**LUISS – Libera Università Internazionale degli Studi Sociali**

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# Understanding investors' decision-making in quantum computing startups: a mixed-methods approach to investment criteria

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# Abstract

This thesis investigates the strategic and operational factors influencing investor decision-making in quantum computing startups, employing an explanatory mixed-methods approach. Specifically, the quantitative analysis, which will be dominant, is supported by a qualitative review. The implemented methodological framework comprises multiple linear regression models based on data sourced from Dealroom and Google Patents, identifying critical predictors of startup funding outcomes, including team strength, patent ownership, and product-market fit.

The study opens with a foundational overview of quantum computing, detailing key technical principles rooted in quantum mechanics, and examining the startup ecosystem's dynamics in this field.

Quantitative investigations include initial dataset cleaning, the creation of a correlation matrix, a set of regression models, and two separate extended analyses of disparities across subfields and regions. The results indicate that team strength, patent counts, number of funding rounds, public resources, completeness, and growth rate have a major impact on the startups' funding prospects, valuation, and organizational growth. No relevant regional difference in investment levels was found, while, conversely, the hardware and infrastructure segment emerged as the most attractive for investors.

The qualitative section, which incorporates interviews with three venture capital investors, emphasizes the necessity of medium-term monetization, strong and diverse founding teams, and proactive IP strategies. Findings uncover a misalignment between traditional VC frameworks and the specific needs of deep-tech sectors like quantum computing, mainly concerning investment time horizons and technical complexity.

The research concludes by suggesting actionable insights for investors and policymakers to better align funding strategies with quantum startups' distinctive characteristics. On top of that, limitations regarding data accuracy, geographical generalizability, and potential endogeneity are acknowledged, alongside proposals for future longitudinal studies and refined methodological designs to enhance comprehension and validity in the emerging quantum computing landscape.

# 1. Introduction to quantum computing

## 1.1 Fundamental principles and concepts

Listed among the key emerging technologies that will shape our future (Eulaerts et al., 2025), quantum computing is one of the most revolutionary technological frontiers currently under development, and while still in its early stages, it is poised to radically transform the way we process information. Its status as a major leap in processing power, capable of solving complex problems beyond the reach of classical computers, stems directly from how it operates.

In fact, to perform calculations, traditional computers rely on bits, which are limited to binary states (they can only assume values 0 or 1), whereas quantum computers use quantum bits, also called qubits. A qubit can exist in a superposition of both states simultaneously: this means that a quantum computer with multiple qubits can represent and compute a vast number of combinations at once. For example, while 10 classical bits represent only 1 of 1,024 combinations at a time, 10 qubits can represent all 1,024 combinations simultaneously. This circumstance is known as superposition and it is just one of the three key principles at the core of quantum mechanics. The other two are entanglement, which occurs when qubits become correlated in such a way that the state of one instantly affects the state of another, enabling coordinated operations across multiple qubits, and quantum interference, which arises when probability amplitudes combine (either constructively or destructively) to guide the computation toward correct results.

The roots of quantum computing lie in quantum mechanics, a field developed in the early 20th century by scientists like Niels Bohr, Werner Heisenberg, and Erwin Schrödinger. Although their work had nothing to do with computing, they set the stage for a new understanding of how the universe behaves at atomic and subatomic levels. Unlike classical physics, which views particles as having definite positions and velocities, quantum mechanics describes a probabilistic world where particles can exist in multiple states at once and influence each other instantaneously. The first attempts to build physical quantum computers date back to the beginning of the 21st century, with different approaches, such as trapped ions, superconducting qubits, photonic systems, and quantum dots. Shor's algorithm, developed by Peter Shor, showed that a quantum computer could factor large numbers exponentially faster than the best-known classical algorithms: that was experimentally implemented by a partnership between IBM and Stanford University on a 7-qubit NMR (nuclear magnetic resonance) quantum computer (IBM Research Division, 2001). While very limited in scope, this was the first experimental demonstration of a quantum algorithm that could outperform its classical counterpart in principle.

The 2010s witnessed a massive acceleration in quantum computing research and development, with all the big tech companies beginning to compete in the quantum race. In 2019, Google announced that it had achieved quantum supremacy, i.e., a point where a quantum computer can perform a task that is impossible or impractical for a classical computer to do, even with the most advanced algorithms. More specifically, this result claimed by the Mountain View corporation was reached by using its 53-qubit Sycamore processor (Arute et al., 2019). Today, quantum researchers are focused on building scalable, fault-tolerant quantum computers, solving technical challenges such as quantum decoherence, which is the loss of quantum information when qubits interact with their environment, leading to errors and instability in computations (Khan et al., 2024).

Meanwhile, countries and international entities are working on building a legal framework for it, with some governments starting to view quantum technology as a matter of strategic importance, considering decisions such as the US Quantum Initiative Act, the EU Quantum Flagship, and China's major national quantum programs.

In this scenario, startups have emerged as key players in the development of quantum computing. While early advancements were mainly driven by academic institutions and government research labs, the last two decades have seen the rise of a vibrant ecosystem pushing the boundaries of what is technologically and commercially possible. As these organizations attempt to turn quantum breakthroughs into viable business models, they enter a highly uncertain and competitive landscape where strategic choices and investor perceptions play a pivotal role in determining their trajectory, mirroring the experience of other disruptive technologies enabled by venture capital (Gompers & Lerner, 2001).

## 1.2 The entrepreneurial landscape and investment challenges

Due to the enormous potential of quantum computing, most major technology companies decided to invest resources in it, pushing the boundaries of hardware, software, and cloud-based solutions. As indicated before, Google is one of the most influential players in this field. Other than the aforementioned quantum computer Sycamore, in 2024 Google Quantum AI team developed Willow and the software Cirq, and aims to build a million-qubit quantum computer within a decade, focusing on practical applications in AI, chemistry, and optimization (Wu & Bosa, 2025). But Google is not the only "Big Tech" carrying innovation in quantum computing; indeed, Amazon and Microsoft are also working to improve the ecosystem. Particularly, the latter is doing so through its Azure Quantum platform and Majorana 1, which is the world's first Quantum Processing Unit (QPU) based on topological qubits (Nayak, 2025). IBM is probably one of the most active tech companies in quantum computing, realizing a high number of quantum hardware and software in recent years and becoming the first-ever company to break the 1,000-qubit barrier with a quantum computer, the Condor (Gambetta, 2023). Despite ongoing difficulties, even Intel decided to allocate resources towards quantum computing, and it is currently working on building scalable silicon-based quantum processors.

However, not just big companies are carrying out R&D in quantum computing. As a matter of fact, a startup ecosystem has rapidly evolved over the past decade related to this field, driven by breakthroughs in hardware, software, and a surge in private and public funding. In this study, a startup is identified as any "human institution designed to create a new product or service under conditions of extreme uncertainty" (Ries, 2011). Also falling within this category are scale-ups (those "with average annual growth in employees or turnover greater than 20 per cent per annum over a three-year period, and with more than 10 employees at the beginning of the period" (Coutu, 2014)) and unicorns (companies "valued at over $1 billion by public or private market investors" (Lee, 2013)). This broader inclusion is justified by the fact that all businesses founded with the intention of developing solutions in the quantum computing sector face critical challenges, and their prospects for success remain uncertain.

Reflecting this growth, global venture capital investment in quantum computing will exceed €1 billion in 2024 (Metinko, 2025), and Europe, the US, and parts of Asia emerge as the biggest hotspots for quantum innovation. The sector is characterized by a diverse range of technological approaches, business models, and ambitious roadmaps, with startups, scale-ups, and unicorns vying to commercialize quantum computing for real-world applications across industries like finance, pharmaceuticals, logistics, and cybersecurity.

Nonetheless, quantum startups in this ecosystem also have to face some relevant challenges. Among them, a significant one is the shortage of quantum computing experts, with demand outpacing supply by a factor of three (Mohr et al., 2022). In addition to talent shortage, another major problem could lie in hardware scalability. Adding qubits while preserving coherence and minimizing errors is difficult, as quantum systems are extremely sensitive to interference. This makes it difficult to build reliable, large-scale quantum computers, slowing down the path to real practical applications.

Within the pioneers of this environment, mention should be made of D-Wave Quantum, whose quantum annealing approach is distinct from the gate-based methods of other players and is particularly effective for solving complex optimization problems, and IonQ, which focuses on trapped-ion technology and was the first pure-play quantum computing company to go public (IonQ, 2021). Another cutting-edge qubit processor manufacturer is Rigetti Computing, while leaders in photonic quantum computing and quantum cybersecurity are respectively Xanadu and Quantinuum.

However, all of these businesses will be considered, studied, and evaluated when running both the quantitative and the qualitative analyses to address a specific gap: understanding the nuanced decision-making processes of investors operating in this highly specialized and uncertain sector. Although technical milestones and macroeconomic investment trends have received some scholarly attention, there is limited empirical evidence on how VC investors assess such factors in practice, especially when traditional indicators such as product-market fit or time-to-market are difficult to apply. Classic works in entrepreneurial finance have extensively explored the criteria venture capitalists use to mitigate risks and exploiting strengths during and after the investments (Kaplan & Strömberg, 2004), but these frameworks may require reinterpretation in the context of highly complex and uncertain deep-tech sectors like quantum computing. Addressing this gap is essential to advancing more informed investment strategies, ultimately supporting the growth of the quantum ecosystem. At the same time, it may help entrepreneurs better align their development roadmaps and operational choices with the expectations and risk frameworks of venture capitalists.

This research positions itself at the intersection of these dynamics, aiming to shed light on the criteria and reasoning that shape investor behavior in the quantum startup space. Understanding these patterns is particularly relevant, given that multiple industries will probably be revolutionized by quantum computing in the future: its applications span logistics, finance, materials science, pharmaceuticals, climate research, and cybersecurity, due to the ability to solve complex problems that classical computers struggle to cope with.

# 2. Methodology

## 2.1 Research gap and relevance of the topic

Regardless of an exponentially growing attention towards quantum computing and, more specifically, towards its business applications (Ukpabi et al., 2023), the literature about its startup ecosystem is relatively limited. Conversely, it would be helpful for both the scientific community and venture capital investors to explore this complex and rapidly evolving world more deeply. This research is designed to address this specific scenario, where critical doubts still lie, despite the quantum revolution getting closer and closer. For greater clarity, the substantial research gap that this study aims to cover concerns understanding the nuanced decision-making processes of investors in this highly specialized sector. Indeed, existing literature on startup investments often focuses on more mature technology sectors, where product-market fit, scalability, and financial performance are well-established criteria (Gompers et al., 2020). Moreover, much of the existing research in entrepreneurial finance tends to generalize investment behavior across sectors, overlooking the distinctive challenges faced in emerging deep-tech fields (Petty et al., 2023). This lack of contextual specificity limits our ability to understand how investment heuristics adapt in response to scientific complexity and long-term uncertainty.

As will be discussed further below, quantum computing startups operate in an environment characterized by profound technical uncertainty, long development timelines, and a lack of clear commercial applications. While numerous studies are planned to identify technical milestones as important factors (Gill et al., 2021), and even finance-oriented investment outlooks (Lee, 2020) are well-analyzed throughout the existing literature, there is limited empirical evidence on how investors actually weigh these technical indicators against traditional criteria. This leaves unanswered crucial questions about how investors evaluate opportunities, manage risk, and develop conviction in a field where both technical and commercial outcomes are highly uncertain, and scientific challenges (e.g., error correction or quantum decoherence) still exist. Addressing this gap is essential and will lead to more aware investment strategies, supporting the growth of the quantum ecosystem and, consequently, helping startups (and the scientists behind their solutions) to better align their development roadmaps with venture capital's expectations. To that end, this study adopts a mixed-methods approach that integrates both quantitative and qualitative data, enabling a richer and more nuanced understanding of how strategic and operational signals shape investment decisions in quantum computing startups.

## 2.2 Methodological framework

The methodological framework built around this study involves a mixed-methods approach. More specifically, a two-phase explanatory sequential design will be adapted, prepending a quantitative analysis of investment patterns to qualitative exploration of investor reasoning (Creswell, 2014). This design is quantitatively dominant, meaning the quantitative phase drives the research, while the qualitative phase serves to deepen and contextualize the findings (Creswell & Plano Clark, 2017). Image #1 shows precisely how the two phases mentioned above will be ordered. This method enables an in-depth exploration of how various startup characteristics interact to influence funding success in the quantum technology field.

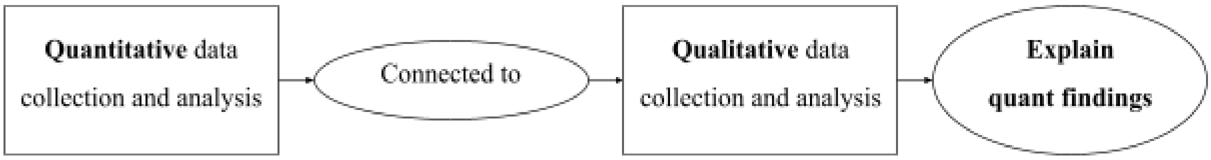


***Image #1**: Explanatory Sequential Mixed Methods Design according to Creswell J. W.*

The precise research question is "How do key strategic and operational factors in quantum computing startups shape investors' decision-making, leading to improved funding outcomes?" and necessitates a methodology that bridges empirical trends with contextual insights. Quantitative methods alone risk oversimplifying market uncertainties linked to deep-tech investments, and, conversely, purely qualitative approaches may lack the generalizability needed to inform actionable strategies. The explanatory sequential design addresses these limitations by first identifying statistical relationships between startup attributes and funding outcomes, followed by in-depth interviews to interpret and contextualize those relationships.

