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Mapping venture capital investments in the (new) space economy with large language models: a comparative analysis of Europe and the United States

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Abstract

This paper maps Venture Capital (VC) investments received by startups operating in the new space economy located in European countries and the United States of America (US). Relying on a Large Language Model few-shot learning text-based classification methodology implemented via the GPT-5 model, we classify 113,910 VC-backed startups from the PitchBook database and identify 2,336 space startups. Results show that European VC-backed startups are relatively more specialized in the new space economy compared to their US counterparts. However, they raise lower amounts of capital, receive fewer VC rounds, less quickly, and are backed by smaller VC syndicates. They are also less likely to exit via IPO or merger and acquisition. These weaknesses are similar to those European VC-backed startups experience in other industries. Our results highlight that, despite their attractiveness to VC investors, European space startups suffer from the relative underdevelopment of the European VC industry. Overall, this paper provides an original overview of the VC funding landscape in the new space economy, offering relevant insights to improve the European industrial policy in this nascent industry.

Keywords Venture capital · Startups · Space economy · Europe · United States

JEL Classification G24 · L26

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1 Introduction

The new space economy is a nascent industrial sector flourishing worldwide, with a projected market value of 1.8 trillion dollars by 2035 (World Economic Forum, 2024). Stemming from the traditional space sector, whose core activities historically consisted of space exploration and scientific research, the "new" space economy has recently emerged following technological breakthroughs, like reusable launch rockets, the miniaturization of satellites and their payloads, and advancements in data communication relating to satellite mega-constellations (Parrella et al., 2022; Punnala et al., 2024; Weinzierl, 2018). Such technological developments have substantially lowered the costs to access space, reducing entry barriers into a sector traditionally populated by large incumbents and public organizations (Lamine et al., 2021). They have also expanded the scope of traditional space applications and related activities, opening up opportunities to create and extract value from space-derived products, services, and knowledge (Veugelers et al., 2025; Vittori et al., 2022). These technological breakthroughs and structural changes have thus kick-started entrepreneurial efforts in this nascent industry and favored the participation of new, private actors (Draghi, 2024).

However, the extent to which startups have been able to seize and benefit from these new business opportunities has varied substantially across countries, particularly between the United States of America (US) and Europe. Startups thrived in the US. New players pioneering radical innovations rapidly scaled to dominate key industry segments, such as SpaceX in launching heavyweight, reusable rockets and managing satellite mega-constellations (through Starlink). They also generated numerous spin-offs, as those founded in the Los Angeles area by SpaceX's employees (described in Veugelers et al., 2025, pp. 64–66). Conversely, Europe still lacks similar success stories (except the UK-based satellite network operator OneWeb, acquired by Eutelsat in 2023). This gap has raised concerns about the competitiveness of the European new space economy, as entrepreneurial endeavors are paramount in promoting the emergence and growth of nascent industries (Agarwal et al., 2017).

Researchers have identified key differences between the European and US new space economies, which can allegedly be at the origin of this gap. While Europe is technologically advanced and home to excellence programs and leading incumbent players such as Airbus, BAE systems, Thales, Safran, and Leonardo, it is characterized by a fragmented institutional context, a stagnating public budget, especially in defense-related expenses, a less vibrant innovation ecosystem, and a weaker supply of private capital to new ventures, especially Venture Capital (VC) (ESA, 2025; ESPI, 2025; Veugelers et al., 2025).[1] Although all these differences may contribute to some extent to generating such a gap, we argue that weaker VC investments play a key role.

Startups are instrumental in exploiting technological discontinuities, promoting innovation (Schumpeter, 1934), economic development, and growth (Audretsch et

[1] For example, according to ESPI (2025), in 2024 US space startups raised \$2.9 billion, as opposed to \$1.5 billion for European startups. VC accounted for more than 80% of total US investment, while the VC share in Europe was less than 70%.

al., 2006). However, they suffer from specific liabilities (Gimenez-Fernandez et al., 2020), stemming from their newness (Bruderl & Schussler, 1990; Freeman et al., 1983; Stinchcombe, 1965), smallness (Aldrich & Auster, 1986), and lack of legitimacy (Aldrich & Fiol, 1994). Financial constraints are particularly binding and detrimental for these firms (Brüderl et al., 1992; Carpenter & Petersen, 2002; Musso & Schiavo, 2008; Stucki, 2013), especially in nascent industries. As traditional lenders are discouraged by information asymmetries, startups' lack of a track record, limited collateral, and the high (technological, market, and regulatory) risks associated with their activities, VC investors offer startups vital support (Denis, 2004). These investors scout for high-potential startups pursuing novel technological and business opportunities, provide them with the required capital, and "coach" them in areas where founders lack expertise (Gorman & Sahlman, 1989), thus increasing their ability to generate and capture value (Chemmanur et al., 2011; Croce et al., 2013; Engel & Keilbach, 2007; Lerner & Nanda, 2020).

The VC industry is historically less developed in Europe than in the US.[2] Investment patterns and practices have historically differed across the two geographical areas (Bertoni et al., 2015, 2019), even though European VC managers have adopted some of the best practices developed by their US counterparts (e.g., in designing VC contracts, see Le Pendeven et al., 2025). In Europe, key financial institutions such as pension funds, banks, and insurance companies are less inclined to invest in this asset class compared to their US counterparts,[3] as the EU's prudential regulation hampers innovation financing (Draghi, 2024). Therefore, public bodies, such as the European Investment Fund, BPI in France, and CDP in Italy, are the most important limited partners, operating as funds of funds. Moreover, formal institutions in Europe are less conducive to VC investments than in the US, due to a less flexible labor market regulation (Jeng & Wells, 2000) and lower investor protections (La Porta et al., 2000), with regulation favoring lenders vis-à-vis equity holders in case of bankruptcy (Armour & Cumming, 2006). Additionally, both the stock and (Jeng & Wells, 2000) M&A markets (Moschieri & Campa, 2014) are less developed and more fragmented, thus hindering VCs' exit prospects. Finally, European culture and society are more risk-averse and less supportive of individual versus collective endeavors (Li & Zahra, 2012) and recognize a lower status for entrepreneurs (Bruton et al., 2005). All these aspects are detrimental to VC investments.

Despite evidence of weaker private investment in the European new space economy compared to the US (ESPI, 2025; Veugelers et al., 2025), we lack a systematic analysis of differences in VC funding dynamics for space startups between Europe and the US. The goal of this paper is to start addressing this gap. For this purpose, we first built a census of VC-backed space startups located in these areas, since there is no publicly available database of this kind. Starting from all firms in the Pitch-

[2] The first VC firm was established in the US in 1946, and the first limited partnership in 1958, while in Europe, the VC industry started developing in the 70s. The US National Venture Capital Association was founded in 1975, while the corresponding European association was established only a decade later.

[3] As stated by Ekaterina Zaharieva, European Commissioner for Startups, Research and Innovation in the 2025 report *Venture & growth capital in Europe – mapping pension funds' attitudes*, available at https://www.europeanwomenvc.org/report-2025 (last accessed on November 2025), EU pension unds allocate less than 0.1% of their assets to VC.

Book database, we sampled startups headquartered in European countries, the United Kingdom (henceforth, as shorthand notation, both referred to as EU) and the US, that were founded from 2005 onwards and have completed at least one round of VC financing. Employing an original Large Language Model (LLM) few-shot learning text-based classification methodology implemented via the GPT-5 model, we then classified the resulting sample of 113,910 VC-backed startups as either active in the new space economy or not and assigned them to industry segments and sub-categories, as defined by OECD guidelines (OECD, 2022). We validated this classification method by benchmarking its performance against an earlier classification of space-economy startups completed by trained research assistants, confirming its soundness and reliability.

