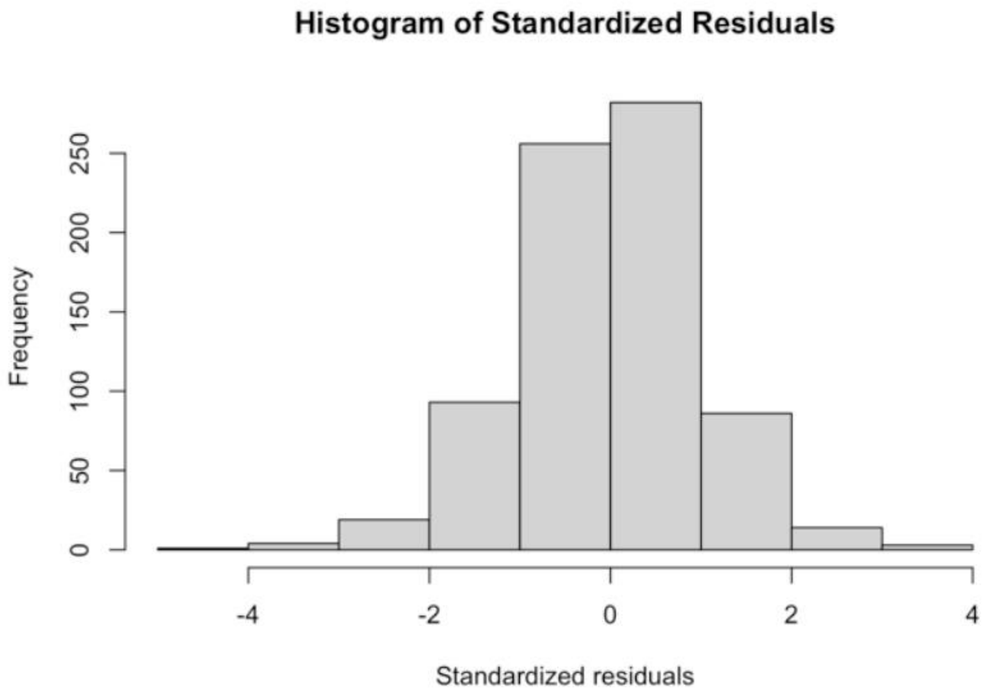
```
##                 GVIF Df GVIF^(1/(2*Df))
## Syndication 1.499712  1        1.224627
## CrossBorder 1.166333  1        1.079969
## Employees   1.482152  1        1.217437
## Segment     1.204851  1        1.097657
## Age         1.297881  1        1.139246
## GrowthStage 1.327246  2        1.073341
## Industry    1.213197  1        1.101452
## RoundType   2.082947  6        1.063057
## Country     1.127606  1        1.061888
```

```
mean(vif(regression))
```