### 2.2.1 Quantitative methodology

To answer the research question of the study, employing a quantitative methodological approach which underlines relationships among variables of interest is crucial. While a broader investigation into startup characteristics will be presented below, this section focuses exclusively on detailing the statistical methods, diagnostics, and model-building strategies that structure the subsequent empirical analysis. The quantitative review will be entirely conducted using R within the RStudio integrated development environment.

In primis, the analysis comprehends a preliminary correlation study, utilizing a Pearson correlation matrix to assess the degree of linear association between the independent and the dependent variables. Although not used as a formal test of causality or inclusion criteria, this step provides a general overview of potential multicollinearity, initial patterns of association, and variable behavior.

The core of the quantitative analysis revolves around the estimation of multiple linear regression models. Given the skewed distribution of the dependent variable, log-linear models were adopted to normalize the outcome and improve interpretability. The initial phase involved estimating a full model containing all theoretically relevant independent variables. This "all-in" model served to evaluate the global fit and test for the joint significance of predictors. To account for potential issues in the estimation of standard errors due to heteroskedasticity or other violations of OLS (that is, Ordinary Least Squares) assumptions, robust standard errors (specifically, heteroskedasticity-consistent standard errors) were employed. Based on the significance of predictors under this robust specification, a refined model was constructed by retaining only those variables that demonstrated statistical significance. This "parsimonious" model was used for the remaining inferential analyses.

Once it had been established, following standard econometric guidelines (Wooldridge, 2019), a full battery of diagnostic tests was conducted to ensure the reliability of the regression results and the validity of inference. Multicollinearity was assessed through the computation of the VIF, i.e., Variance Inflation Factor, for each explanatory variable. Instead, the normality of residuals was evaluated using the Shapiro-Wilk test, alongside graphical inspections via histograms and density plots, while homoscedasticity was tested through the Breusch-Pagan method to determine whether the residuals exhibit constant variance. Ultimately, the Durbin-Watson statistic was used to assess autocorrelation in residuals. Complementary to these tests, visual diagnostics were employed, and also a correlation matrix of the explanatory variables has been included to offer a more focused view of inter-variable relationships in the refined specification.

In addition to the regression-based framework, two separate exploratory analyses were conducted to assess patterns within categorical subgroups. Specifically, an analysis was performed to compare funding levels across distinct sectoral and geographical classifications (referred to here as "subfields" and “regions”). This investigation proceeded through summary statistics to describe funding distributions across categories, and the generation of boxplots to visualize the dispersion and central tendencies in funding (with funding values log-transformed also here to account for skewness). Subsequently, a one-way ANOVA, which stands for Analysis of Variance, was conducted on the dependent variable to test whether mean funding levels differ significantly across subfields and regions, and a log-linear regression model (i.e., $\%\Delta Y \approx 100 \times \beta X$) was estimated using subfield and region membership as a categorical predictor. In conclusion, two Tukey range tests, one per exploratory analysis, were performed as a post-hoc comparison to identify which subfield and which region exhibit statistically significant differences in their average funding levels.

### 2.2.2 Qualitative methodology

To complement the statistical findings and provide deeper interpretative value, the study integrates a qualitative component based on semi-structured interviews with a selected group of early-stage investors and technology experts. These interviews are designed to collect primary data, exploring the subjective dimensions that cannot be captured through quantitative models alone, like investor perceptions, risk assessments, strategic priorities, and the role of narratives in decision-making processes related to quantum computing startups. Each interview will combine a set of general questions, whose aim is to address overall perceptions and strategic approaches to investments in quantum computing, with targeted questions specifically related to the most robust and significant patterns identified through the quantitative analysis. By discussing these patterns directly with investors, the qualitative phase aims to uncover potential causal mechanisms, clarify perceptions behind observed trends, and distinguish between sector- and region-specific dynamics and broader structural correlations. Furthermore, this approach is expected to help contextualize anomalies, contradictions, or unexpected results that may have emerged from the statistical models.

# 3. Quantitative analysis

## 3.1 Data source and rationale

To offer a robust and up-to-date resource for analyzing the quantum computing startup landscape, the quantitative part of this research is based on a comprehensive database transferred from Dealroom, a leading European business intelligence platform tracking startups and high-growth companies globally (Dealroom, n.d.). Founded in 2013 and headquartered in Amsterdam, Dealroom has become a widely used tool among venture capitalists, innovation agencies, policymakers, and academic researchers for its structured and curated coverage of technology-driven firms. The platform provides detailed information on company profiles, funding history, valuation estimates, investor affiliations, and sectoral categorization. It aggregates data from multiple verified sources, including public records, investor disclosures, company press releases, and direct submissions from the startups themselves. Dealroom's dynamic data infrastructure combines automated web crawling, manual verification, and proprietary algorithms to compute standardized indicators such as the Dealroom Signal Scores, which evaluate startups' growth potential based on factors like team experience, product-market fit, market timing, and ecosystem engagement, and which will be treated as reliable indicators during the research. The platform also offers advanced analytics and customizable dashboards that facilitate the monitoring of sectoral trends, investment flows, and the evolution of innovation ecosystems. As such, Dealroom adds substantial value to data-driven decision-making in the fields of entrepreneurship, innovation policy, and venture capital.

More precisely, data come from the list "Global Quantum Computing startups", curated by Lorenzo Chiavarini and Felix Ullmer (Chiavarini & Ullmer, 2025), updated as of April 8, 2025, at the time of download. This initial dataset anchored the early stages of the study, as it reflected the most recent and relevant landscape of quantum computing ventures worldwide, collecting information on 309 startups from across the globe. Recognizing the critical importance of data quality for subsequent analyses, an extensive and accurate data cleaning process was undertaken, which will be further discussed in the "Description of Variables" section. This process included removing duplicates, inserting dummy variables where data were non-numerical, resolving inconsistencies in country and founding year information, entering NA where incorrect or no data was reported, and cross-referencing multiple sources to ensure the reliability and accuracy of the dataset.

A particularly challenging aspect of the data collection concerned the number of patents associated with each startup. Due to numerous discrepancies in the Dealroom database, the study relied on Google Patents, an online platform developed by Google in 2006 that is dedicated exclusively to patent information, making it more accessible and easier to navigate for a broad audience (Google Patents, n.d.). Originally launched with a focus on US patents, the platform has since expanded to include patent documents and applications from over 100 jurisdictions worldwide, including data from the United States Patent and Trademark Office (USPTO), China National Intellectual Property Administration (CNIPA), and the European Patent Office (EPO). Over the years, it has evolved into a valuable resource not only for inventors and researchers but also for legal professionals, business analysts, and anyone interested in technological innovation and intellectual property. The rationale is that the platform became user-friendly, providing access to millions of patent records and enhanced by smart tools such as semantic querying, citation analysis, and cross-referencing with academic publications through Google Scholar.

To be more specific about the methodology employed, the compilation of patent counts was carried out through targeted searches by entering company names under the "Assignee" field and the names of founders under the "Inventor" field. This approach aimed to offer an exhaustive picture of the Intellectual Property generated by these startups and their key personnel. In each case, a careful review of the results has been conducted to include all patents either assigned directly to the company or invented by the founders, regardless of the assignee.

Despite these efforts to maximize accuracy, several inherent limitations in this methodology must be reported. First, many patents relevant to a startup's activities may not be officially assigned to the company itself. Often, inventors file patents during their academic careers or prior to the founding of the startup, resulting in patents assigned to universities or other institutions rather than the startup. Conversely, some patents may be developed within the company by employees who are not among the original founders, making it difficult to attribute these patents directly to the startup's core founding team. These factors introduce a degree of uncertainty and potential under- or over-counting in the patent variable. Nevertheless, by systematically searching both assignees and inventors, efforts were made to minimize these issues and to provide the most representative measure possible of each startup’s patent portfolio within the constraints of available data. Although not immune to imperfections, construct validity is deemed acceptable (the topic will be revisited in section 5.3), as the resulting variable is considered sufficiently robust to be used as a proxy for assessing the Intellectual Property intensity of each company, particularly when interpreted in conjunction with other strategic and operational indicators.

## 3.2 Model and variable foundations

A rigorous quantitative analysis requires a clear and transparent definition of both the model structure and the variables involved. This section therefore details how the model is built and clarifies all relevant variables. The aim is to ensure that the methodological approach is both replicable and interpretable, laying a solid foundation for the subsequent empirical analysis.

### 3.2.1 Detailed variable descriptions

To ground the empirical analysis and allow for a structured investigation of the research question, a diverse set of variables has been compiled. These variables come from the data explained in the "Data source and rationale" section and try to capture multiple dimensions of startup activity, including financial performance, organizational structure, innovation signals, business models, and technological specialization. Each variable has been selected to align with the research aim of understanding which internal and external features of startups most strongly shape funding outcomes.

Note that, to construct explanatory variables for assessing funding outcomes in relation to startup quality and momentum, as aforementioned, Dealroom signals are treated as reliable and granular indicators. These signals are derived from a proprietary algorithm that integrates over a dozen variables, ultimately condensed into four core dimensions: team strength, growth rate, timing, and completeness. Each of these components reflects aspects that are critical to investor decision-making. More specifically, they derive from an algorithm which «includes over a dozen inputs, which can be summarised as follows:

- Growth rate (employee growth, product growth)
- Completion score and contextual data (does the company fit into segments of interest)
- Founding team composition (e.g. serial founders, past work experience and education)
- Timing (is the startup likely to raise their next round soon). The general logic for startups that have received funding is that the score goes back to zero right after

the round, peaks at one year, and then gradually declines. The timing score exact shapes varies by stage and is based on Dealroom proprietary benchmarks of timing between rounds» (Foy, 2022).

Together, these dimensions are averaged to generate a composite signal, offering a multidimensional, yet standardized, view of a startup's traction and readiness.

It is relevant to note that, from the list downloaded from Dealroom, startups were categorized into the following subfields: "Quantum computers & processors", "Quantum computing software", "Quantum cryptography", "Post-quantum era encryption", "Quantum computing for biotech and chemical applications", "Quantum communication", "Quantum sensing", "Photon detection & counting", "Photonic integrated circuits & photonics IP", "Quantum cascade lasers, laser tech for sensing & LiDAR", "Next gen laser & photonics", and "Refrigeration for quantum". To streamline statistical analyses, in particular the log-linear regression models, and avoid overcomplication from redundant variables, related subfields have been grouped into four cohesive categories, that are:

- "Quantum hardware & infrastructure", combining "Next gen laser & photonics", "Photonic integrated circuits & photonics IP", "Quantum computers & processors" and "Refrigeration for quantum", as these all address physical systems and enabling technologies;
- "Quantum softwares & applications", which bundles "Quantum computing software", "Post-quantum era encryption" and "Quantum computing for biotech and chemical applications", focusing on computational tools and applied use cases;
- "Quantum communication & cryptography", merging "Quantum communication" and "Quantum cryptography", both tied to secure data transmission;
- "Quantum sensing & detection", aggregating "Photon detection & counting", "Quantum cascade lasers, laser tech for sensing & LiDAR", and "Quantum sensing", which share a focus on precise measurement.

In addition to reducing multicollinearity risks in regression models, this categorization reflects the layered architecture of quantum technologies, where hardware and infrastructures form the  foundational layer, software and applications drive utility (by translating quantum advantage into real-world problems), communication and cryptography solve critical problems in the quantum era such as data transfer, and new challenges arise from high-precision measurement areas.

Before presenting the full table of variable descriptions, a final specification concerns the valuation data: since Dealroom provides only value ranges, the lower bound of each one was selected to ensure consistency across observations.

Unfortunately, a multitude of NA (e.g., Not Available) data was present in the dataset across all categories (some more, some less), which represents another limitation of the study, but it is relevant to add that this did not compromise the robustness or validity of the statistical analyses performed.