Overall, we identified 2,336 space startups, observed from January 2005 up to February 2025. We analyzed their VC funding dynamics and comparted them between US and EU startups, considering the number and speed of VC rounds, the amount of capital raised, the number of VC investors involved, as well as their exits. Our results show that VC-backed space startups based in the EU are relatively more specialized in the new space economy, given the higher share of VC-backed startups active in this nascent industry compared to the US. However, EU VC-backed space startups complete fewer VC rounds, less quickly, raise lower amounts of capital, and are backed by smaller VC syndicates than US startups. In particular, on average, US space startups complete their 1st VC round 3 months earlier than their European counterparts, raising 2.8 times as much capital, and are backed by one additional VC investor. Finally, a higher share of US startups complete an IPO or exit via M&A over the period considered. These differences are similar across upstream, downstream, and space-derived segments. Post-hoc analyses show that such differences have not been reducing over time and that similar differences exist between EU and US VC-backed non-space startups. Results thus highlight how the observed differences are not specific to the space economy, but rather stem from the relative underdevelopment of the European VC industry.

This paper offers valuable contributions to both scholars and policymakers. First, we systematically investigate and document the weaknesses in funding startup development in the new space economy characterizing Europe compared to the US. The shortage of VC resources and investors is a fundamental issue that risks jeopardizing policy initiatives specific to the space economy, such as larger-scale public procurement oriented to favoring the entry of innovative new players, and should be tackled at the European level (e.g., through regulatory changes that remove the traditional aversion of European financial institutions to this asset class). Second, our employment and validation of an LLM-based classifier contribute to the recent stream of scholarly research exploring their effectiveness in large-scale categorization exercises (Carlson & Burbano, 2025). Third, in so doing, we also contribute to the broader literature on venture capital and entrepreneurial finance, highlighting the effectiveness of a new methodological tool that can be instrumental in investigating these phenomena in challenging settings such as nascent industries.

2 Method and data

2.1 Method

Identifying firms active in nascent industries, such as the new space economy, poses a significant challenge for researchers, given the unreliability of traditional industry classification systems like the NACE or SIC industry codes. These classifications are static and backward-looking, failing to capture the nuances of dynamic, evolving industrial sectors that often span the boundaries of existing ones.

Text-based classification techniques offer a solution to this issue, as the analysis of textual data directly related to firms, such as descriptions of their activities and self-reported statements, allows to pinpoint firms' actual operational focus through contextual analysis. They have already proved effective in assessing startup differentiation (Guzman & Li, 2023) and the uniqueness of technology portfolios (Arts et al., 2025). Text-based classification is a fundamental task in natural language processing, in which text is categorized into predefined labels or classes based on its content. Initially undertaken by human evaluators, these classifications are now mostly performed via machine learning (ML) and deep learning (DL) methods. However, despite their effectiveness, their key limitation is the dependence on extensive, task-specific labelled training datasets (Wang et al., 2023).

In this study, we employ a Large Language Model (LLM) few-shot learning text-based classification methodology to classify firms based on their descriptions and self-reported industry tags. LLM-based techniques have recently emerged as a promising alternative to ML and DL methods, achieving remarkable performance on complex classification tasks by leveraging their ability to learn from minimal data through in-context learning (Carlson & Burbano, 2025; Kostina et al., 2025). This approach harnesses LLMs' reasoning ability, combining a capable model with a robust prompting strategy that provides essential domain knowledge (Fechner & Dörpinghaus, 2024). This provides a distinctive advantage when labelled data is scarce or unavailable.

Specifically, we use the GPT-5 (OpenAI) model and engineer a detailed prompt that includes the definitions of the categorization to be performed, followed by one clear example for each proposed category. LLM prompting can be either zero-shot learning (ZSL), where the model is provided only with task instructions, or few-shot learning (FSL), where a small number of examples is also provided to guide the model's response (Brown et al., 2020). Examples provide crucial context to the model, significantly improving upon ZSL performance, which can be inconsistent when the task formats deviate from the model's pre-training data (Brown et al., 2020). In fact, human evaluators may also struggle to understand a task format without prior examples. Moreover, LLM FSL reduces the need for a large, custom-labelled dataset, which is both time-consuming and computationally expensive to produce (Brown et al., 2020; Wang et al., 2023). While this LLM-based method incurs a higher inference cost (i.e., the time and computational resources needed to classify each firm) compared to traditional, fine-tuned ML and DL models, these are becoming increasingly negligible given the efficiency of modern LLM API services and are arguably outweighed by adaptability, accuracy, and savings gained from the elimination of the extensive human data labelling, pre-processing, and feature extraction (Kostina et al., 2025; Wang et al., 2024).

Our prompt design follows recent methodological guidance on LLM-based data annotation in management research (Carlson & Burbano, 2025) and uses official definitions (OECD, 2022), ensuring transparency, external validation, and replicability.

2.2 Data and variables

To investigate VC funding dynamics in the new space economy, we first need to identify VC-backed space startups. For this purpose, we rely on PitchBook, a comprehensive commercial database that provides information on over 4,000,000 companies worldwide and collects historical investment data across both private and public equity markets.

In line with existing literature, we define a space startup as "*a new business entity that develops space technologies*, *products*, *or services*, *such as satellite or launch vehicle manufacturing*, *ground equipment production*, *space-based services*, *or data analytics integrating space and terrestrial systems*" (BRYCE, 2018, p.1; Lamine et al., 2021). Before categorizing startups as belonging to this nascent industry, we select them based on their founding year, geographic location, and funding status, consistent with the goal of our analysis. First, given the recent emergence "new" space economy, we consider startups with a non-missing founding year that were founded from January 2005 through February 2025. Second, we consider startups headquartered in European countries[4] or the United Kingdom (as shorthand notation, both referred to as EU), and the US. Third, we consider only startups that received at least one VC investment round between January 2005 and February 2025. In particular, we isolate startups completing at least one investment round labelled as "Seed round", "Early VC round", or "Later VC round" and involving at least one investor labelled as "Venture Capitalist" by PitchBook. We thus exclude other forms of financing (e.g., private equity or angel investing) and investments that failed or were still pending as of February 2025. The resulting sample comprises 113,910 VC-backed startups, of which 47,981 (42.12%) are headquartered in the EU and 65,929 (57.88%) in the US.

To identify space startups, we rely on a LLM FSL text-based classification model implemented via GPT-5. We also employ the classifier to categorize startups across the three main segments characterizing this industry, namely *upstream*, *downstream*, or *space-derived*, defined in line with OECD guidelines (OECD, 2022).[5] The full prompt provided to the classifier is reported in Appendix A, Supplementary Material 1. The upstream segment includes firms undertaking activities primarily related to the scientific and technological foundations of space activities, such as satellite manufacturing and launch. The downstream segment includes firms whose activities are primarily focused on providing "down-to-earth" services and products based on space technologies (such as data or signals produced by satellites). Finally, space-

[4] Namely: Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, and Sweden.

[5] Further details on the subcategories' definitions are in Table B1, Appendix B, Supplementary Material 1.

derived startups perform "activities that are derived/induced from space activities but are not dependent on it to function (e.g., technology transfers from the space sector to the automotive or medical sectors)" (OECD, 2022, p.30). We further unpack each segment into subcategories. For this purpose, we feed GPT-5 with a second prompt including seven upstream subcategories (namely: *Design & manufacturing; Integration and supply of full systems; Supply of materials and components; Future activities; Scientific & engineering support; Ancillary services; Research*) and five downstream subcategories (namely: *Supply of consumer services; Supply of data-added-value services; Supply of devices; Systems operations (space & ground); Data distribution services*), followed by an example for each of them. This second prompt is also available in Appendix A.

Of 113,910 startups, 2,336 were identified as active in the new space economy. To investigate differences in VC funding dynamics between EU and US startups, we consider the number of completed VC rounds, their timing, the amount of capital startups raised, and the number of VC investors per round. Furthermore, we consider the status of startups as of February 2025, distinguishing between VC-backed startups that were out of business, had a successful exit via a merger or an acquisition (M&A) or an initial public offering (IPO), and were still active and privately held.