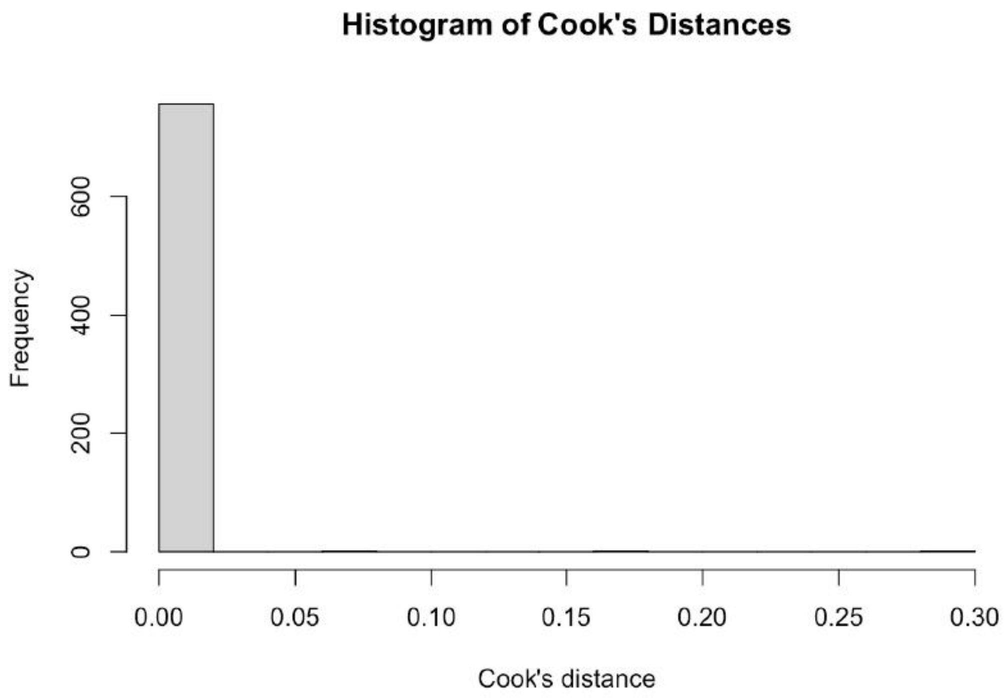
```
## [1] 1.38743
```

```
# Standardized residuals and Cook's distances
dataset_model <- dataset_round[as.numeric(names(regression$residuals
)), ]
dataset_model$StdResid <- rstandard(regression)
dataset_model$CooksD <- cooks.distance(regression)
```

```
# Plot residuals
hist(dataset_model$StdResid, xlab = "Standardized residuals", main =
"Histogram of Standardized Residuals")
```




```
hist(dataset_model$CooksD, xlab = "Cook's distance", main = "Histogr
am of Cook's Distances")
```




```
# Shapiro-Wilk test for normality
shapiro.test(dataset_model$StdResid)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  dataset_model$StdResid
## W = 0.99292, p-value = 0.001159
```

```
# Top standardized residuals and Cook's distances
head(dataset_model[order(dataset_model$StdResid), c("ID", "NAME", "S
tdResid")], 7)
```

ID <int>	NAME <chr>	StdResid <dbl>
704	Lilium	-4.132961
705	Lilium	-3.285185
989	Rated Power	-3.176421
988	Rated Power	-3.151412
990	Rated Power	-3.034470
343	EnduroSat	-2.596888
987	Rated Power	-2.590955

7 rows

```
head(dataset_model[order(-dataset_model$StdResid), c("ID", "NAME", "
StdResid")], 7)
```

ID <int>	NAME <chr>	StdResid <dbl>
102	Arqit	3.807084
103	Arqit	3.488232
178	CONTEC	3.244801
635	Kineis	2.993069
1181	Space Hero (Formerly TDGA Holdings)	2.934415
309	E-Space	2.755727
108	Arralis	2.543624

7 rows

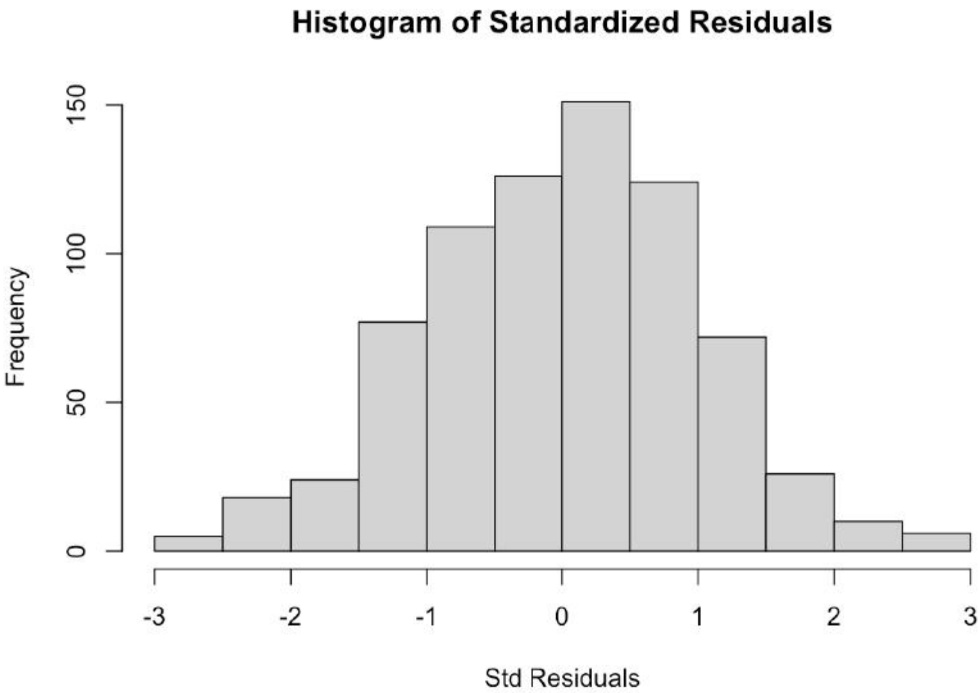
```
head(dataset_model[order(-dataset_model$CooksD), c("ID", "NAME", "Co
oksD")], 7)
```