Therefore, the variables considered in this quantitative part are summarized in Table #1.

| variable_name | Description | Values |
|---|---|---|
| launch_year | Year the startup was launched | Numeric year (e.g., 2019, 2022) |
| seed_year | Year the startup received seed funding | Numeric year (e.g., 2019, 2022) |
| hq_europe | Whether the HQ is inEurope | Binary (1 = yes, 0 = no) |
| hq_asia | Whether the HQ is in Asia | Binary (1 = yes, 0 = no) |

| | | |
|---|---|---|
| hq_america | Whether the HQ is in America | Binary (1 = yes, 0 = no) |
| hq_oceania | Whether the HQ is in Oceania | Binary (1 = yes, 0 = no) |
| valuation | Latest known company valuation in EUR | Integer |
| total_funding | Total amount of funding in €M raised as of April 8, 2025 | Floating-point number |
| rounds | Number of funding rounds | Integer |
| public_funding | Whether the company has received public funding | Binary (1 = yes, 0 = no) |
| university_backed | Whether the startup is backed by a university | Binary (1 = yes, 0 = no) |
| patents | Number of patents held or filed | Integer |
| employees | Latest known number of employees | Integer |

| | | |
|---|---|---|
| rev_model_marketplace | Whether the revenue model is reported to be "Marketplace" | Binary (1 = yes, 0 = no) |
| rev_model_saas | Whether the revenue model is reported to be "SaaS" | Binary (1 = yes, 0 = no) |
| rev_model_manufacturing | Whether the revenue model is reported to be "Manufacturing" | Binary (1 = yes, 0 = no) |
| signal_completeness | Dealroom signal of completeness | Numeric value that goes from 0 to 100 |
| signal_team_strength | Dealroom signal of team strength | Numeric value that goes from 0 to 100 |
| signal_growth_rate | Dealroom signal of growth rate | Numeric value that goes from 0 to 100 |
| signal_timing | Dealroom signal of timing | Numeric value that goes from 0 to 100 |
| subfield_hardware_infra | Whether the company belongs to the "Quantum hardware & infrastructure" category | Binary (1 = yes, 0 = no) |

| | | |
|---|---|---|
| subfield_software_apps | Whether the company belongs to the “Quantum softwares & applications” category | Binary (1 = yes, 0 = no) |
| subfield_comm_crypto | Whether the company belongs to the “Quantum communication & cryptography” category | Binary (1 = yes, 0 = no) |
| subfield_sensing_detection | Whether the company belongs to the “Quantum sensing & detection” category | Binary (1 = yes, 0 = no) |

***Table #1****: Detailed variable descriptions*

### 3.2.2 Model structure and variable roles

Restating the research question is fundamental to better understand the model design behind the quantitative part of this study: “How do key strategic and operational factors in quantum computing startups shape investors’ decision-making, leading to improved funding outcomes?”. Indeed, the analyses that will be carried out are designed to explore how quantum startups’ characteristics influence investor behavior and contribute to more favorable funding outcomes. To do so, a series of regression models were constructed with a clear structure: different financial or growth-related performance indicators were treated as target variables, while a consistent set of explanatory factors captured key startup features.

In particular, total funding received, startup valuation, and number of employees were selected as dependent variables. Each sends back to a distinct dimension of a startup’s success and perceived potential, and each can be assumed to reflect investor confidence.

Total funding represents the direct outcome of investment decisions, which is arguably the clearest signal of market endorsement and the primary dependent variable in the study. Valuation offers a second measure, integrating market expectations and investor assumptions about future returns. While funding reflects actual capital committed, valuation will incorporate more qualitative investor sentiment, strategic positioning, and growth potential. Together, these two variables offer a complementary view of startup attractiveness, capturing both realized investment and perceived future promise. Lastly, the number of employees is used as a proxy for organizational scaling and capacity growth, which is often correlated with financial backing. The independent variables used across the models are all the remaining ones, whose aim is to capture the strategic, structural, and operational signals that startups send to potential investors.

### 3.3 Correlation structure and preliminary insights

Before proceeding, it is essential to hark back that the modeling approach involves estimating log-linear regression models, depending on the distribution of the dependent variables. Specifically, all three dependent variables are log-transformed to normalize their distributions and allow for easier interpretation of elasticity-like effects. This means that the coefficients of the independent variables can be interpreted as percentage changes in the dependent variable, offering a clearer lens into proportional relationships. The models are initially estimated using standard OLS procedures and subsequently corrected for heteroskedasticity using robust standard errors where diagnostic tests indicate a violation of homoscedasticity assumptions.

OLS regressions in this study aim to identify which variables have statistically significant relationships with the three dependent variables, recalling that, since the raw distributions of these Ys are typically highly skewed, natural logarithmic transformations were applied to to reduce skew and enhance interpretability. This transformation enables the interpretation of coefficients as semi-elasticities, i.e. the percentage change in the dependent variable for a one-unit change in the independent variable.

Once the transformed variables were prepared, three separate OLS regressions were run with the same set of independent variables. It is crucial to note that the models were carefully specified to avoid issues of multicollinearity and overfitting. In particular, headquarters location variables (e.g., `hq_europe`, `hq_asia`, `hq_america`, and `hq_oceania`) were excluded from the model because, while geographical location can certainly influence startup success, in preliminary tests, their inclusion tended to lower the adjusted R-squared, suggesting that they contributed noise rather than meaningful variance to the models. Their omission, thus, reflects both theoretical justification (location may matter less in a globally distributed, deep-tech ecosystem like quantum) and empirical efficiency. However, an exploratory analysis will follow regarding quantum computing startups’ geography. Furthermore, to prevent the dummy variable trap, that is, a form of perfect multicollinearity that arises when all categories of a qualitative variable are included, one category per group of dummy variables was intentionally omitted. This applies to both revenue models (`rev_model_marketplace` omitted) and subfields (`subfield_hardware_infra` omitted). These reference categories serve as baselines, meaning the coefficients of the included dummies should be interpreted in contrast to them. In particular for subfields, having noted that the hardware's one was the most correlated variable, this approach allows the regression to correctly estimate the independent contribution of each category without redundancy.

For each regression, heteroskedasticity-robust standard errors were computed using the HC3 estimator via the `coeftest()` function from the `lmtest` package (Zeilis, 2004). This ensures that inference remains valid even in the presence of non-constant variance in the residuals, which represents a common issue in cross-sectional startup data.

Another thing to note before presenting the OLS regressions is that each one has at least a $R^2$ value of 70%, which, in finance, is generally seen as showing a high level of correlation (Fernando, 2024).

However, in the preliminary stage, Pearson correlation coefficients are computed to understand the linear relationships among variables in the dataset. This serves a dual purpose: spotting strong associations that may influence model behavior and revealing potential issues of multicollinearity among the regressors. To visualize coefficients, a rectangular correlation heatmap was generated using RStudio. The R code first defines all relevant variables and separates dependent and independent ones, then computes the correlation matrix between the two sets and produces Image #2 using `ggplot2`.


***Image #2**: Rectangular Pearson correlation heatmap*

Key observations could still be drawn from this picture. In fact, patents exhibit a strong positive correlation with all three dependent variables, suggesting yet that Intellectual Property is a strong signal of both investor and organizational size in quantum startups. Signal team strength is consistently correlated as well, confirming the central role of human capital. Completion score and employee and product growth are positively correlated with all three variables as well, while the same affirmation cannot be made about timing, as it signals “is the startup likely to raise their next round soon?”. As expected, startups that go through more funding rounds tend to be larger and more highly valued, and older startups tend to have raised more capital (as indicated by -0.44 of seed year vs. total funding, and -0.17 of launch year vs. total funding). Between subfields, startups working in hardware infrastructure appear to be better funded and more developed in terms of workforce and valuation compared to those focused on applications in software, photonics, communications, and biotechnologies.

## 3.4 Patterns across regression models

The first OLS regression, which examined `log_total_funding` as the dependent variable, indicated that `public_funding`, `patents`, `signal_team_strength`, and `rounds` had a statistically significant impact, confirming patterns already visible in the correlation heatmap. These findings suggest that both tangible achievements (like rounds and patents) and perceived quality signals (like a strong team) play a substantial role in attracting investment. Notably, the results indicate that startups supported by public programs are less likely to secure higher levels of funding. The adjusted R-squared value remained high at 0.8577, indicating that approximately 85.77% of the variance in the dependent variable is explained by the model. When re-estimated using robust standard errors, the model continued to confirm the statistical significance and reliability of the identified predictors.

The second regression focused on `log_valuation` and was likewise estimated with robust standard errors. Here again, patents, team strength, and public investments were positively associated with startup valuation, while revenue models and subfield variables showed limited explanatory power, suggesting that, when controlling for other factors, the specific quantum technology developed by a firm may not be a primary driver of its valuation.

Finally, the third OLS regression model centralized on `log_employees`. From this comprehensive model, three variables emerged as statistically significant: `signal_team_strength` ($p < 0.001$), `signal_growth_rate` ($p < 0.001$), and `signal_completeness` ($p \approx 0.033$). These results were further validated by applying robust standard errors, which confirmed the same three predictors as statistically significant, reinforcing the robustness of the model's conclusions.

Multicollinearity was assessed using Variance Inflation Factor (VIF) analysis, and all `vif` values in all the regression models were below the critical threshold of 5, which confirms that multicollinearity is not a concern.

To ensure model parsimony and robustness, cleaned versions of the three models were estimated using only the statistically significant predictors. After refining the log_total_funding regression, it is crucial to note that public_funding was no longer relevant. This led to the construction of an additional model, called ols_clean_funding1, which excludes it.

Both cleaned models for valuation and employees retained a strong explanatory capacity, with adjusted R-squared values of respectively 0.793 and 0.702, and all coefficients that remained statistically significant at the 1% level.

Chiefly, the regression results confirm that the number of funding rounds, the number of patents, and team quality are all statistically significant predictors of the total funding received by quantum startups. In particular, the signal of team strength shows the strongest effect, with a one-unit increase associated with an estimated 5.33% increase in total funding (given the log-transformed dependent variable). Patents also have a significant and positive impact, with each additional patent being associated with approximately a 2.10% increase in total funding. Finally, funding rounds contribute positively as well, with each additional round corresponding to a 5.06% increase in total funding.

For valuation, the robust model confirmed the statistical significance of all three predictors, further reinforcing the reliability of the results. Specifically, a one-unit increase in signal_team_strength corresponds to an estimated 7.72% increase in valuation, highlighting the substantial weight that investors place on perceived team quality. Likewise, each additional patent is associated with a 2.29% increase in valuation, underscoring the importance of technological innovation and Intellectual Property in this sector. In contrast, being backed by public funding is associated with a 6.02% decrease in valuation, a result that may reflect market skepticism toward publicly funded ventures, possibly due to assumptions about lower competitiveness or a lack of private validation. That said, it is important to note that public funding's negative coefficient does not necessarily imply lower overall potential.

Interpreting the results of the cleaned model for employees, signal_team_strength is found as the most influential predictor: a one-unit increase is associated with an estimated 3.13% increase in the number of employees. This suggests that teams perceived as stronger are more likely to scale in terms of human capital. In addition, signal_growth_rate shows a significant and positive effect, with each unit increase contributing to an approximate 0.49% increase in employees, indicating that signals of fast growth translate into actual workforce expansion. Lastly, signal_completeness contributes a 4.32% increase per unit, highlighting that startups that best fit in their segment of interest are likely to employ more people.

### 3.4.1 Diagnostic checks and model robustness

Before drawing up conclusions, a crucial check on OLS assumptions will be made. That means that three inspections will be carried out: the Breusch-Pagan test (checking for heteroskedasticity), the Shapiro-Wilk test (which evaluates the normality of residuals), and the Durbin-Watson test (used for assessing autocorrelation in residuals).

The Durbin-Watson test results indicated no evidence of autocorrelation in any of the three cleaned models. For log_total_funding, the test returned a DW value of approximately 2.21 ($p = 0.9089$); for log_valuation, DW = 1.99 ($p = 0.4684$); and for log_employees, DW = 1.97 ($p = 0.433$). All values are close to 2, which is consistent with the absence of autocorrelation in residuals.

Shapiro-Wilk test results revealed mixed outcomes. For log_total_funding, the test was highly significant, suggesting that residuals deviate from a normal distribution. Similarly, for log_employees, the p-value was also highly significant (approximately 2.6e-05), again indicating non-normality. In contrast, for log_valuation, the null hypothesis of normality was accepted ($p = 0.068$), meaning that the residuals are normally distributed. It is worth noting, however, that the assumption of normality can be relaxed in the case of large sample sizes (over 200 observations in this study), as justified by the Central Limit Theorem.

Breusch-Pagan test results showed no evidence of heteroskedasticity for the models on log_total_funding ($p = 0.154$) and log_employees ($p = 0.8843$). However, the test for the log_valuation model yielded a p-value below 0.001, indicating the presence of heteroskedasticity. As a result, this model was re-estimated using robust standard errors to ensure the validity of coefficient estimates.

To strengthen the empirical analysis and address potential endogeneity, Propensity Score Matching (PSM) was applied. This method reduces bias in estimating treatment effects by comparing startups with similar observable characteristics, differing only in the treatment variable, through balancing covariates across groups (Rosenbaum & Rubin, 1983). In this analysis, PSM was applied to `university_backed` and `public_funding` dummy variables, using `log_total_funding` as the outcome, with the aim of isolating the effect of university affiliation on startups' ability to attract capital, and to evaluate the impact of public support on total funding levels. When selecting covariates for the propensity score estimation, Dealroom signals were deliberately excluded, as they are algorithmically generated indicators that may change following the treatment itself, violating the core PSM assumption that all covariates must temporally precede the treatment.

The results show a strong covariate balance in the case of `university_backed`, with good overlap in propensity scores between the treated and control groups, both visually (via jitter and histogram plots) and in terms of standardized mean differences. In contrast, matching for `public_funding` proved less effective, with persistent imbalances in key covariates (such as the number of funding rounds), suggesting the presence of unobserved or structural selection. These results do not invalidate the main analysis as PSM was used for checking robustness, not as the sole basis for causal inference. In particular, the successful matching for `university_backed` supports the conclusions of the OLS models, while the difficulties encountered with `public_funding` call for more cautious interpretation, without compromising the overall consistency of the framework.

Furthermore, as anticipated, the use of PSM helped partially address potential endogeneity arising from startup self-selection into treatment groups. By balancing the comparison based on a set of pre-treatment covariates, the risk that estimated effects were driven by pre-existing differences (then translated into selection bias) rather than the treatment itself was mitigated. While PSM cannot fully eliminate endogeneity due to unobserved factors, it helps reduce bias and improve the plausibility of causal claims.

### 3.5 Exploratory and extended models

Exploratory analyses were conducted to investigate the extent to which the subfield and geographic region of operation influence the total funding raised by quantum computing startups globally. The purpose was to determine whether belonging to a specific technological subfield or region significantly affects investment levels.