2.3 Validation of the FSL LLM-based classification

To assess the goodness and robustness of our method, we follow recent guidelines and best practices (Carlson & Burbano, 2025) and benchmark the classification obtained via our FSL LLM-based classifier against one produced by human experts. In particular, we consider a classification performed manually by two trained research assistants on a sample of 834 startups, which was instrumental in building the dataset analyzed in Cavallo et al. (2025). Although such sample and classification were not produced for the purpose of this specific validation exercise, they offer a suitable benchmark because they were built with the same goal: identifying startups active in the new space economy, either in the upstream or downstream segment, considering PitchBook data and firms' descriptions.[6]

We thus use the same FSL LLM-based classifier presented above to analyze the PitchBook descriptions of the 834 startups included in this sample, code them as either active in the new space economy or not, and, if so, as either in the upstream or

[6] Further details are available in Cavallo et al. (2025). Here, we provide a brief summary of the procedure employed to identify and classify the sample of space startups. Startups included in the PitchBook database were first selected based on founding year (from 2005 onwards) and geographic location (European countries), regardless of whether they received VC investment. They were then filtered using an array of keywords, validated by industry experts, which synthesized the nature of activities and technologies underlying the new space economy. The resulting set of startups was then independently evaluated and classified by the two research assistants, who were first trained to ensure they were knowledgeable about the new space economy. They classified startups independently, but dubious cases were discussed with one of the study's authors. A key difference with the current classifier is that research assistants may not have limited their judgment to PitchBook descriptions, but may also have consulted firms' websites. Nevertheless, this does not impair this validation exercise, but arguably makes it even more binding, increasing the precision of the benchmark.

downstream segments.[7] Out of 834 startups, research assistants agreed on the classification of 815 (Cohen's Kappa coefficient for inter-rater agreement 94.7%), highlighting the challenges faced when evaluating information on startups potentially active in nascent industries. We consider this consensus sample as our benchmark. In robustness checks, we also consider the individual classifications performed by the two researchers.

We rely on confusion matrices to compare classification results from our LLM-based method with those from the two research assistants' method. We categorize results as True Positives (TP) and True Negatives (TN) when both our model and research assistants were unanimous in classifying startups as either space or non-space. Conversely, False Positives (FP) are startups classified as space by our model but non-space by research assistants, while False Negatives (FN) are startups classified the opposite way. We then calculate the metrics of precision, recall (or sensitivity), and accuracy, as well as the F1-score (Schütze et al., 2008).[8] Table 1 (Panel A) summarizes the performance metrics for the consensus sample. The full confusion matrices, including robustness checks for the individual researchers (referred to as R_A and R_B), are detailed in Table C1 of Appendix C, Supplementary Material 1. Results highlight the robust and consistent performance of our algorithm when benchmarked against the researchers' classification. The algorithm achieved 90.9% precision, 88.7% recall, 86.0% accuracy, and an F1-score of 89.8%, underscoring its high reliability.

We then replicate this validation for the *upstream* and *downstream* segments. The performance of our classifier was benchmarked against a consensus sample of 728 startups that research assistants unanimously categorized as upstream, downstream, or unclear (N/A). Table 1 (Panel B) reports the performance metrics for this classification. Detailed confusion matrices and robustness checks for each assistant's classification are provided in Table C2 of Appendix C. The robust performance of the FSL LLM-based classifier is confirmed, as the model's classification accuracy is 84.1% for the downstream segment, 90.7% for the upstream segment, and 87.3% for

Table 1 LLM validation, performance metrics

	Panel A	Panel B			Panel C
	Space vs. Non-space	Downstream	Upstream	*N*/A	Space vs. Non-space, ESA BICs
Precision	0.909	0.759	0.892	0.820	0.911
Recall	0.887	0.857	0.748	0.801	0.932
Accuracy	0.860	0.841	0.907	0.873	0.857
F1 score	0.898	0.805	0.813	0.873	0.921

[7] Classifying startups in the space-derived sub-category was not part of the researcher assistants' original task, since this category was excluded from the analysis of Cavallo et al. (2025).

[8] *Precision* measures the validity of the model's positive predictions (i.e., the percentage of identified "space" ventures that are truly space ventures). *Recall* measures the model's completeness (i.e., the percentage of all actual space ventures that the model managed to find). *Accuracy* reflects the ratio of correct predictions (both positive and negative) to the total number of observations. The F1-score provides the harmonic mean of precision and recall, serving as a robust metric particularly useful when class distributions are imbalanced.

the residual category (N/A). Furthermore, in line with researchers' task, our model classified only two firms as space-derived.

Although expert-coded classifications offer a compelling benchmark (Carlson & Burbano, 2025), we conduct an additional, more stringent validation exercise by cross-checking such classifications against an external data source comprising startups supported by the European Space Agency's Business Incubation Centers (ESA BICs).[9] Within our expert-classified sample, we identified 149 ESA-BIC-supported startups (out of 834). Startups are incubated only after passing a rigorous selection process, which allows them to access financing, laboratories, professional services, and networking opportunities. Therefore, being supported by ESA BICs can be considered a gold-standard benchmark for startups that are indeed active in the new space economy. Of note, PitchBook descriptions of startups' activities may still provide insufficient information to classify them as space startups. Therefore, comparing whether our LLM-based classifier and research assistants both succeed or fail in classifying incubated startups provides a clear indication of their ability to effectively process the information actually available.

For the 149 ESA BIC startups, the research assistants reached consensus on 147 startups (Cohen's Kappa coefficient of 98.66%). When benchmarked against this consensus sample, our classifier performed remarkably well, achieving 91.1% precision, 93.2% recall, 85.7% accuracy, and a F1-score of 92.1% (Table 1, Panel C; further detail is reported in Table C3 of Appendix C). Discrepancies primarily occurred among the 15 startups out of 147 that researchers categorized as non-space, 12 of which were classified as space by our classifier. This finding reinforces the LLM classifier's sensitivity and highlights the non-trivial challenges inherent in classification tasks of firms in nascent industries.

3 Results

3.1 The distribution of VC-backed space startups

Table 2 reports the geographical distribution of the 2,336 VC-backed space startups' headquarters. 1,254 startups are headquartered in the US (53.16%), while 1,082 are in the EU (46.32%). Since 42.03% of the startups included in the remaining PitchBook sample are based in the EU, we deduce that EU VC-backed startups are relatively more specialized in this nascent industry than their US counterparts. Nearly half of the EU startups are located in three countries, namely the United Kingdom (UK) (23.11%), France (15.16%), and Germany (10.44%), followed by Spain (7.49%) and Italy (5.73%). Comparing these data with the national shares of VC-backed startups in PitchBook shows that the UK and Germany are relatively less specialized in the new space economy compared to other European countries, while France, Spain, and particularly Italy are relatively more specialized.

[9] For further information, the Reader may refer to https://commercialisation.esa.int/esa-business-incubation-centres/ (last accessed on November 2025).

Table 2 Distribution of startups, by headquarter location

	Space startups		Pitchbook startups	
	N. space startups	Share (%)	*N.* non-space startups	Share (%)
EU	1,082	46.32	46,899	42.03
US	1,254	53.16	64,675	57.97
Total	2,336	100.00	111,574	100.00
within EU				
United Kingdom	250	23.11	12,249	26.12
France	164	15.16	6,203	13.23
Germany	113	10.44	6,085	12.97
Spain	81	7.49	2,830	6.03
Italy	62	5.73	1,570	3.35
Netherlands	62	5.73	2,824	6.02
Sweden	60	5.55	2,985	6.36
Poland	37	3.42	1,525	3.25
Belgium	36	3.33	1,426	3.04
Ireland	36	3.33	1,698	3.62
Finland	28	2.59	1,374	2.93
Denmark	25	2.31	1,539	3.28
Portugal	24	2.22	588	1.25
Austria	15	1.39	705	1.50
Lithuania	14	1.29	280	0.60
Estonia	11	1.02	484	1.03
Hungary	11	1.02	663	1.41
Czech Republic	10	0.92	370	0.79
Others	43	3.97	1,501	3.22
Sub-total	1,082	100.00	46,899	100.00

Figure 1 plots the founding years of sampled startups, which peaked in 2015, with more than 200 startups incorporated. The number of incorporations steadily declined afterwards. On average, sample startups are 9.74 years old, with minor, weakly statistically significant differences between US (9.88 years old) and EU (9.57 years old) startups (t-test=-1.689, p-value = 0.091).