ID <int>	NAME <chr>	CooksD <dbl>
704	Lilium	0.28393314
705	Lilium	0.16843075
178	CONTEC	0.07138607
988	Rated Power	0.01326175
102	Arqit	0.01312515
1076	Sen Corporation	0.01305016
635	Kineis	0.01246634

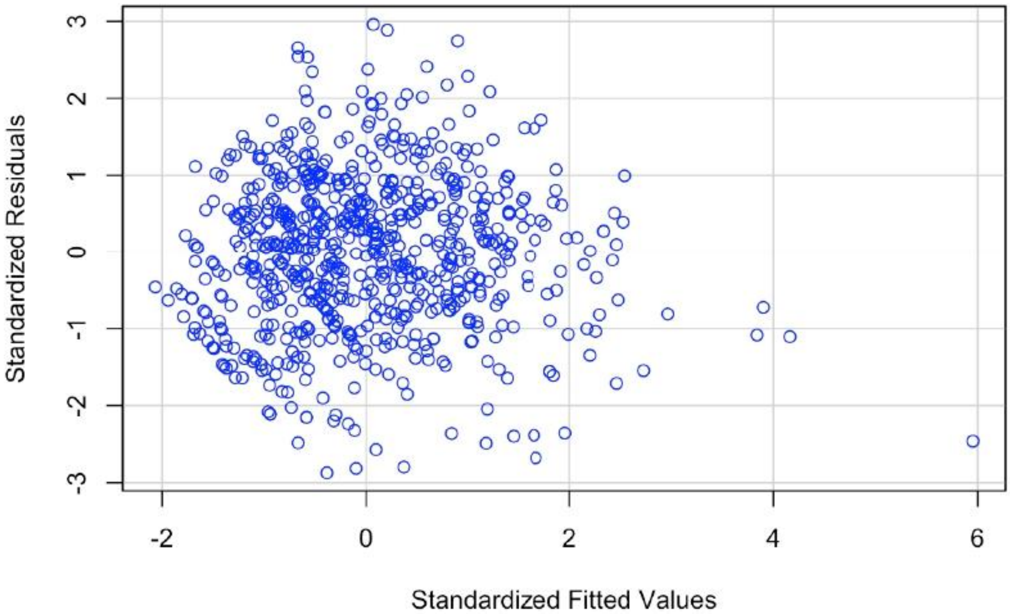
7 rows

```
# Remove influential observations
ids_to_remove <- c(704, 705, 989, 988, 990, 102, 103, 635, 1181, 178
)
dataset_model <- dataset_model %>% filter(!ID %in% ids_to_remove)

# Refit regression
regression <- lm(logValuationYear ~ Syndication + CrossBorder + Empl
oyees + Segment + Age + GrowthStage +
                   Industry + RoundType + Country,
                 data = dataset_model)

# Recompute residuals
dataset_model$StdResid <- rstandard(regression)
dataset_model$CooksD <- cooks.distance(regression)
```

```
# Residual diagnostics
hist(dataset_model$StdResid, main = "Histogram of Standardized Resid
uals", xlab = "Std Residuals")
```




```
scatterplot(y = dataset_model$StdResid, x = scale(regression$fitted.
values),
            ylab = "Standardized Residuals", xlab = "Standardized Fi
tted Values",
            boxplots = FALSE, regLine = FALSE, smooth = FALSE)
```




```
ols_test_breusch_pagan(regression)
```

```
##
##  Breusch Pagan Test for Heteroskedasticity
##  -----------------------------------------
##  Ho: the variance is constant
##  Ha: the variance is not constant
##
##                     Data
##  ---------------------------------------------
##  Response : logValuationYear
##  Variables: fitted values of logValuationYear
##
##         Test Summary
##  ----------------------------
##  DF            =    1
##  Chi2          =    0.9050208
##  Prob > Chi2   =    0.341439
```

```
summary(regression)
```

```
##
## Call:
## lm(formula = logValuationYear ~ Syndication + CrossBorder + Emplo
yees +