To begin, the dataset was prepared by transforming dummy variables that indicated subfield classification (i.e., hardware infrastructure, software and applications, communications and cryptography, and sensing and detection) into a single categorical variable, called `subfield`. This variable allowed each startup to be assigned to one specific subfield. Observations with missing values for total funding or subfield classification were removed to ensure the validity of subsequent analyses. A similar approach was taken for geographic regions, where startups were assigned to a defined region variable (that is, `region`), and entries with missing data were excluded.

Descriptive statistics were computed for both subfields and regions. These included the number of startups, average funding, median funding, standard deviation, minimum, and maximum funding values within each group. Boxplots illustrating funding distributions across subfields and regions are provided in Image #3 and Image #4.

Regarding subfields, this shows that the number of startups and their corresponding funding varies significantly across them. Startups classified under hardware infrastructure exhibit the highest average and median funding, with a mean of 64.0 million and a median of 15.6 million. In contrast, those in communications and cryptography and sensing and detection report considerably lower average funding, both around 8.9 million. Software and applications companies show an intermediate position, with an average funding of 33.0 million. The standard deviations also reflect notable dispersion, particularly for hardware infrastructure and software and applications, suggesting the presence of large-scale investments in a subset of companies.

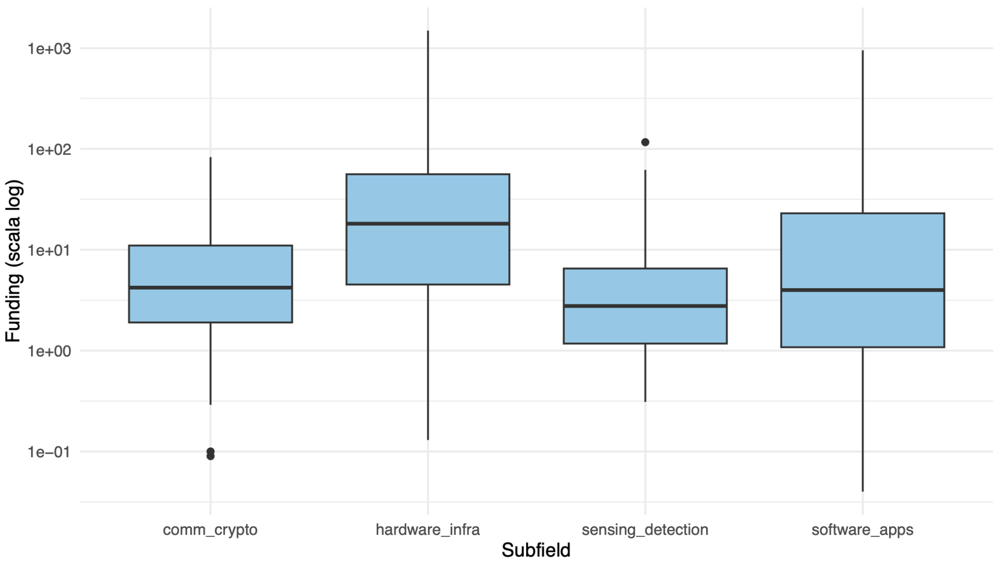


***Image #3****: Log-scale distribution of total funding by subfield*

Descriptive statistics by headquarters region indicate that startups located in America exhibit the highest average funding at 73.1 million, although their median is relatively low at 3.42 million, reflecting a skewed distribution influenced by a small number of very large investments. In contrast, Oceania shows a lower average funding of 44.7 million but a much higher median of 43.0 million, suggesting a more consistent level of funding across startups in that region. Europe and Asia record average funding levels of 22.5 million and 28.1 million respectively, with comparable median values around 5 million, and less extreme dispersion compared to America.

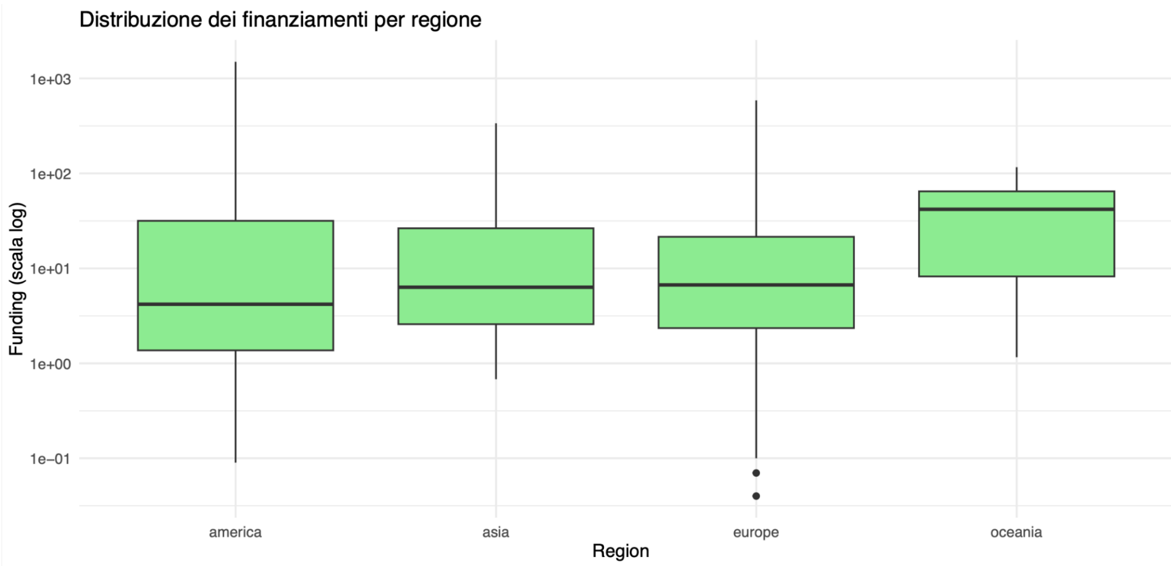


***Image #4****: Log-scale distribution of total funding by region*

Inferential analysis was carried out using Analysis of Variance (ANOVA) on the log-transformed total funding, with separate models specified for subfield and region as categorical independent variables. And to further quantify these effects, log-linear regression models were estimated with the log of total funding as the dependent variable and either subfield or region as the explanatory variable. Following the ANOVA, post-hoc comparisons were performed using Tukey's Honest Significant Difference (HSD) test and visualized through dedicated plots. This test identified which specific pairs of subfields or regions had statistically significant differences in mean funding.

The ANOVA conducted on the log-transformed total funding variable to assess whether the differences in mean funding across subfields are statistically significant yielded an F-statistic of 12.25 and a p-value of 1.64e-07, indicating a highly significant effect of subfield classification on funding at the 0.001 level. This confirms that the differences observed in the descriptive statistics and visual analysis are not due to random variation. Conversely, ANOVA results for regions report an F-statistic of 1.508 and a p-value of 0.213, suggesting that region alone does not explain a meaningful proportion of the variation in funding among startups.

Consequently, the situations in the two exploratory models are diverse. The regression performed with log-transformed total funding as the dependent variable and subfield as the categorical predictor further expands these differences. The regression results indicate that startups in the hardware infrastructure subfield receive significantly higher funding compared to the reference category, communications and cryptography, with a coefficient of 1.3343 and a p-value of 2.43e-06. This suggests that, on average, being in the hardware infrastructure subfield is associated with nearly a 3.8-times higher funding amount compared to the communications and cryptography subfield. This estimate results from exponentiating the regression coefficient ($\exp(1.3343) \approx 3.8$), given the log-transformation of the dependent variable. Instead, the results of the log-linear regression model estimated to further investigate potential differences between regions show that none of the regional coefficients gain statistical significance.

A post-hoc Tukey's Honest Significant Difference (HSD) test was conducted following the exploratory models to assess pairwise differences in mean log-transformed funding levels across both subfields and regions. For subfields, the test revealed that startups operating in hardware infrastructure raise significantly more funding than those in communications and cryptography ($p < 0.001$), software and applications ($p < 0.001$), and sensing and detection ($p < 0.001$). These differences are confirmed by confidence intervals that do not include zero, indicating robust statistical significance. All other pairwise comparisons between subfields did not show significant differences, suggesting that the observed funding gap is primarily driven by the standout position of the hardware infrastructure category. This pattern is further visualized (Image #5) in the corresponding Tukey plot, where the confidence intervals for hardware infrastructure are clearly separated from the others. In contrast, the Tukey HSD test applied to regions showed no statistically significant differences in mean funding levels between any pairwise regional comparisons. All adjusted p-values exceeded 0.15, and confidence intervals spanned zero in every case, reinforcing the conclusion that regional affiliation does not significantly affect funding outcomes. The related Tukey plot is reported in Image #6 and illustrates this clearly, as all confidence intervals cross the zero line.

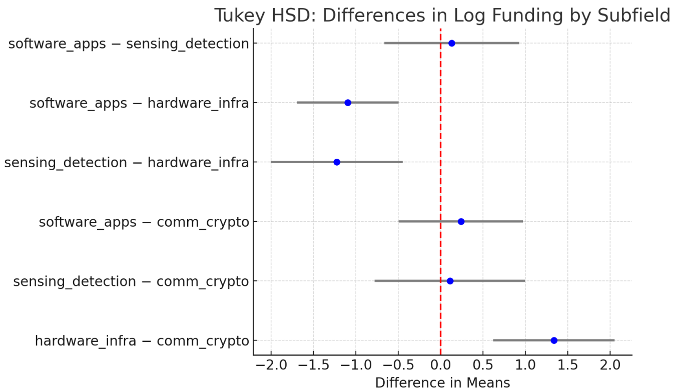


***Image #5**: Tukey HSD plot for pairwise comparisons of log funding across subfields*

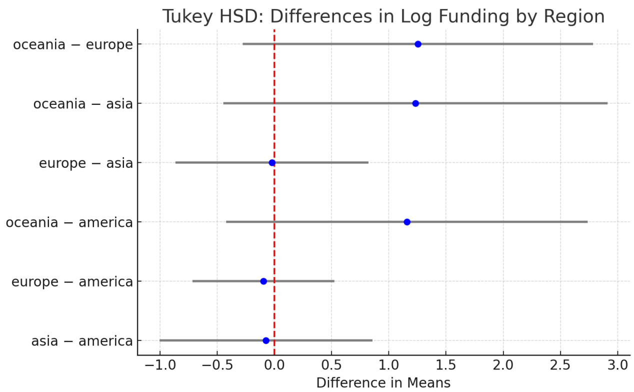


***Image #6**: Tukey HSD plot for pairwise comparisons of log funding across regions*

## 3.6 Key findings and groundwork for qualitative analysis

The regression analyses conducted on global quantum computing startups reveal a compelling narrative: success in this sector is not primarily driven by the specific subfield of quantum technology or business model, but rather by a combination of perceived team quality, demonstrable innovation, and strategic positioning. Across all three outcome variables, recalling that are total funding, valuation, and number of employees, the perceived strength of the founding team consistently emerged as the most powerful and reliable predictor. A strong team signal is associated with a 5.33% increase in funding, a 7.72% increase in valuation, and a 3.13% increase in employee number, underlining investor confidence in human capital as a proxy for long-term viability. However, this observation may be applied to startups in all industries, not only in quantum computing: every business idea that penetrates a market is supported by a formidable team, otherwise investors are unlikely to place their trust in it (Magni, 2013). On account of this, it is unquestionably true that team strength is a key factor for quantum computing startups, but it is necessary to be aware that this is a characteristic shared by many sectors.

Also technological output, captured by the number of patents, plays a decisive role in attracting investment and increasing valuation. Each additional patent corresponds to a 2–2.3% uplift in both funding and valuation, validating the high premium placed on IP in deep-tech sectors. This growing emphasis on patents is particularly relevant as deep-tech domains continue to expand, prompting reflection on whether Intellectual Property now serves not just as protection but also as a strategic lever for value creation.

The positive impact of the number of rounds on total funding raised is normal and self-evident. Interestingly, instead, public funding correlates negatively with company valuation, making it crucial to inquire whether this reflects market skepticism about the commercial competitiveness of publicly backed ventures. This dichotomy underscores a potential tension between short-term resource acquisition and longer-term market credibility, providing a cue for further investigation in the qualitative part.

Concerning the other two predictors positively correlated with employees, namely, the signal of growth rate and that one measuring completeness, a different explanation is required. While the first one incorporates employee growth (Foy, 2022), so it was quite predictable its impact on staff size, it will be particularly insightful to assess, through qualitative analysis, whether a better market fit truly drives faster organizational growth.

For what concerns the combined analysis of funding determinants for quantum computing startups, it reveals that technological specialization is a far more decisive factor than geographic location in explaining disparities in capital raised. Startups operating in the hardware infrastructure subfield receive significantly higher funding compared to those in software, communications, or sensing, with results robust across descriptive statistics, ANOVA, regression modeling, and post-hoc testing. This suggests that investors perceive hardware-based quantum ventures as more capital-intensive, possibly due to their foundational role in enabling the broader ecosystem, and that this is an ideal moment for such startups, especially for quantum computers and processors manufacturers, to tap into the market. It remains to be investigated whether this perception reflects a strategic inflection point for such startups, particularly quantum computer and processor manufacturers, to effectively tap into the market.