Table 3 shows the joint distribution of space startups by segment and geographic area. 1,629 out of 2,336 startups (69.73%) operate in the downstream segment, while 355 and 359 startups respectively operate in the upstream (15.07%) and space-derived segments (15.20%). The distribution of startups across the three segments, however, is statistically different between the two geographical areas (Pearson's test $\chi^2(2) = 6.876$, p-value = 0.032). The upstream segment accounts for a higher share of VC-backed startups in the US (211 startups, 16.83%) than in Europe (144 startups, 13.31%), while the opposite holds for the downstream segment (848 US startups vs. 781 EU startups, respectively 67.62% and 72.18%). This evidence mirrors the dominance of the US in the upstream segment of the space economy and the presence in this segment of young US firms like SpaceX, which have become world leaders, pioneering radically new technologies (Veugelers et al., 2025).

Table 4 illustrates the distribution of US and EU startups across all upstream and downstream segment subcategories. Overall, among upstream startups, the majority conduct activities related to Design & manufacturing (32.39%) and to the Integra-

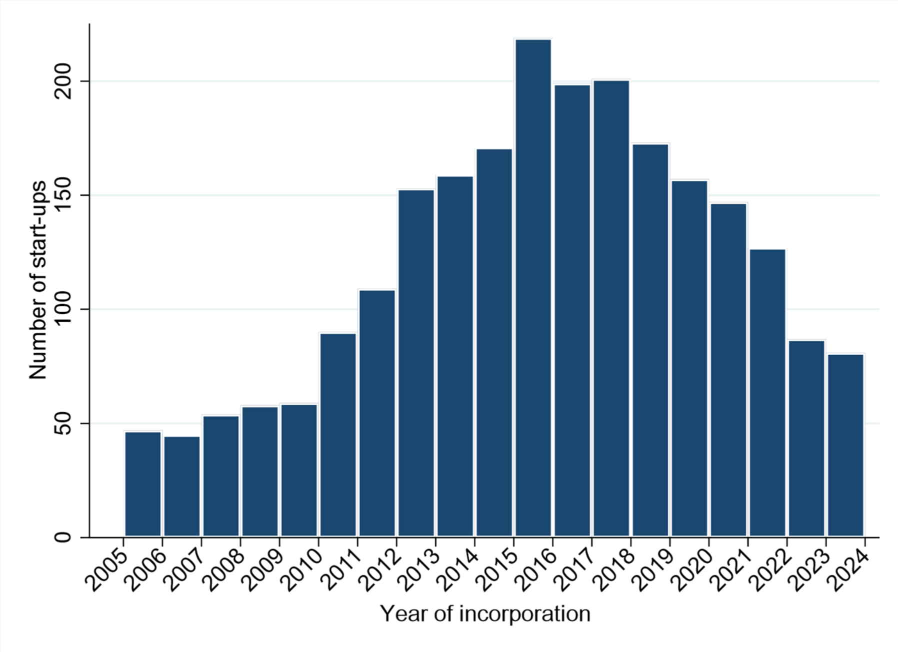

Fig. 1 Number of startups created over the years

Table 3 Distribution of startups, by segment and geographic area

	EU		US		Total	
	N.	Share (%)	*N.*	Share (%)	*N.*	Share (%)
Upstream	144	13.31	211	16.83	355	15.20
Downstream	781	72.18	848	67.62	1,629	69.73
Space-derived	157	14.51	195	15.55	352	15.07
Total	1,082	100.00	1,254	100.00	2,336	100.00

tion and supply of full systems (27.61%), followed by the Supply of materials and components (13.80%). The distribution of upstream subcategories does not differ significantly between EU and US ($\chi^2(6)=4.583$, p-value $=0.598$). Among downstream startups, the majority fall within the Supply of consumer services (64.52%), Supply of data-added-value services (17.19%), and Supply of devices for consumers (12.38%). In this case, geographical differences are significant ($\chi^2(2)=20.410$, p-value $=0.000$), with EU startups being relatively more specialized in the Supply of data-added-value services and devices.

3.2 VC funding and exits: general evidence

Overall, the 2,336 space startups in our sample completed 4,553 VC investment rounds over the observation period. On average, space startups completed 1.95 VC rounds (the median is 1) across all segments. The distribution of rounds across space-

Table 4 Distribution of startups, by sub-category and geographic area

Segment	Sub-categories	EU N.	EU Share (%)	US N.	US Share (%)	Total N.	Total Share (%)
Upstream	Design & manufacturing	53	36.81	62	29.38	115	32.39
	Integration and supply of full systems	37	25.69	61	28.91	98	27.61
	Supply of materials and components	19	13.19	30	14.22	49	13.80
	Future activities	13	9.03	27	12.80	40	11.27
	Scientific & engineering support	17	11.81	21	9.95	38	10.70
	Ancillary services	5	3.47	8	3.79	13	3.66
	Research	0	0.00	2	0.95	2	0.56
	Total	144	100.00	211	100.00	355	100.00
Downstream	Supply of consumer services	480	61.46	571	67.33	1,051	64.52
	Supply of data-added-value services	157	20.10	123	14.50	280	17.19
	Supply of devices	113	14.47	96	11.32	209	12.83
	Systems operations (space & ground)	23	2.94	35	4.13	58	3.56
	Data distribution services	8	1.02	23	2.71	31	1.90
	Total	781	100.00	848	100.00	1,629	100.00

economy segments is almost identical to the distribution of startups, with 15.14% of rounds involving upstream startups, 69.71% involving downstream startups, and 15.15% involving space-derived startups. Figure 2 plots the number of rounds by completion year, from 2005 to 2024[10]. The number of completed rounds consistently rose from 7 in 2005 to a peak of 511 in 2021, but declined afterwards. The pattern differs across the three segments of the space economy. In particular, while the drop in the number of VC rounds is marked for downstream startups and less so for space-derived ones, the number of VC rounds continues increasing for upstream startups (see Fig. 3a). However, when distinguishing 1st and subsequent rounds (Fig. 3b and c), we observe that the number of 1st rounds drops from 2021 onwards across all segments. The rising trend for upstream startups is determined by a higher number of subsequent rounds.

Table 5 provides descriptive statistics on the time elapsed from startup founding to VC rounds (in years), the amount of capital raised (in millions of $), and the number of VC investors per round across the three segments. Overall, space startups received their first VC round 2.38 years after founding, the second round after 3.64 years, and subsequent rounds after 5.99 years. There are no statistically significant differences in the time elapsed from founding to the first, second, and following VC rounds between startups in the upstream and downstream segments. Conversely, space-derived startups received VC rounds on average later than other startups, with the difference being statistically more significant when they are compared to downstream rather than upstream startups and in rounds from the 2nd onwards.

Space startups raised on average $24.3 million per round. However, the distribution is skewed: in half of the rounds, they raised no more than $3 million. The average funding in the first and second VC rounds is significantly higher in the upstream

[10] Information on completion dates is non-missing for 4,286 rounds out of 4,553. Furthermore, only 3 rounds were completed in 2025 (January and February). Year 2025 is therefore not included in the Figures.