##     Segment + Age + GrowthStage + Industry + RoundType + Country,
##     data = dataset_model)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -2.4205 -0.5660  0.0522  0.5610  2.4836
##
## Coefficients:
##                           Estimate Std. Error t value Pr(>|t|)
## (Intercept)              0.5699130  0.1396643   4.081 4.99e-05 *
**
## SyndicationYes           0.2999880  0.0764512   3.924 9.53e-05 *
**
## CrossBorderYes           0.1452626  0.0711765   2.041 0.041621 *
## Employees                0.0074943  0.0005824  12.868  < 2e-16 *
**
## SegmentUpstream          0.2237121  0.0707407   3.162 0.001629 *
*
## Age                      0.1542287  0.0153584  10.042  < 2e-16 *
**
## GrowthStageearly growth  0.4114623  0.1287069   3.197 0.001449 *
*
## GrowthStagelate growth   1.0110459  0.1343653   7.525 1.55e-13 *
**
## Industryspace            0.2625354  0.1016192   2.584 0.009972 *
*
## RoundTypeEARLY VC        0.5846491  0.1097796   5.326 1.34e-07 *
**
## RoundTypeGRANT           0.3273575  0.1072255   3.053 0.002348 *
*
## RoundTypeSERIES A        0.8383827  0.1043387   8.035 3.74e-15 *
**
## RoundTypeSERIES B        1.1960678  0.1537772   7.778 2.51e-14 *
**
## RoundTypeSERIES C       -0.0485029  0.2494717  -0.194 0.845899
## RoundTypeOther           0.3437011  0.1008695   3.407 0.000692 *
**
## CountryTop5_SpaceEconomy  0.2405093  0.0670565   3.587 0.000357 *
**
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.85 on 732 degrees of freedom
## Multiple R-squared:  0.6543, Adjusted R-squared:  0.6472
## F-statistic: 92.34 on 15 and 732 DF,  p-value: < 2.2e-16
```

```
anova(regression)
```

	Df	Sum Sq	Mean Sq	F value	Pr
	<int>	<dbl>	<dbl>	<dbl>	<
Syndication	1	91.293559	91.2935591	126.371697	3.698706
CrossBorder	1	41.014739	41.0147391	56.774018	1.445515
Employees	1	508.033973	508.0339727	703.238167	3.987623e
Segment	1	38.822942	38.8229418	53.740057	6.071421
Age	1	103.423258	103.4232582	143.162045	2.926618
GrowthStage	2	122.972300	61.4861498	85.111252	5.837917
Industry	1	4.442772	4.4427718	6.149838	1.336631
RoundType	6	81.378121	13.5630201	18.774401	2.202788
Country	1	9.293345	9.2933451	12.864169	3.572020
Residuals	732	528.812123	0.7224209	NA	

1-10 of 10 rows