Conversely, geographic region shows no statistically significant impact on funding levels, despite initial impressions from descriptive statistics. This implies that global investment flows in quantum technologies are relatively decoupled from regional boundaries and may be increasingly influenced by technological edge and business strategy rather than location alone. The distribution of funding is also highly skewed within subfields and particularly within regions such as America, indicating that a small number of high-profile startups attract a disproportionate share of capital. However, this concentration of capital among a few standout players, coupled with the apparent irrelevance of geographic location in determining funding levels, points to a landscape where technological excellence and strategic positioning outweigh regional affiliation. In this context, qualitative interviews should explore whether quantum computing may represent a valuable opportunity for Europe to reinforce its position in a field that is still taking shape, especially considering that it has fallen behind in other technological races, such as AI, where over 80% of global funding goes to U.S. and Chinese firms, while only around 7% reaches EU-based businesses (Verbeek & Lundqvist, 2021).

# 4. Qualitative analysis

## 4.1 Qualitative design and interview sample

This section expands on the qualitative methodological approach introduced in Section 2.2.2, now implemented and refined based on the concrete development of the study. Following the attainment of concrete quantitative results, the design of the qualitative analysis was adopted accordingly to better interpret the significant patterns identified. The objective of this phase, following Creswell's explanatory mixed-methods approach, is precisely to provide a logical and discursive explanation of the statistical results, uncovering mechanisms, perceptions, and narratives that shape investment behavior in the quantum computing sector.

To achieve this, the qualitative part consists of three semi-structured interviews with a small, purposefully selected group of early-stage investors. This format allows for both thematic comparability and openness to respondent-specific insights, in line with established practices in qualitative interview design (Adhabi & Anozie, 2017). The interviews were designed to serve two complementary objectives: first, to explore general investment philosophies, risk assessment strategies and sectoral perceptions; second, to directly interrogate the key patterns that emerged from the quantitative phase, such as those related to geography, team structure or technological maturity.

Following a realist and interpretive approach, this phase adopted an iterative design, allowing early observations to shape the development of subsequent interviews. This ensured stronger alignment between the two methodological components and made it possible to adapt the interview guide in response to both emerging themes and quantitative results. Rather than being treated as an isolated layer, the qualitative data is integrated into the overall analysis to provide interpretive depth, clarify causal assumptions, and illuminate the logic behind outlier cases.

The final sample consists of three venture capital investors, each with a different background. Luca Adinolfi, who took part in the first interview, has an academic background in economics and is a Partner at Lumen Ventures and Business Management professor at LUISS Guido Carli, as well as the former founder of the insurance broker Value Spa. The second perspective is provided by Arianna Tibuzzi, who operates as a Principal at a VC firm focused on deep technologies, namely, Obloo Ventures, and has prior experience as a researcher in interdisciplinary groups on microsystems, silicon technology, and sensor systems. Finally, Section 4.3 explores the reflections of Emilia Garito, Chairman and Founder of Deep Ocean Capital, whose professional trajectory began with a Bachelor's degree in Computer Engineering from Sapienza University and spans engineering, defense, and deep-tech, including roles at Leonardo Finmeccanica, the founding of Quantum Leap IP, and advisory work for the European Commission on AI and robotics.

The selection followed a purposive logic, privileging individuals with first-hand involvement in decision-making processes concerning deep-tech and quantum technologies. Although limited in number, the sample offers concentrated insights into the investor perspective and gives detailed, context-sensitive interpretations of the patterns uncovered during the quantitative analysis, thanks also to the diverse and extensive professional backgrounds of the investors involved.

All interviews were conducted via video calls on Microsoft Teams between 14 May 2025 and 22 May 2025, lasted approximately 30 minutes each, and were recorded and transcribed with the participants' consent (interview transcripts are available in Appendix C). The interviews combined broad thematic questions on investment rationales, expectations, and perceived risks, with targeted probes related to specific quantitative findings. This structure allows for a dual-level analysis by balancing openness to emergent insights with a theory-driven exploration of empirically grounded hypotheses.

## 4.2 VC perspective I: Leadership and capital dynamics

The conversation with Luca Adinolfi centers on two key findings emerging from the empirical analysis, namely, investor perceptions of team quality and leadership, and the strategic implications of public versus private capital on startup valuation. The interviewee's dual background in venture capital and academia helps reconcile the divide between data and practice, offering concrete interpretations of the findings from an investor's standpoint. In addition to addressing these core topics, the interview also explores broader, cross-cutting issues that shape investor behavior in the deep-tech space, with a focus on quantum computing. Adinolfi emphasizes that quantum technologies pose a distinct array of difficulties that go beyond conventional investment logic. From the perspective of a regulated VC fund like Lumen Ventures, quantum computing is considered exceptionally challenging to evaluate, both because of the intrinsic technical complexity and because it is often hard to communicate its potential convincingly to institutional investors such as banks and pension funds. This lack of comprehensibility is compounded by a critical market limitation, that is, the absence of a historical track record in venture capital returns.

This set of challenges translates directly into stricter and more resource-intensive evaluation processes for investors. Given the inherent complexity of quantum technologies, due diligence processes in investment decisions frequently require greater support from specialized industry experts. Technical understanding of the sector is a prerequisite for most venture capitalists, and if they do not understand the industry, they do not invest. There is no blind faith in technological potential. Another issue is that deep technologies require a lot of time to generate major returns. Except for dedicated funds, this timeline often does not align with the temporal constraints of initial-stage VCs, which are typically around 10 years. As a result, quantum startups are frequently perceived as higher-risk ventures, particularly at the seed or early-growth phase, where Adinolfi's venture capital firm operates.

Nevertheless, team quality emerges again as a critical success factor when evaluating investments, confirming what emerged from the quantitative analysis, namely, that the linked variable was statistically significant in all three models. Despite a limited activity of Lumen Ventures in investing in deep-tech, the professor recognizes the crucial role of team strength across all funding decisions, particularly in relation to early-stage ones. It is not a coincidence that the investment thesis of his fund is "100% team-driven" with people always being evaluated before the business model or innovation.

However, a few new insights emerge in regard to this topic. In fact, the professor highlights the importance of complementarity and diversity: according to him, it is relevant for a team to be diversified, both at demographics- and at competencies-level. Complementary teams are preferred by investors, while "having been colleagues" is sometimes considered a red flag. That said, this is not the case when two founders have the same background, but also have a well-diversified and broad team behind them. In such situations, the managerial forefront is considered on par with the founding team. Still, that circumstance would represent the exception that proves the rule.

Another predilection by investors is reflected by second-time teams. Having to mitigate risks, VC funds hardly allocate money to founders with zero working experience. Obviously, even in this case, there are exceptions, but, all else equal, teams composed of individuals with previous experience in large corporates, consulting, or finance, or by serial entrepreneurs, are preferred. This preference is consistent with empirical evidence in the literature, which shows that entrepreneurs with a track record of success are more likely to succeed in subsequent ventures (Gombers et al., 2010). Rookie teams do not give too many guarantees, especially in deep-tech sectors, where most founders have just finished their master's degree and launch their project without any managerial skill.

One key takeaway from this discussion is that, while team quality is undeniably crucial in quantum computing, its importance is not specific to this domain. Rather, the emphasis on a strong, complementary, and experienced founding team reflects a broader principle that applies across all early-stage startups, regardless of sector. It is therefore essential to contextualise this insight: although a good leadership significantly impacts total funding raised, company valuation, and organizational growth in quantum computing startups, this dynamic mirrors a general trend in venture capital decision-making, not a distinctive trait of the field itself.

Founding teams aside, the quantitative analysis also revealed findings that are more specific to the quantum computing sector. Among these, one particularly counterintuitive result emerges: surprisingly, in fact, public funding influences the valuation of quantum startups negatively. Consequently, questions such as "Are investors biased against public funding?" have been formulated to clarify the nature of this effect, especially given the abundance of support programs for emerging technologies provided by public institutions, from local ones to continental (as an example, the European Union provides Horizon, the EIC Accelerator, and the European Investment Fund as funding instruments in this environment). However, Luca Adinolfi offers another point of view in relation to that statistical outcome: public investors carry broader responsibilities and are therefore often reluctant to engage in highly speculative ventures or startups with inflated valuations. This caution stems from their dual mandate: unlike private investors, public venture capital actors are not solely focused on generating returns. They are also tasked with building a public ecosystem of emerging technologies that can benefit their region and generate positive societal impact. In contrast, private investors are exclusively return-driven and can afford to pursue high-valuation opportunities if they perceive strong potential upside. Public entities, on the other hand, rarely participate in late-stage funding rounds for mature startups with aggressive valuations. Instead, they tend to support early-stage deep-tech ventures, aiming to foster systemic innovation and identify transformative niche opportunities.

In addition, Luca Adinolfi goes on to say that there is no investor bias against publicly-backed startups. On the contrary, while abroad the public role is seen as neutral, in Italy, being funded by sovereign funds or having taken part in public programs is viewed as a sign of high credibility for a startup. In general, public funding needs private co-investments, and there is a mutual respect between the two entities, as they often have to allocate capital jointly. Moreover, public funds tend to play a passive role, offering financial support but rarely engaging in operational development, governance, or commercial scaling. This stands in contrast to privately held VC funds, accelerators, and incubators, which actively monitor their investments and participate in the day-to-day activities of portfolio startups in order to ensure higher returns and greater market visibility. As a result, collaboration between public and private actors is not only common, but also necessary.

## 4.3 VC perspective II: Market fit and geographic strategies

The second perspective on the quantitative findings regarding the success of quantum computing startups is provided by Arianna Tibuzzi, who offered valuable insights into the relationship between product-market fit and organizational growth, as well as the geographic dynamics of investment in the quantum computing sector.

Preliminary considerations confirm what Luca Adinolfi said, highlighting that a major challenge for quantum computing startups facing traditional investors is the long time horizons required for success, often exceeding ten years. This translates also into dilated time-to-market and time-to-exit, that most traditional VC funds cannot afford, due to their plans of action, which in the majority of cases expect five years of investments and five years of divestments. This adds to the knowledge gap that still persists regarding quantum mechanics, and to the large funding rounds required by quantum startups since their pre-seed stage. However, all these considerations are not meant to discourage the field, but offer an initial explanation as to why the sector is still in its growth phase. The interviewee has in fact clarified immediately that quantum computing remains one of the most disruptive enabling technologies, with potentially extraordinary returns, and might be compared, in some respects, to the early days of the Internet.

Being in contact with the research finding pointing out the importance of completeness for organizational growth, Tibuzzi signals it as a prerequisite for scalability. A quantum startup is considered ready to go to market only if it presents a clear roadmap, a solid team, and a sellable sub-product. The latter is crucial: since their core products (e.g., quantum processors or computers) take years to develop, it becomes essential to launch alternative products, often derived from or related to the main technology, to generate revenues in the meantime. In summary, medium-term monetisation is necessary.

The team also plays a key role in the growth of deep-tech startups, although the situation differs somewhat in the quantum computing sector, according to the Obloo investor. While in deep-tech more generally, founders with scientific or technical backgrounds often seek external support to fill key managerial roles such as that of CEO, in quantum computing this is not always the case. On the contrary, it is more accepted that the CEO is a scientist rather than a manager or businessperson, as investors tend to place greater trust in experts in physics and mathematics when operating in such a complex domain. Moreover, in quantum computing, founders are typically men over the age of 50, meaning that internal team members already possess a certain level of seniority. Team expansion will only occur if the business model is sustainable, so a clear value proposition is proposed and a roadmap capable of generating investor trust is in place, including a sub-product, as mentioned above.

A focus was placed by Dr. Tibuzzi on manufacturers of hardware, for whom patents are considered a must-have, along with carefully selected strategic partnerships that help ensure access to critical technologies. As an instance, many foundries are based in Asia, and still having a clear understanding from the early stages of growth about whom to contact and how to access these key infrastructures is essential for demonstrating credibility and reliability in the eyes of a VC. Use-cases can also be beneficial, as they enhance a startup's credibility as well, but they are not decisive. For software providers, the situation is different, as they typically receive less capital but benefit from a shorter time-to-market by taking advantage of existing hardware infrastructures.

Instead, regional disparities revealed in the quantitative analysis did not surprise Arianna Tibuzzi. Indeed, she noted that quantum computing is globally perceived as a disruptive technology and its value is universally recognized, making it less subject to geographical bias. Every government wants to jump on the bandwagon, but substantial differences lie in investment approaches: in the US, it is easier to raise a seed round of 5 to 6 million dollars, while in Europe such figures are largely outside the scope of investors. This ties back to what was explained above: quantum computing startups, especially hardware manufacturers, require above-average capital, and regularly exhibit significantly high pre-money valuations. Nevertheless, the EU is still in the running, largely in comparison to its position in AI or Space, where it lags far behind the US and Asia. This is mainly because it remains notably competitive at a scientific level, with many top-tier scientists, registered patents, and excellent universities. Its evident limitations, such as the difficulty in securing large early-stage rounds and the technical knowledge gap among private investors, are now being partially offset by access to skilled technical labor and public support instruments, such as the EIC Accelerator which offers up to €15 million in equity funding along with €2.5 million in grants.

## 4.4 VC perspective III: IP strategy and technological positioning

Emilia Garito’s perspective begins with a clarification of the term "deep-tech", which was coined only in 2014 to distinguish it from high-tech and digital innovation. Unlike technologies built on existing software infrastructures and user-facing applications, deep-tech originates at the frontier of scientific research. It typically involves long development timelines, complex R&D processes, and a higher degree of technical uncertainty. As a result, it requires distinct evaluation criteria, longer investment horizons, and dedicated innovation strategies, often necessitating close collaboration between academia and industry. Unlike other technological domains, the foundation of deep-tech does not lie in the innovative application of existing tools. Rather, it generates entirely new technologies. This is why Intellectual Property is central to the valuation of startups in this sector. The technological content of a solution is defined by its ability to create IP, which should be intended not just as patents, but also as protecting know-how.