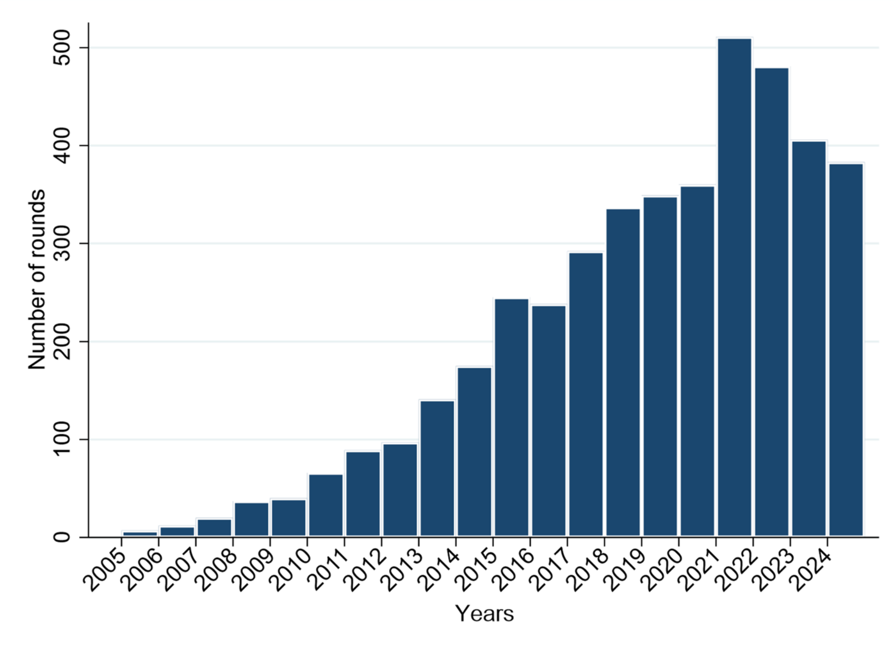

Fig. 2 Number of VC rounds completed by startups over the years

segment than in the others (except for the difference between the upstream and space-derived segments in the 2nd round, which is close to statistical significance). Specifically, the average amounts raised in the 1st and 2nd rounds by upstream startups are $4.06 million and $13.8 million respectively, compared to $2.91 million and $8.18 million for downstream startups and $2.84 million and $8.76 million for space-derived startups. Conversely, at an average of $21.2 million, the amount raised by space-derived startups in the following rounds is significantly smaller than that of both upstream ($41.2 million) and downstream ($68.6 million) startups.

The average number of investors per round is 3.15. The number of investors increases over rounds, averaging 2.24 in the 1st round, 3.3 in the 2nd, and 4.28 thereafter (median values increase gradually from 1 to 2, and then to 3). Overall, upstream startups are backed on average by 3.71 investors per round, downstream startups by 3.19, and space-derived startups by 2.43. This ranking remains consistent across rounds, and differences are statistically significant at conventional confidence levels (the only exception relates to the difference between upstream and downstream startups in rounds from the 3rd one onwards).

Table 6 presents descriptive statistics on startups' exits. Overall, 390 space startups went through a successful exit (IPO or M&A, 16.7% of the total), mostly through an M&A (359 startups). 360 startups ceased operations (15.4%). The large majority were still privately held and independent at the end of the observation period. Startups' exit patterns are statistically different across segments (Pearson's $\chi^2(2)$ test = 108.592, p-value = 0.000). Upstream startups are the most likely to complete an IPO (2.25%), but also the least likely to exit via M&A (6.76%) or be out of business

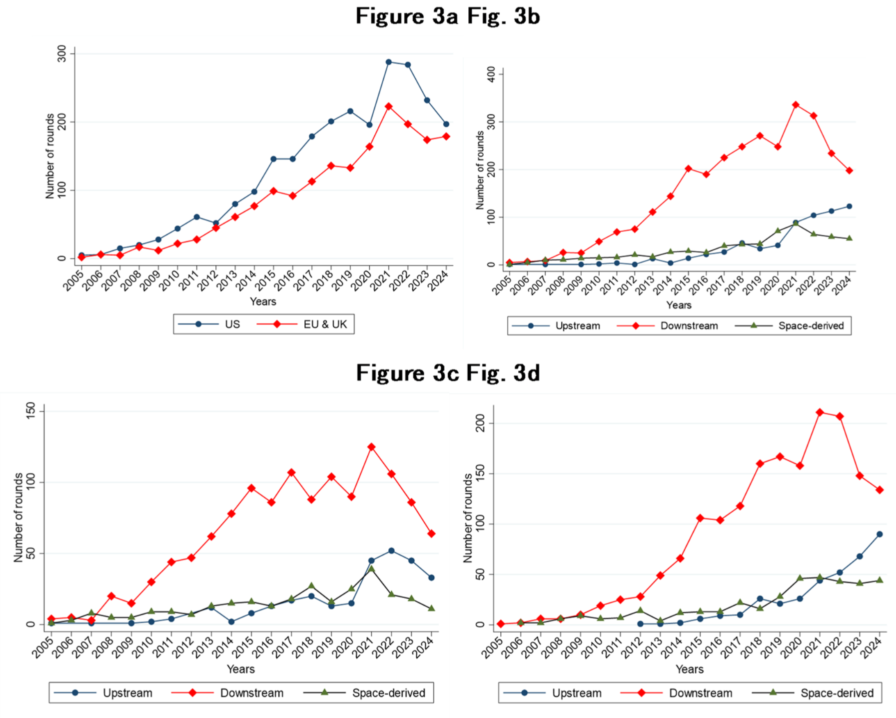

Fig. 3 Number of VC rounds completed by startups over the years by geographic area (**a**), by segment (**b**), by segment and considering only 1st VC rounds (**c**), by segment and considering only rounds from the 2nd onwards (**d**)

(4.51%). Downstream startups are the least likely to be still privately held and independent as of February 2025 (61.82%) and are more likely than other space startups to be out of business (18.85%) or acquired (18.11%).

3.3 VC funding and exits: comparing US and EU startups

In this section we compare VC funding dynamics of EU and US space startups and their exit outcomes. US startups account for 57.59% of VC rounds (2,622 out of 4,553), a relatively higher share than EU startups (42.41%), despite representing 46.32% of the startups in our sample. Consequently, the average number of VC rounds per startup is significantly higher in the US than in Europe (2.09 vs. 1.78; t-test = 5.061, p-value = 0.000).

In Table 7 we show by area the time elapsed between the foundation of US and EU startups and their 1st, 2nd, and follow-on VC rounds, the average capital raised in these rounds, and the average number of VC investors involved. US startups completed their 1st VC round on average about 3 months earlier than their EU counterparts (2.27 years in the US vs. 2.51 years in the EU, t-test = 2.124, p-value = 0.034). Although the time between founding and the 2nd VC round is not statistically different across the two geographic areas (3.54 years vs. 3.78 years, t-test = 1.48,

Table 5 Descriptive statistics on VC rounds, by segments

Panel A: Descriptive statistics

		Time				Amount				Number of investors			
Overall	VC round	N	Mean	SD	p50	N	Mean	SD	p50	N	Mean	SD	p50
All space	Overall	4,286	3.91	3	3	3,520	24.3	134	3	4,553	3.15	3.32	2
	1st round	1,825	2.38	2.35	2	1,387	3.08	6.66	1.2	2,040	2.24	2.16	1
	2nd round	990	3.64	2.44	3	857	9.13	22	3.4	1,018	3.3	2.82	2
	other rounds	1,471	5.99	2.84	6	1,276	57.6	218	10	1,495	4.28	4.39	3
By segment													
Upstream	Overall	643	3.86	3.12	3	523	19.2	66.9	4.02	690	3.71	3.76	2
	1st round	284	2.43	2.6	2	214	4.06	8.95	1.89	323	2.61	2.62	2
	2nd round	155	3.77	2.69	3	130	13.8	35.1	5.14	161	4.42	4.14	3
	other rounds	204	5.9	2.98	6	179	41.1	107	10	206	4.87	4.42	3
Downstream	Overall	2,988	3.83	2.89	3	2,454	28.4	157	3	3,174	3.19	3.42	2
	1st round	1,262	2.33	2.23	2	960	2.91	6.23	1.16	1,413	2.24	2.17	1
	2nd round	677	3.46	2.27	3	589	8.18	18.4	3.16	694	3.19	2.55	2
	other rounds	1,049	5.87	2.75	6	905	68.6	252	10.5	1,067	4.44	4.65	3
Space-derived	Overall	655	4.35	3.31	4	543	10.8	34.4	2.57	689	2.43	2	2
	1st round	279	2.58	2.6	2	213	2.84	5.71	1.06	304	1.88	1.43	1
	2nd round	158	4.27	2.76	4	138	8.76	19.9	3	163	2.67	1.93	2
	other rounds	218	6.67	3.06	6	192	21.2	53.4	6.24	222	2.99	2.46	2

Panel B: t-tests, differences in means (H0: no difference)

	Overall	1st r.	2nd r.	other r.	Overall	1st r.	2nd r.	other r.	Overall	1st r.	2nd r.	other r.
Upstream vs. Downstream	0.217	0.671	1.496	0.157	-1.323	2.222	2.609	-1.432	3.556	2.66	4.825	1.226
	[0.828]	[0.502]	[0.135]	[0.875]	[0.186]	[0.027]	[0.009]	[0.152]	[0.000]	[0.008]	[0.000]	[0.220]
Upstream vs. Space-derived	-2.743	-0.673	-1.597	-2.596	2.575	1.682	1.467	2.301	7.906	4.26	4.897	5.477
	[0.006]	[0.501]	[0.111]	[0.010]	[0.010]	[0.093]	[0.144]	[0.022]	[0.000]	[0.000]	[0.000]	[0.000]
Downstream vs. Space-derived	-4.038	-1.635	-3.847	-3.819	2.602	0.172	-0.327	2.591	5.636	2.73	2.467	4.512
	[0.000]	[0.102]	[0.000]	[0.000]	[0.009]	[0.864]	[0.744]	[0.009]	[0.000]	[0.006]	[0.014]	[0.000]

Note: t-values reported; p-values in squared brackets p-value = 0.139), the one between founding and VC rounds from the 3rd onwards is again significantly shorter for US space startups than for EU ones (5.88 vs. 6.18 years, t-test = 1.92, p-value = 0.055).

Even more interesting, our results highlight a large funding gap between EU and US space startups. In particular, while EU startups raised on average $12.1 million, US firms raised $32.7 million, 2.7 times the amount, with the difference being highly statistically significant (t-test = 4.503, p-value = 0.000). The median values confirm this difference, being respectively $1.73 million and $4.84 million, 2.8 times the amount. The gap persists when distinguishing among the 1st, the 2nd, and the subsequent VC rounds. US startups raised, on average, more than twice as much as EU startups across all rounds, and differences are all highly significant. In addition, US startups are backed by more VC investors across all rounds than their EU peers. The difference is equal to at least one investor and is statistically significant (p-values < 0.001).

In Table 8 we compare the exit outcomes of US and EU space startups. The distribution of US startups across the four outcomes is significantly different from that of EU startups (Pearson $\chi^2(3) = 13.665$, p-value = 0.003). A higher share of US space startups has gone through an IPO or exited via M&A than EU startups (IPO: 1.7% vs. 0.9%; M&A: 17.5% vs. 12.8%). The share of startups that ceased operations is comparable (15.6% in the US and 15.3% in the EU). Conversely, the share of startups that were still independent and privately held at the end of the observation period is higher in the EUthan in the US (71.0% vs. 65.2%).

To further investigate startups' exit modes, we consider a discrete time competing risk model estimating a multinomial logit model with robust standard errors. The dependent variable is the hazard rate of three competing events, namely exit via *M&A*, exit via *IPO*, or going *Out of business*. The time elapsed between founding and exit events is measured in years. Startups remaining privately held and independent up to the end of the observation period (i.e., survived) are censored and serve as the baseline category. The key explanatory variable is *US*, a dummy equal to 1 for US space startups and 0 for EU ones. We also control for the segment in which startups operate, considering the dummy variables *upstream* and *downstream*, equal to 1 for each corresponding segment and 0 otherwise (*space-derived* is the baseline). We further control for startups' *entry cohorts*, considering if they were founded between 2011 and 2015, between 2016 and 2020, or after 2020 through a set of dummy variables (those founded prior to 2010 are the baseline). Finally, we include time-varying variables capturing the (log-transformed) *amount of capital raised* and the *number of investors* in the 1st VC round, as well as the *time elapsed founding-1st round,* the number of years elapsed between founding and the first VC round (all these variables are equal to 0 up to the year of the 1st VC round.

Estimates, reported in Table 9, confirm that US VC-backed space startups are more likely to exit via M&A (β = 0.389, p-value = 0.019). With all else equal, the hazard rate of exit via M&A for US startups is on average 47.6% higher than that of their EU counterparts. As to the controls, downstream startups are more likely to exit via M&A and go out of business (respectively β = 1.038, p-value = 0.000, and β = 0.992, p-value = 0.000). A higher amount of capital received in the 1st VC round increases the risk of exit via M&A (β = 0.347, p-value = 0.000) and IPO (β = 0.687,

Table 6 Descriptive statistics on exits, by segment

	Upstream		Downstream		Space-derived		Total	
	N.	Share (%)	*N.*	Share (%)	*N.*	Share (%)	*N.*	Share (%)
IPO	8	2.25	20	1.23	3	0.85	31	1.33
M&A	24	6.76	295	18.11	40	11.36	359	15.37
Out of Business	16	4.51	307	18.85	37	10.51	360	15.41
Privately held	307	86.48	1,007	61.82	272	77.27	1,586	67.89
Total	355	100.00	1,629	100.00	352	100.00	2,336	100.00

p-value = 0.034), while it lowers the risk of going out of business (β=-0.308, p-value = 0.043). The number of years elapsed between founding and the 1st round is negatively related to all forms of exit. Conversely, a higher number of VC investors significantly increases the risk of IPO (β = 0.169, p-value = 0.006), but does not affect the other modes of exit. Finally, the entry cohort dummies have increasingly negative coefficients, as startups founded in years closer to 2025 are less likely to exit via any mode due to shorter follow-up periods.[11]

In an additional analysis, we further assess the differences between EU and US startups in terms of both VC funding and exit outcomes by comparing them separately for the three segments of the space economy. We report the results in the Supplementary Material 2, Tables D2-D3. They closely mirror those illustrated above. In particular, across all three segments, US space startups raise considerably more VC funding than their EU counterparts, from more VC investors, and are more likely to achieve a successful exit through M&A. However, the distribution of exit modes between EU and US startups significantly differs only in the downstream segments (Pearson $\chi^2(2) = 19.159$, p-value = 0.000). Among US downstream startups, there is the lowest share of privately held firms and the highest share of exits via M&A.

3.4 Post-hoc analyses

We further enrich our investigation by conducting three post-hoc analyses. First, we examine the persistence over time of the differences we highlighted in the previous sections. So far we considered differences between EU and US space startups over 20 years (2005–2025). A key question is whether the relative weaknesses of EU startups, relating especially to the amount of capital raised and the number of VC investors, persist over time or improved in the more recent period (see e.g., ESPI, 2025). We thus replicate the analysis on the sub-sample of VC deals completed from 2020 onwards (2,141 overall, 1,202 for US startups and 939 for EU startups). Results remain unchanged (see Table D4, Supplementary Material 2), though in a few cases differences in favor of US startups are only marginally significant (e.g., in the comparison of the time elapsed from foundation to the years of VC rounds), possibly due to reduced statistical power. Therefore, we deduce that the weaknesses of EU

[11] In robustness checks we further tackle this issue excluding startups founded after 2020 (Models 1–3) or censoring the period of observation from 2020 onwards (Models 4–6). Results, available in the Supplementary Material 2, Table D1, remain consistent.