However, as Emilia Garito points out, Intellectual Property must be assessed qualitatively as well as quantitatively. Thorough technological due diligence is essential in order to evaluate the actual innovation embedded in a patent and to estimate the robustness of a proposed solution. Several tools such as IP intelligence, patent landscaping, and related analyses, can assist in gathering concrete data, but they require proper interpretation to provide evidence of the technological strength of a given solution. In the specific context of quantum computing, Intellectual Property becomes even more important. As this is still an emerging industry, those who manage to secure protection for key innovations ahead of competitors will gain a competitive advantage. In such a scenario, nothing should be left to chance. Effective IP planning should be viewed not only as a strategic lever for growth, but also as a defensive asset to prevent competitors from reappropriating and exploiting future technologies.

Other than that, the industry relevance of a technology is crucial: even a breakthrough innovation may fail if it lacks a viable market. If a technology cannot be industrialized due to a market that is latent or embryonic, it may prove economically unsustainable despite its technical potential. Garito notes that their history offers many examples of companies capable of transforming an entire sector that did not manage to succeed because they entered the market too early or in a historical moment where it was too small. This highlights how, while Intellectual Property plays a key role in the success of deep-tech startups, achieving product-market fit is equally crucial.

However, according to Garito, quantum computing still requires more time to become fully viable within the venture capital framework, primarily because most VC funds operate within a ten-year horizon, while significant breakthroughs in the quantum sector are not expected within such a short timeframe. Meanwhile, it is crucial for quantum startups, especially those focused on hardware, to develop key enabling technologies that are already applicable in existing markets. Investor preferences tend to favor areas such as photonic chips and super-computers, where current applications are more readily achievable. Indeed, any intermediate application is viewed as a positive asset by venture capitalists, who are generally unable to wait until the final product materializes beyond the lifecycle of their fund.

Engaging with the quantitative finding that highlights differences in funding across quantum computing subfields, Emilia Garito links these disparities to regional variation and, again, to the relevance of the Intellectual Property. In the US, for instance, patenting software and algorithms is considerably easier than in Europe, and this distinction extends to quantum technologies as well. In Europe, the regulatory framework for software safeguarding remains unclear. While patenting hardware is relatively more straightforward, the protection of software-related innovations continues to pose significant challenges. Only in recent years, the European Commission has standardized the documentation required for hardware manufacturers to receive guidance on IP strategies, highlighting how much further the software domain still has to go. In this context, cultural awareness plays a significant role. This different attitude is often evident also among some early-stage deep-tech startups, where founders may be unaware of the strategic value of both patents and trade secrets. Some even assume their innovations are not patentable, thereby underestimating the defensive and competitive functions of Intellectual Property, leaving their technologies exposed to market imitation. This situation tends not to happen in the US, where founders are more informed, despite coming from a scientific background.

Nonetheless, Garito argues that Europe may hold a comparative advantage in quantum technologies in relation to sectors such as Artificial Intelligence. This advantage stems from Europe’s strong scientific foundations in fields like physics, quantum optics, and advanced materials. She suggested that major investments should target not only quantum computer manufacturing, but also adjacent subfields such as quantum communication and photonics. Within this landscape, participating in European public funding programs such as the EIC Accelerator (which was already mentioned by Arianna Tibuzzi) is crucial as they offer significant grant and equity support that can be decisive for a startup's growth potential, often helping to unlock additional private investment. In this regard, the interviewee underscores the strategic value of receiving a "Seal of Excellence" from the European Commission, which serves as a strong endorsement of technological quality and, in many countries, triggers access to complementary national funding mechanisms.

# 5. Conclusion

## 5.1 Integrated summary and comparison of findings

The direct voices of investors add depth to the quantitative data, offering a more grounded and realistic understanding of investment logic in quantum technologies. Their insights reveal how investment decisions in this space are rarely driven by a single variable.

Before answering the research question, which is worth recalling as follows: "How do key strategic and operational factors in quantum computing startups shape investors' decision-making, leading to improved funding outcomes?", it is important to highlight that several issues have emerged regarding traditional VCs, which, for the most part, are still not ready to invest in quantum computing. In fact, they raise capital from third parties, including banks, pension funds, and public institutions. Since they already manage a high-risk asset class (namely, startup investments), they tend to minimize risk by avoiding rounds involving players operating in uncertain, though high-potential, markets such as quantum computing. In addition, a significant knowledge gap persists among investors, who generally come from economic or financial backgrounds and often lack the technical expertise needed to fully understand the solutions proposed by startups in this sector. As a result, they tend to avoid investing unless accompanied by industry experts and supported by in-depth technological due diligence. A third and final issue that emerged from the interviews concerns the typical duration of venture capital funds, which is structured over a ten-year horizon: five years dedicated to investments and five to divestments. This second phase is the period in which investors aim to exit from portfolio startups, those that have survived, in order to secure a profitable return. Quantum technologies, by contrast, require many more years to mature, surpassing the temporal constraints imposed by venture capital funds and their limited partners.

This context provides a first significant answer to the research question. A factor that significantly shapes investor decision-making in quantum computing startups is the go-to-market strategy. In line with what has been said, in order to convince an investor to fund a quantum startup, it is necessary to present a clear roadmap that includes the possibility of medium-term monetization. Supporting the quantitative finding that shows a strong positive relationship between product-market fit and organizational growth, it is crucial for quantum startups to consider developing a commercializable product in the early stages, which may also be a subcomponent of the final output. This becomes even more critical in light of the fact that the main product may take decades to reach full commercial viability. If the roadmap and business model are structured accordingly, and the time-to-market is less extended, venture capitalists are more likely to invest, as this increases their chances of achieving a successful exit during the second half of the fund's cycle.

Another factor that emerged as decisive both in the quantitative analysis (where it proved statistically significant in all three regression models) and in the interviews is the team. In the startup world, across all sectors, the founding team is a core factor, and many traditional funds base a large part of their decision-making on its quality and cohesion. In the case of quantum computing, which is among the most complex deep-tech sectors, team strength becomes even more relevant. Given the knowledge gap discussed above, quantum computing stands out as one of the few sectors where a technical background among founders is not only acceptable but expected. Having a team with a scientific academic path that is also skilled in communication is crucial to ensure that those who are supposed to invest can understand what they are investing in. This is why the experience of the founding team sometimes represents a fundamental prerequisite, often carrying more weight than the technology itself or the business model. It should also be noted that a well-balanced mix of profiles is always positively received, whether in terms of demographics or competencies. When the skill sets are diverse, they are considered a strong asset in the eyes of investors. Indeed, beyond quality and communication ability, team complementarity is another key factor in VCs' evaluation.

With regard to the scientific background required by venture capital funds in relation to the teams of quantum computing startups, the interviewees considered it very useful to emphasize the importance of Intellectual Property. Patenting is fundamental, as a deep-tech startup that does not own patents will find it very difficult to attract investors.

This confirms the quantitative result according to which an increase in the number of patents held by a startup leads to a higher valuation and a greater amount of capital raised. Moreover, a good IP strategy is also positively evaluated in terms of protection: patenting a specific technology can help prevent competitors from imitating it, thus highlighting to the market the uniqueness of the solution. Therefore, Intellectual Property is not only regarded as a strategic lever, but also as a defensive asset. In both cases, however, the outcome is the same: tthe stronger the protection of innovation ownership, the higher the consideration from investors. However, the interviews also revealed that the culture of patenting is far more widespread in the United States than in Europe. Scientists often refrain from protecting their inventions, either because they are not clearly informed about what can be protected, and therefore unaware of the strategic benefits of securing Intellectual Property for technological innovation, or because the regulatory framework in Europe remains relatively complex and inefficient. While a clearer path has recently been established in the hardware domain, in the area of software the European Union still lags behind, as it does not easily allow algorithm or program developers to secure patent protection for their innovations.

In relation to this last observation, it is worth recalling the quantitative result that emerged from the exploratory analysis on subfields, according to which quantum hardware and infrastructure producers receive more funding. This is in fact linked to a very specific dynamic, namely, that companies working in quantum software, quantum communication, and quantum sensing require less capital compared to those developing quantum computers and processors. This difference in capital intensity is reflected both in the supply chain (considering, for example, the costs of securing certain raw materials, accessing suitable semiconductor foundries, and acquiring specialized labour) and in the commercialization of intermediate products, as previously discussed. Software developers, in fact, will need fewer resources to monetize in the medium term, since it may be sufficient for them to create something that is also compatible with classical computers. For hardware developers, on the other hand, this process is more difficult, because they must develop something physical, tangible, and functional, whether it be optical accelerators or photonic chips. In this way, the disproportionate flow of large investments in favor of quantum hardware and infrastructure producers can be explained. This asymmetry does not imply any lack of relevance towards the other subfields, which, on the contrary, are considered equally strategic by the interviewed investors.

A final consideration must be made regarding the importance of public support programs. This goes against what was reported in the quantitative analysis, which showed that being public-backed is negatively correlated with valuation. However, this should not be seen as a contradiction. From the interviews, it emerged that this result can be explained by the fact that public funding is mostly directed toward early-stage startups and, more generally, toward companies that do not yet have high or market-inflated valuations. There is no systemic prejudice from private investors against startups that have participated in public programs. On the contrary, in the case of quantum computing, this is seen as a positive signal, since public institutions conduct very thorough technological due diligence. If they decide to allocate funding to a specific startup in this sector, it means that the technological solution being developed is considered valid. It should be noted, however, that public capital is often passive and not deeply involved in corporate governance. For this reason, public-private collaboration is essential to support the scaling process. Among the interviewees, particular emphasis was placed on the key role played by the EIC Accelerator in the European quantum computing landscape. It is important that startups with high technological value take advantage of the fact that the European Union offers up to 15 million euros in equity and 2.5 million in grants. This is especially noteworthy given that such large amounts are uncommon in the European venture capital landscape, particularly when compared to the United States, where seed rounds of 5 or 6 million dollars are nearly standard in the deep-tech segment.

## 5.2 Theoretical and practical implications

The findings discussed above have several important implications for both investors and policy-makers. They highlight a structural misalignment between the operational logic of traditional venture capital and the specific requirements of deep-tech innovation. VC funds typically operate on investment cycles that are significantly shorter than the time needed for breakthrough technologies to mature, aiming to enter and exit their positions within a relatively brief time frame. Moreover, they often lack in-depth technical expertise and tend to be risk-averse, in part to avoid unsettling their limited partners, who are the ultimate sources of capital. As a result, many VC firms struggle to confidently assess or support early-stage quantum startups, which typically operate at the frontiers of physics, mathematics, and engineering, and evolve on significantly longer timescales. In fact, the path from foundational research to commercial application can span over a decade, requiring sustained investment, deep domain expertise, and the ability to navigate complex stages of technological readiness. The previously discussed focus on medium-term monetisation through the development of intermediate products or subcomponents may serve as a valuable meeting point between capital allocators and founders, helping to align expectations.

Further relevant observations emerge from structural characteristics of the European innovation ecosystem. While the quantitative analysis had a global perspective, the interviews specifically shed light on dynamics within Europe, as all three case studies are based in this region. On one hand, the European Union furnishes a very appreciated support program, namely, the EIC Accelerator, investors generally express satisfaction with startups that have participated in this program. On the other hand, there is a notable lack of widespread Intellectual Property literacy among scientific founders, many of whom are transitioning from academic research with limited exposure to entrepreneurial practices. Additionally, the absence of a coherent and accessible regulatory framework for software-related IP, including quantum algorithms and middleware, introduces further uncertainty. Such regulatory ambiguity can discourage investment and slow down technology transfer.

Given these multifaceted challenges, a coordinated policy response is needed. Governments and regulatory bodies should prioritize the simplification and clarification of IP systems, with a specific focus on quantum software, where current patentability standards remain opaque. Simultaneously, dedicated educational efforts should target researchers, engineers, and scientists to improve their understanding of IP strategy, equity financing, and startup management, thereby helping to bridge persistent knowledge gaps and enabling more productive interactions with investors.

On the financial side, public institutions have a crucial role to play in de-risking deep-tech ventures through active co-investment models. These initiatives can be especially impactful in capital-intensive segments like quantum hardware, where the need for advanced fabrication facilities and high upfront costs can deter private investors. Beyond providing access to public R&D infrastructure, preventing startups from seeking more affordable production options overseas, these collaborations also enable an effective division of labour: public actors can contribute technical due diligence capabilities, while VC funds bring their close and continuous monitoring of startups. Concrete initiatives already in place can serve as valuable models: beyond the reiterated EIC Accelerator, the US National Quantum Initiative Act and its implementation via the Quantum Economic Development Consortium (QED-C) demonstrate a coordinated effort to bring together the entire ecosystem that is going to be needed to realize quantum technology for all kinds of benefits (Underwood, 2025).

Instead, to reduce uncertainty and improve comparability in investment decisions, a standardized valuation framework for early-stage deep-tech startups should be developed and adopted by both public and private actors. Such a model could include not only traditional financial indicators, but also intangible assets like patents, technical implementation trajectories, advisory boards, and scientific reputation. By making pre-revenue ventures more legible to investors, especially in highly technical fields such as quantum computing, these benchmarks would support more objective and informed capital allocation.