Table 7 Descriptive statistics on VC rounds, by area

Panel A: Descriptive statistics

		Time				Amount				Number of investors			
		N	Mean	SD	p50	N	Mean	SD	p50	N	Mean	SD	p50
EU	Overall	1,787	3.9	2.98	3	1,434	12.1	56.4	1.73	1,931	2.37	2.13	2
	1st round	845	2.51	2.37	2	616	1.92	5.96	0.783	967	1.69	1.1	1
	2nd round	400	3.78	2.36	3	339	5.05	9	2.1	410	2.57	1.82	2
	other rounds	542	6.18	2.85	6	479	30.1	94.6	5.66	554	3.41	3.05	2
US	Overall	2,499	3.92	3.02	3	2,086	32.7	167	4.84	2,622	3.72	3.87	2
	1st round	980	2.27	2.33	2	771	4	7.04	2	1,073	2.74	2.7	2
	2nd round	590	3.54	2.49	3	518	11.8	27.1	4.91	608	3.8	3.25	3
	other rounds	929	5.88	2.83	6	797	74.1	265	14.7	941	4.8	4.95	3

Panel B: t-tests, differences in means (H0: no difference)

	Overall	1st r.	2nd r.	other r.	Overall	1st r.	2nd r.	other r.	Overall	1st r.	2nd r.	other r.
EU vs. US	-0.111	2.124	1.48	1.92	-4.503	-5.839	-4.441	-3.509	-13.885	-11.304	-6.929	-5.966
	[0.912]	[0.034]	[0.139]	[0.055]	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]

t-values reported; p-values in squared brackets

VC-backed startups documented in this study are structural and unlikely to disappear "naturally" in the future without dedicated policy interventions.

Second, we empirically assess whether the differences observed in VC funding for US and EU space startups are specific to the new space economy or indeed reflect the broader weakness of the EU VC sector compared to the US one. We thus investigate whether such differences are also observed among VC-backed non-space startups located in the same areas. To this aim, we replicate the analyses considering the PitchBook sample composed of 111,574 VC-backed startups classified as not active in the new space economy (i.e., the initial sample of 113,910 startups excluding the 2,336 space startups identified). We then compare the results, reported in the Supplementary Material 2, Tables D5-D6, with those illustrated in the previous section. The results highlight the same pattern of discrepancies in VC funding and exit outcomes characterizing EU and US space startups. US non-space startups complete more VC rounds, raise capital more quickly, in greater amounts, from more VC investors, and are more likely to have a successful exit through IPO or M&A than their EU counterparts. All these differences are statistically significant and their magnitudes are comparable to those detected for space startups.

Third, we examine differences in VC funding and exit across space startups located in different European countries and the UK. While so far we have considered the EU as a whole, VC is heterogeneously distributed across countries, some of which are home to larger VC hubs (e.g., London in the UK and Paris in France) and active governmental venture capital institutions (e.g., BPI in France; see Bertoni et al., 2015; Bertoni et al., 2019). There are also historical institutional differences across European countries, relating notably to the characteristics of the financial system (market-based in the UK, bank-based in Germany and, to some extent, in France. See e.g., Allen & Gale, 2000). Results, available upon request, are mixed. While most countries show similar distributions across the three industry segments, we see some patterns of national specializations. In particular, Spain, Italy, Poland, and Belgium are characterized by higher shares of upstream VC-backed startups, Ireland of downstream ones, and the Netherlands, Sweden, Poland, and Belgium account for larger shares of space-derived startups. Given our sample size, we explored VC funding in the three countries with the largest number of space startups in our sample, namely the UK, France, and Germany. We do not identify clear-cut differences across the three countries. French space startups complete fewer VC rounds than UK ones, but not German ones. German space startups are the quickest to complete the 1st VC round, followed by UK and French startups. They also involve a higher number of VC investors in VC rounds and complete larger VC rounds from the 3rd onwards than France and UK startups. However, French space startups complete larger 1st VC rounds. Considering exit modes, we do not observe any statistically significant differences.

Table 8 Descriptive statistics on exits, by area

	EU		US	
	N.	Share (%)	*N.*	Share (%)
IPO	10	0.92	21	1.67
M&A	139	12.85	220	17.54
Out of Business	165	15.25	195	15.55
Privately held	768	70.98	818	65.23
Total	1,082	100	1,254	100

4 Discussion and conclusions

Although the new space economy is a nascent industry thriving with opportunities for new, private companies (Lamine et al., 2021; Parrella et al., 2022; Punnala et al., 2024; Weinzierl, 2018), recent evidence has highlighted that Europe is lagging behind the US in terms of entrepreneurial dynamism in this sector. The EU space economy mainly relies on established large incumbent firms and lacks "star" new players like SpaceX and other successful (mainly US) rapidly scaling startups. An important reason identified by previous studies and reports is that startups based in European countries attracted a smaller volume of private investments, especially VC (ESA, 2025; ESPI, 2025; Veugelers et al., 2025). In this paper, we contribute to this debate by providing a comprehensive analysis of VC funding dynamics of space startups in the EU and US over a 20-year period (2005-2025), distinguishing the upstream, downstream, and space-derived segments of the new space economy. Notably, we systematically investigate differences between EU and US space startups relating to the number and speed of their VC rounds, the amount of capital raised, the number of VC investors per round, as well as startups' exits. For this purpose, we rely on a novel few-shot learning LLM text-based classification methodology implemented via GPT-5 model to classify a large sample of 113,910 VC-backed startups from PitchBook as either space or non-space. We identified 2,336 space startups and highlighted substantial differences in VC funding between US and EU startups.

Our findings offer valuable contributions to both scholars and policymakers. First, we show that EU VC-backed startups have a higher relative specialization in the new space economy than their US counterparts, as the share of space startups out of the total number of VC-backed startups is greater in the EU than in the US. Within the new space economy, EU VC-backed space startups are less specialized in the upstream segment, which is characterized by a higher R&D intensity, higher capital requirements, and longer development times for products (Lamine et al., 2021; OECD, 2022) than their US counterparts. Furthermore, and more importantly, our results highlight several weaknesses in the VC funding dynamics of EU space startups. EU VC-backed space startups completed fewer investment rounds, raised lower amounts of capital, less quickly, and were backed by a lower number of VC investors than their US peers. EU startups were also less likely to achieve a successful exit through an IPO or M&A. These differences are statistically significant and their magnitude is generally large. In particular, US space startups completed their 1st VC round on average 3 months earlier than EU startups, a time advantage that persists over subsequent rounds. US startups raised 2.8 times more capital than EU startups and were backed by at least 1 more investor. Finally, the detected gap proved persis-

Table 9 Competing risks, multinomial logit model

	(1)	(2)	(3)
	IPO	M&A	Out of business
US	0.514	0.389**	0.217
	(0.613)	(0.166)	(0.157)
	[0.402]	[0.019]	[0.166]
Upstream	1.190	-0.122	-0.481
	(0.906)	(0.386)	(0.443)
	[0.189]	[0.751]	[0.278]
Downstream	0.873	1.038***	0.992***
	(0.755)	(0.231)	(0.234)
	[0.248]	[0.000]	[0.000]
ln(amount of capital raised)	0.687**	0.347***	-0.308**
	(0.324)	(0.095)	(0.153)
	[0.034]	[0.000]	[0.043]
Time elapsed founding-1st round	-0.263*	-0.152***	-0.132***
	(0.136)	(0.038)	(0.037)
	[0.053]	[0.000]	[0.000]
N. investors	0.169***	0.033	0.009
	(0.062)	(0.028)	(0.045)
	[0.006]	[0.249]	[0.836]
Founded 2011–2015	-0.865	-0.248	-0.163
	(0.553)	(0.175)	(0.173)
	[0.118]	[0.158]	[0.348]
Founded 2016–2020	-1.032	-0.375*	-0.386*
	(0.819)	(0.216)	(0.223)
	[0.208]	[0.083]	[0.084]
Founded 2021–2025	-13.815***	-14.729***	-1.747*
	(0.799)	(0.215)	(1.030)
	[0.000]	[0.000]	[0.090]
ln(time)	1.945***	1.098***	1.065***
	(0.481)	(0.107)	(0.092)
	[0.000]	[0.000]	[0.000]
Constant	-11.388***	-6.868***	-6.156***
	(1.420)	(0.330)	(0.315)
	[0.000]	[0.000]	[0.000]
N. observations	12,919		
p-value, F-test	0.000		
log-likelihood	-2,008		
Pseudo R-squared	0.091		

Robust standard errors in brackets round brackets, p-values in squared brackets; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

tent over time, showed no substantial variation across space economy segments, and mirrored the longstanding weakness of the European VC industry compared to the US one.

This evidence contributes to previous studies highlighting various weaknesses characterizing the European space economy (e.g., ESA, 2025; Veugelers et al., 2025), beyond traditional scientific, technological, and industrial strengths characterizing the EU space economy, evident in successful programs like Copernicus and Galileo and in the presence of large global players. First, these weaknesses relate to the fragmentation of the institutional context and the variety of public bodies, both at national and EU levels, responsible for supporting the European space economy, including the European Space Agency (ESA), the European Commission's Defense Industry and Space Directorate General and its operational agency, the EU Agency for Space Programme, and national governmental bodies. Second, the lack of effective coordination among these public bodies is an evident, serious weakness compared to the US, where NASA and DARPA (Defense Advanced Research Projects Agency) have clearly defined and complementary mandates. Third, the stagnating European space budget, especially in the defense component, and the absence of a procurement strategy oriented to promoting radical innovations with large yet long-term payoffs and the entry and scaling of new players – a strategy successfully adopted by DARPA and NASA in the US – are other serious weaknesses.

Several policy initiatives specific to the space economy have been proposed to address these gaps. Nevertheless, scholars have long emphasized that the impact of policy initiatives needs to be understood in the context of the "policy mix" they compose and the super-modularity they generate (e.g., Mohnen & Röller, 2005; Rogge & Reichardt, 2016). Complementary policy initiatives reinforce each other and one individual policy scheme implemented in isolation may have no positive effect in the absence of its complements[12]. In the context of the new space economy, the shortage of private early-stage financial resources and VC investors in Europe is a fundamental challenge that risks jeopardizing the above-mentioned policy initiatives. For example, the orientation of public procurement to innovative new entrants with the aim of developing radically new technologies, products, and services will be ineffective if beneficiaries cannot obtain the amount (and quality) of the VC funding necessary to complete these generally costly and long-term projects and effectively scale operations. As we highlighted above, this weakness in funding is not specific to the EU space economy, but concerns more generally the supply of VC in Europe and the organization and funding of the European VC industry, which differ substantially from those of the US (see e.g., Bertoni et al., 2015; Bertoni et al., 2019). Therefore, policy measures in this domain need to address the general weaknesses of the European VC industry, e.g., through regulatory changes that alleviate the traditional

[12] For instance, while analyzing policy initiatives that favor the transitions to clean energy, Grubb et al. (2023) highlighted the "carbon pricing paradox". Policies setting adequate carbon prices, which represent key policy initiatives in this domain, are only feasible if policy makers devote equal attention to the other pillars of the policy mix, including the wider context of macroeconomic and fiscal policies. See also Greco et al. (2022) on policy mixes promoting global warming-related eco-innovations. Note also that policy initiatives can also be substitutes, and that whether they are substitute or complements may depend on "boundary conditions" (e.g., firm size, see Pless, 2025 on R&D grants and tax credits).

aversion of European financial institutions to this asset class and remove the national fragmentation of European VC markets.

A second important contribution of this study consists of the employment of a LLM few-shot learning text-based classification methodology, performed via the GPT-5 model, to identify startups that are active in the new space economy. Our validation of the LLM-based classifier confirms its robustness and effectiveness, contributing to the recent stream of scholarly research exploring the reliability of these methods in large-scale categorization exercises (Carlson & Burbano, 2025; Fechner & Dörpinghaus, 2024). Moreover, given the declining costs of commercial API services and the limited technical expertise required for their implementation with respect to alternative methodologies, this paper supports the case for a wider adoption of LLM-based classifiers by researchers, practitioners, and policymakers. Such classifiers are especially useful in timely mapping nascent industries and identifying the economic actors that operate in them, as these industries defy standard classifications.

Third, in developing this methodology, we also contribute to the broader literature on VC and entrepreneurial finance. Indeed, entrepreneurial finance channels (especially VC, but also business angels and crowdfunding platforms) are especially important for startups in nascent industries (like AI, fintech, nanomaterials, etc.). Identifying them by leveraging information from commercial databases and other Internet sources is a valuable methodological advancement.

Our analysis is not exempt from limitations. First, while our novel classification methodology offers advantages, we also acknowledge that the choice of the GPT model and the prompt design are potential sources of bias. In particular, the performance of the classifier can be influenced by the specific wording of the prompt or the examples provided. While our validation confirms the reliability and effectiveness of the classifier employed, recent research highlighted how both the choice of model and prompt should be tested for robustness against various alternatives (Carlson & Burbano, 2025). Second, while PitchBook data offer unique coverage and detail on funded startups worldwide, it provides better coverage of US firms than of firms located elsewhere. Furthermore, as highlighted in our validation exercise, firms' descriptions may not always provide sufficient detail to correctly classify startups. On top of testing different models and prompts, future research may therefore also consider additional data sources. Third, while our analysis is rooted in the literature on entrepreneurial finance and considers differences between US and EU startups at an aggregate geographical level (i.e., at country-level and above), future research may investigate VC funding at a more disaggregated geographical level. VC investments are heavily concentrated worldwide in a limited number of VC hubs, coinciding with great metropolitan areas (like the Silicon Valley, the Boston-Cambridge and New York areas in the US, and London and Paris in Europe), but the level of agglomeration is not the same across different geographical areas. Determining whether the differences we detected persist when EU and US VC hubs are compared, or whether they are influenced by the level of agglomeration of VC in the two areas, could be an interesting extension of this study. Fourth, our analysis can be expanded to other characteristics of VC funding. One could consider the characteristics of VC investors, such as their reputation and status (Nahata, 2008; Pollock et al., 2015) or governance, distinguishing between independent, corporate, and governmental VCs (e.g., Dimov and Gedajlovic, 2009). As to this latter aspect, different VCs have different objectives, and financial returns are not always their unique or primary goal. In particular, governmental VCs pursue social goals (Cumming et al., 2017), while corporate VCs' investments aim to open a window on promising new technologies (Dushnitsky & Lenox, 2005; Siegel et al., 1988). Furthermore, while we observe exit via M&A, we did not qualify these events further, based for instance on target start-ups' valuation or the acquirers' identity, the countries where they are located and the industries where they operate. Finally, in addition to exit via IPO or M&A, one may want to investigate to what extent VC contributes to the scale-up of the invested start-ups' operations, boosting their market shares, revenues, and consequently returns.

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Author contributions All authors contributed to the study conception, design, and writing, as well as to the analysis. Materially, the data analysis was performed by Alessandro Lucini-Paioni, the classification by Bogdan Tofan. All authors read and approved the final manuscript.

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Declarations

Conflict of interest On behalf of all Authors, the Corresponding Author states that there is no conflict of interest.

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