Finally, from the founders' point of view, the formation of complementary teams, particularly involving experienced, second-time entrepreneurs, should be encouraged. This may further reduce perceived execution risk and strengthen overall venture resilience. In addition, in order to secure the necessary capital, startups must be able to present a clear and credible roadmap outlining their development strategy. Demonstrating awareness of key milestones and identifying or formalizing strategic partnerships can represent a significant advantage when engaging with investors.

## 5.3 Limitations of the study and suggestions for future research

Despite the methodological rigor and the comprehensive dataset employed in this study, several limitations must be acknowledged. These concern, above all, the nature of the data, certain modelling choices, and the scope of the analysis, all of which open up promising directions for future research.

The first limitations of the research concern construct validity, which is the extent to which a measurement tool is truly assessing what it has been designed to assess (Drew, 2023). More specifically, among the most critical issues is data incompleteness, particularly in the attribution of patents to startups. This deficiency is significant, as it affects the reliability of core variables and, consequently, the generalizability of the findings. The analysis assumes that the data reported on Dealroom and Google Patents are complete and accurate, which in reality cannot be fully guaranteed. In fact, the number of patents associated with a startup may be underestimated or overestimated depending on how the filing was made or to whom the patent is assigned (as previously discussed in section 3.1), while some startups may not have updated their information on Dealroom. Related to the latter, an observation must also be made regarding the Dealroom signals, which are derived from a proprietary algorithm and, without full transparency into its components, it is impossible to fully assess whether it accurately captures the theoretical construct of "startup quality".

Problems of external validity, which refers to whether the results of a study generalize to the real world or other situations, may instead be concealed by the interviews which, although rich in content, are not generalizable to the entire international landscape, as the interviewees are active only in the European context. Possible comparisons with investors in North America or China could provide different perspectives. Moreover, three interviews constitute a relatively small sample size, which is constrained in methodological rigor and should be expressly recognized. Returning to the quantitative part, instead, the reliance on the Dealroom dataset limits the replicability of the findings, although it is rich and up-to-date, and it must be specified that the results are tailored to quantum computing startups and may not fully apply to other emerging deep-tech sectors without further empirical validation.

Finally, internal validity, meaning to whether or not the results of an experiment are due to the manipulation of the independent variables, is limited first of all by the absence of a dynamic analysis using longitudinal data. The model is entirely cross-sectional and captures the situation at a specific moment (2025) but does not reflect the temporal evolution of startups. Other than that, while this study applied Propensity Score Matching to partially address it, endogeneity remains a concern. Further methodological refinements, such as instrumental variable techniques or longitudinal designs, would be required to fully address the remaining risks. Furthermore, the analysis focuses on main effects without testing for interaction effects or non-linear relationships, both of which could uncover subtler dynamics, and even the adoption of polynomial or non-parametric models, such as regression trees, could help capture threshold effects or diminishing returns.

In light of these limitations, future research can develop in various directions in order to improve the methodological design and strengthen the validity of the study, whether internal, external, or construct. In particular, the adoption of longitudinal data to analyze the temporal evolution of startups and reinforce causal inference would be crucial to provide a more structured and forward-looking answer to the research question. It would also be useful to expand the model by strengthening data robustness through triangulation with additional sources beyond those already used, and to explore interaction effects between variables and non-linear relationships, in order to capture more complex dynamics that might escape traditional linear models. Additionally, expanding the number of qualitative interviews and diversifying the geographical scope of the participants would enhance the external validity and provide a thorough picture of global investment dynamics. Finally, it is worth highlighting that the methodological application of this research in other emerging deep-tech sectors would allow for the verification of its generalizability and the reinforcement of its theoretical soundness.

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# Appendix A – Codes

*All codes were run in R Studio.*

List of R packages used throughout the quantitative analysis:

```
library(reshape2)
library(ggplot2)
library(dplyr)
library(tidyverse)
library(readxl)
library(knitr)
library(kableExtra)
library(sandwich)
library(lmtest)
library(car)
library(GGally)
library(corrplot)
library(multcomp)
```

Code for generating the rectangular Pearson correlation heatmap:

```
allvars <- c("launch_year", "seed_year", "hq_europe", "hq_asia",
             "hq_america", "hq_oceania", "valuation", "total_funding",
             "rounds", "public_funding", "university_backed", "patents",
             "employees", "founder_serial","rev_model_marketplace",
             "rev_model_saas", "rev_model_manufacturing",
             "signal_completeness", "signal_team_strength",
             "signal_growth_rate", "signal_timing", "subfield_software_apps",
             "subfield_hardware_infra", "subfield_comm_crypto",
             "subfield_sensing_detection")

depvars <- c("valuation","total_funding","employees")
indepvars <- setdiff(allvars,depvars)

rect_cor <- cor(quantumdataset[, depvars], quantumdataset[, indepvars],
                use = "complete.obs")

melted_cor <- melt(rect_cor)

ggplot(melted_cor, aes(x = Var2, y = Var1, fill = value)) +
  geom_tile(color = "white") +
  geom_text(aes(label = sprintf("%.2f", value)), size = 4, color = "black") +
  scale_fill_gradient2(low = "blue", high = "red", mid = "white",
                       midpoint = 0, limit = c(-1, 1), space = "Lab",
                       name = "Correlation") +
  labs(x = "Independent Variables", y = "Dependent Variables", +
       title = "Rectangular Correlation Heatmap") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 90, hjust = 1))
```

### OLS regression models

Code for log-transforming the dependent variables:

```
quantumdataset$log_total_funding <- log(quantumdataset$total_funding + 1)
quantumdataset$log_valuation <- log(quantumdataset$valuation + 1)
quantumdataset$log_employees <- log(quantumdataset$employees + 1)
```

Code for estimating OLS regressions with heteroskedasticity-robust standard errors:

```
ols_log_total_funding <- lm(log_total_funding ~ launch_year + seed_year +
                            rounds + public_funding + university_backed +
                            patents + founder_serial + rev_model_saas +
                            rev_model_manufacturing + signal_completeness +
                            signal_team_strength + signal_growth_rate +
                            signal_timing + subfield_software_apps +
                            subfield_comm_crypto + subfield_sensing_detection,
                            data = quantumdataset)

summary(ols_log_total_funding)

ols_log_valuation <- lm(log_valuation ~ launch_year + seed_year +
                        rounds + public_funding + university_backed +
                        patents + founder_serial + rev_model_saas +
                        rev_model_manufacturing + signal_completeness +
                        signal_team_strength + signal_growth_rate +
                        signal_timing + subfield_software_apps +
                        subfield_comm_crypto + subfield_sensing_detection,
                        data = quantumdataset)

summary(ols_log_valuation)

ols_log_employees <- lm(log_employees ~ launch_year + seed_year +
                        rounds + public_funding + university_backed +
                        patents + founder_serial + rev_model_saas +
                        rev_model_manufacturing + signal_completeness +
                        signal_team_strength + signal_growth_rate +
                        signal_timing + subfield_software_apps +
                        subfield_comm_crypto + subfield_sensing_detection,
                        data = quantumdataset)

summary(ols_log_employees)

coeftest(ols_log_total_funding, vcov = vcovHC(ols_log_total_funding,
                                              type = "HC3"))
coeftest(ols_log_valuation, vcov = vcovHC(ols_log_valuation,
                                          type = "HC3"))
coeftest(ols_log_employees, vcov = vcovHC(ols_log_employees,
                                          type = "HC3"))
```

Code for testing multicollinearity (VIF):

```
vif(ols_log_total_funding)
vif(ols_log_valuation)
vif(ols_log_employees)
```

Code for fitting simplified (parsimonious) OLS models:

```
ols_clean_total_funding <- lm(log_total_funding ~ rounds + public_funding +
                                 patents + signal_team_strength,
                               data=quantumdataset)
summary(ols_clean_total_funding)

ols_clean_total_funding1 <- lm(log_total_funding ~ rounds + patents +
                                signal_team_strength, data=quantumdataset)
summary(ols_clean_total_funding1)

ols_clean_valuation <- lm(log_valuation ~ public_funding + patents +
                          signal_team_strength, data=quantumdataset)
summary(ols_clean_valuation)

ols_clean_employees <- lm(log_employees ~ signal_completeness +
                          signal_growth_rate + signal_team_strength,
                          data=quantumdataset)
summary(ols_clean_employees)
```

Code for automated diagnostic checks (heteroskedasticity, normality, autocorrelation):

```
modelli <- list(
  funding = ols_clean_total_funding1,
  employees = ols_clean_valuation,
  valuation = ols_clean_employees
  )

for (nome in names(modelli)) {
  modello <- modelli[[nome]]

  cat("\n\n", "=== Analisi per il modello:", nome, "===\n")

  par(mfrow = c(2, 2))
  plot(modello)

  cat("\nBreusch-Pagan test:\n")
  print(bptest(modello))

  cat("\nShapiro-Wilk test (normalità residui):\n")
  print(shapiro.test(residuals(modello)))

  cat("\nDurbin-Watson test:\n")
  print(dwtest(modello))
}

coeftest(ols_clean_valuation, vcov = vcovHC(ols_clean_valuation, type = "HC1"))
```

Code for residuals vs fitted plots, residual distribution, and correlation matrix (funding model):

```
res_funding <- residuals(ols_clean_total_funding1)
fitted_funding <- fitted(ols_clean_total_funding1)

png("residuals_vs_fitted_funding.png", width = 800, height = 600)
plot(fitted_funding, res_funding,
     xlab = "Fitted values",
     ylab = "Residuals",
     main = "Residuals vs Fitted (Funding)")
abline(h = 0, col = "red")
dev.off()

png("residuals_distribution_funding.png", width = 800, height = 600)
ggplot(data.frame(res_funding = res_funding), aes(x = res_funding)) +
  geom_histogram(aes(y = ..density..), bins = 30, color = "black", fill =
                  "lightblue") +
  geom_density(col = "red", size = 1) +
  labs(title = "Distribuzione dei Residui (Funding)", x = "Residuals", y =
         "Density") +
  theme_minimal()
dev.off()

X_funding <- quantumdataset[, c("rounds", "patents", "signal_team_strength")]
cor_matrix_funding <- cor(X_funding, use = "complete.obs")
png("correlation_matrix_funding.png", width = 800, height = 600)
corrplot(cor_matrix_funding, method = "color", type = "upper", addCoef.col =
           "black", tl.cex = 0.8)
dev.off()
```

Code for residuals vs fitted plots, residual distribution, and correlation matrix (valuation model):

```
res_valuation <- residuals(ols_clean_valuation)
fitted_valuation <- fitted(ols_clean_valuation)

png("residuals_vs_fitted_valuation.png", width = 800, height = 600)
plot(fitted_valuation, res_valuation,
     xlab = "Fitted values",
     ylab = "Residuals",
     main = "Residuals vs Fitted (Valuation)")
abline(h = 0, col = "red")
dev.off()

png("residuals_distribution_valuation.png", width = 800, height = 600)
ggplot(data.frame(res_valuation = res_valuation), aes(x = res_valuation)) +
  geom_histogram(aes(y = ..density..), bins = 30, color = "black", fill =
                  "lightblue") +
  geom_density(col = "red", size = 1) +
  labs(title = "Distribuzione dei Residui (Valuation)", x = "Residuals", y =
         "Density") +
  theme_minimal()
dev.off()

X_valuation <- quantumdataset[, c("public_funding", "patents",
                                   "signal_team_strength")]
cor_matrix_valuation <- cor(X_valuation, use = "complete.obs")
png("correlation_matrix_valuation.png", width = 800, height = 600)
corrplot(cor_matrix_valuation, method = "color", type = "upper", addCoef.col =
           "black", tl.cex = 0.8)
dev.off()
```

Code for residuals vs fitted plots, residual distribution, and correlation matrix (employees model):

```
res_employees <- residuals(ols_clean_employees)
fitted_employees <- fitted(ols_clean_employees)

png("residuals_vs_fitted_employees.png", width = 800, height = 600)
plot(fitted_employees, res_employees,
     xlab = "Fitted values",
     ylab = "Residuals",
     main = "Residuals vs Fitted (Employees)")
abline(h = 0, col = "red")
dev.off()

png("residuals_distribution_employees.png", width = 800, height = 600)
ggplot(data.frame(res_employees = res_employees), aes(x = res_employees)) +
  geom_histogram(aes(y = ..density..), bins = 30, color = "black", fill =
                   "lightblue") +
  geom_density(col = "red", size = 1) +
  labs(title = "Distribuzione dei Residui (Employees)", x = "Residuals", y =
         "Density") +
  theme_minimal()
dev.off()

X_employees <- quantumdataset[, c("signal_completeness", "signal_growth_rate",
                                  "signal_team_strength")]
cor_matrix_employees <- cor(X_employees, use = "complete.obs")
png("correlation_matrix_employees.png", width = 800, height = 600)
corrplot(cor_matrix_employees, method = "color", type = "upper", addCoef.col =
           "black", tl.cex = 0.8)
dev.off()
```

Code for Propensity Score Matching (PSM) on *public_funding*:

```
public_psm_vars <- c(
  "launch_year", "seed_year", "rounds", "patents", "university_backed",
  "rev_model_marketplace", "rev_model_saas", "rev_model_manufacturing",
  "hq_europe", "hq_asia", "hq_america", "hq_oceania",
  "subfield_hardware_infra", "subfield_software_apps",
  "subfield_comm_crypto", "subfield_sensing_detection"
)

covariate_set_public <- c("public_funding", public_psm_vars)
quantum_clean_public <- quantumdataset[complete.cases
                              (quantumdataset[, covariate_set_public]),
                              ]

ps_formula_public <- as.formula(
  paste("public_funding ~", paste(public_psm_vars, collapse = " + "))
)

ps_model_public <- matchit(ps_formula_public,
                           data = quantum_clean_public,
                           method = "nearest",
                           ratio = 1)

summary(ps_model_public)
plot(ps_model_public, type = "jitter")
plot(ps_model_public, type = "hist")
```

Code for Propensity Score Matching (PSM) on *university_backed*:

```
univ_psm_vars <- c(
  "launch_year", "seed_year", "rounds", "patents", "public_funding",
  "rev_model_marketplace", "rev_model_saas", "rev_model_manufacturing",
  "hq_europe", "hq_asia", "hq_america", "hq_oceania",
  "subfield_hardware_infra", "subfield_software_apps",
  "subfield_comm_crypto", "subfield_sensing_detection"
)

covariate_set_univ <- c("university_backed", univ_psm_vars)
quantum_clean_univ <- quantumdataset[complete.cases
                              (quantumdataset[, covariate_set_univ]), ]

ps_formula_univ <- as.formula(
  paste("university_backed ~", paste(univ_psm_vars, collapse = " + "))
)

ps_model_univ <- matchit(ps_formula_univ,
                         data = quantum_clean_univ,
                         method = "nearest",
                         ratio = 1)

summary(ps_model_univ)
plot(ps_model_univ, type = "jitter")
plot(ps_model_univ, type = "hist")
```

**Exploratory models**

Code for exploratory model by subfield:

```
quantumdataset <- quantumdataset %>%
  mutate(subfield = case_when(
    subfield_hardware_infra == 1 ~ "hardware_infra",
    subfield_software_apps == 1 ~ "software_apps",
    subfield_comm_crypto == 1 ~ "comm_crypto",
    subfield_sensing_detection == 1 ~ "sensing_detection",
    TRUE ~ NA_character_
  )) %>%
  filter(!is.na(total_funding) & !is.na(subfield))  # rimuove NA

quantumdataset %>%
  group_by(subfield) %>%
  summarise(
    n = n(),
    avg_funding = mean(total_funding, na.rm = TRUE),
    median_funding = median(total_funding, na.rm = TRUE),
    sd_funding = sd(total_funding, na.rm = TRUE),
    min_funding = min(total_funding, na.rm = TRUE),
    max_funding = max(total_funding, na.rm = TRUE)
  )

ggplot(quantumdataset, aes(x = subfield, y = total_funding)) +
  geom_boxplot(fill = "skyblue") +
  scale_y_log10() +
  theme_minimal() +
  labs(title = "Distribuzione dei finanziamenti per subfield",
       x = "Subfield",
       y = "Funding (scala log)")

anova_model <- aov(log_total_funding ~ subfield, data = quantumdataset)
summary(anova_model)

lm_model <- lm(log_total_funding ~ subfield, data = quantumdataset)
summary(lm_model)

tukey <- TukeyHSD(anova_model)
print(tukey)

plot(tukey, las = 1, col = "blue")
```

Code for exploratory model by HQ region:

```
quantumdataset <- quantumdataset %>%
  mutate(region = case_when(
    hq_europe == 1 ~ "europe",
    hq_america == 1 ~ "america",
    hq_asia == 1 ~ "asia",
    hq_oceania == 1 ~ "oceania",
    TRUE ~ NA_character_
  )) %>%
  filter(!is.na(total_funding) & !is.na(region))

quantumdataset %>%
  group_by(region) %>%
  summarise(
    n = n(),
    avg_funding = mean(total_funding, na.rm = TRUE),
    median_funding = median(total_funding, na.rm = TRUE),
    sd_funding = sd(total_funding, na.rm = TRUE),
    min_funding = min(total_funding, na.rm = TRUE),
    max_funding = max(total_funding, na.rm = TRUE)
  )

ggplot(quantumdataset, aes(x = region, y = total_funding)) +
  geom_boxplot(fill = "lightgreen") +
  scale_y_log10() +
  theme_minimal() +
  labs(title = "Distribuzione dei finanziamenti per regione",
       x = "Region",
       y = "Funding (scala log)")

anova_model_region <- aov(log_total_funding ~ region, data = quantumdataset)
summary(anova_model_region)

lm_model_region <- lm(log_total_funding ~ region, data = quantumdataset)
summary(lm_model_region)

tukey_region <- TukeyHSD(anova_model_region)
print(tukey_region)

plot(tukey_region, las = 1, col = "green")
```

# Appendix B – Statistical analyses

### OLS regression results: *log_total_funding*

OLS regression with log_total_funding as dependent variable, including all independent variables:

```
Call:
lm(formula = log_total_funding ~ launch_year + seed_year + rounds +
    public_funding + university_backed + patents + founder_serial +
    rev_model_saas + rev_model_manufacturing + signal_completeness +
    signal_team_strength + signal_growth_rate + signal_timing +
    subfield_software_apps + subfield_comm_crypto + subfield_sensing_detection,
    data = quantumdataset)

Residuals:
     Min       1Q   Median       3Q      Max 
-1.46946 -0.19598 -0.02274  0.25035  1.08440 

Coefficients:
                            Estimate Std. Error t value Pr(>|t|)    
(Intercept)                2.368e+01  6.410e+01   0.369  0.71291    
launch_year                2.384e-02  2.813e-02   0.847  0.39956    
seed_year                 -3.615e-02  3.243e-02  -1.115  0.26866    
rounds                     9.886e-02  3.083e-02   3.206  0.00201 ** 
public_funding            -3.943e-01  1.271e-01  -3.103  0.00274 ** 
university_backed         -2.052e-01  1.377e-01  -1.491  0.14043    
patents                    1.816e-02  5.960e-03   3.046  0.00324 ** 
founder_serial            -9.319e-02  1.205e-01  -0.774  0.44168    
rev_model_saas            -2.203e-01  1.947e-01  -1.131  0.26163    
rev_model_manufacturing    1.590e-01  2.193e-01   0.725  0.47073    
signal_completeness       -1.032e-02  1.871e-02  -0.552  0.58299    
signal_team_strength       5.635e-02  4.228e-03  13.327  < 2e-16 ***
signal_growth_rate         2.499e-03  2.524e-03   0.990  0.32547    
signal_timing              9.573e-05  2.146e-03   0.045  0.96454    
subfield_software_apps     1.957e-01  1.934e-01   1.012  0.31495    
subfield_comm_crypto       1.488e-03  1.971e-01   0.008  0.99400    
subfield_sensing_detection -7.316e-02  1.653e-01  -0.442  0.65947    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4871 on 72 degrees of freedom
  (220 observations deleted due to missingness)
Multiple R-squared:  0.8836,	Adjusted R-squared:  0.8577 
F-statistic: 34.15 on 16 and 72 DF,  p-value: < 2.2e-16
```

OLS regression with log_total_funding as dependent variable, including all independent variables, estimated with robust standard errors:

```
t test of coefficients:

                            Estimate  Std. Error t value  Pr(>|t|)    
(Intercept)               2.3679e+01  1.0325e+02  0.2294  0.819246    
launch_year               2.3837e-02  2.8174e-02  0.8461  0.400314    
seed_year                -3.6153e-02  3.8233e-02 -0.9456  0.347511    
rounds                    9.8859e-02  4.2775e-02  2.3111  0.023692 *  
public_funding           -3.9435e-01  1.7359e-01 -2.2717  0.026093 *  
university_backed        -2.0519e-01  1.3812e-01 -1.4856  0.141747    
patents                   1.8156e-02  5.4296e-03  3.3438  0.001314 ** 
founder_serial           -9.3187e-02  1.4945e-01 -0.6235  0.534913    
rev_model_saas           -2.2027e-01  2.5179e-01 -0.8748  0.384570    
rev_model_manufacturing   1.5900e-01  2.3994e-01  0.6627  0.509661    
signal_completeness      -1.0316e-02  1.9671e-02 -0.5245  0.601574    
signal_team_strength      5.6355e-02  8.0045e-03  7.0404 9.311e-10 ***
signal_growth_rate        2.4986e-03  2.6671e-03  0.9368  0.351986    
signal_timing             9.5729e-05  2.2854e-03  0.0419  0.966705    
subfield_software_apps    1.9572e-01  2.7189e-01  0.7198  0.473965    
subfield_comm_crypto      1.4877e-03  3.0148e-01  0.0049  0.996076    
subfield_sensing_detection -7.3155e-02  1.5149e-01 -0.4829  0.630629    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Multicollinearity analysis for funding regressions:

```
               launch_year                  seed_year                     rounds 
                  1.987461                   2.214364                   2.393196 
            public_funding          university_backed                    patents 
                  1.353686                   1.711872                   1.936738 
            founder_serial             rev_model_saas    rev_model_manufacturing 
                  1.195341                   3.517449                   4.152553 
       signal_completeness       signal_team_strength         signal_growth_rate 
                  1.688167                   2.023312                   1.618802 
             signal_timing     subfield_software_apps       subfield_comm_crypto 
                  1.391075                   2.762809                   1.816403 
subfield_sensing_detection 
                  1.511683 
```

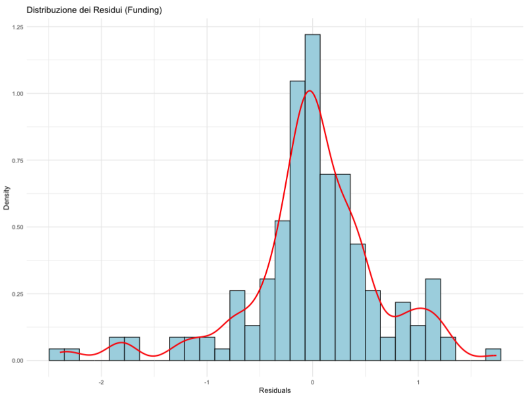
OLS regression with log_total_funding as dependent variable, including only statistically significant independent variables:

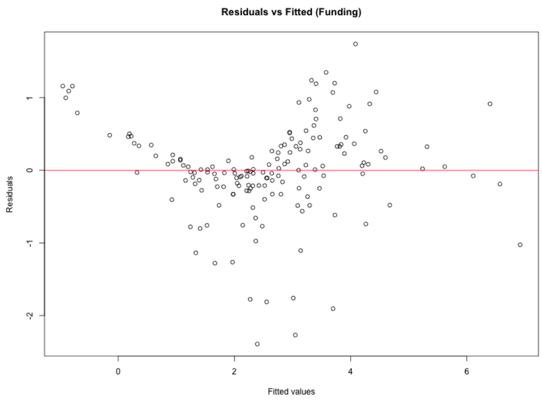
```
lm(formula = log_total_funding ~ rounds + public_funding + patents +
    signal_team_strength, data = quantumdataset)

Residuals:
     Min       1Q   Median       3Q      Max
-2.46235 -0.21966  0.00622  0.33197  1.61770

Coefficients:
                      Estimate Std. Error t value Pr(>|t|)
(Intercept)          -1.884347   0.220496  -8.546 1.09e-14 ***
rounds                0.058192   0.018261   3.187  0.00174 **
public_funding       -0.150483   0.119528  -1.259  0.20992
patents               0.020373   0.002833   7.190 2.52e-11 ***
signal_team_strength  0.053503   0.003158  16.941  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.6573 on 156 degrees of freedom
  (148 observations deleted due to missingness)
Multiple R-squared:  0.8244,	Adjusted R-squared:  0.8199
F-statistic: 183.2 on 4 and 156 DF,  p-value: < 2.2e-16


Call:
lm(formula = log_total_funding ~ rounds + patents + signal_team_strength,
    data = quantumdataset)

Residuals:
     Min       1Q   Median       3Q      Max
-2.39334 -0.22643  0.00881  0.33311  1.73955

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)
(Intercept)          -1.93750    0.21682  -8.936 1.04e-15 ***
rounds                0.05057    0.01726   2.930   0.0039 **
patents               0.02103    0.00279   7.535 3.63e-12 ***
signal_team_strength  0.05329    0.00316  16.866  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.6585 on 157 degrees of freedom
  (148 observations deleted due to missingness)
Multiple R-squared:  0.8227,	Adjusted R-squared:  0.8193
F-statistic: 242.8 on 3 and 157 DF,  p-value: < 2.2e-16
```

Breusch-Pagan test, Shapiro-Wilk test, Durbin-Watson test for funding regressions:

```
 === Analisi per il modello: funding ===

Breusch-Pagan test:

        studentized Breusch-Pagan test

data:  modello
BP = 5.2559, df = 3, p-value = 0.154


Shapiro-Wilk test (normalità residui):

        Shapiro-Wilk normality test

data:  residuals(modello)
W = 0.93559, p-value = 1.172e-06


Durbin-Watson test:

        Durbin-Watson test

data:  modello
DW = 2.2109, p-value = 0.9089
alternative hypothesis: true autocorrelation is greater than 0
```

“Residual distributions” and “Residual vs Fitted” for funding regressions:



**OLS regression results: *log_valuation***

OLS regression with log_valuation as dependent variable, including all independent variables:

```
Call:
lm(formula = log_valuation ~ launch_year + seed_year + rounds +
    public_funding + university_backed + patents + founder_serial +
    rev_model_saas + rev_model_manufacturing + signal_completeness +
    signal_team_strength + signal_growth_rate + signal_timing +
    subfield_software_apps + subfield_comm_crypto + subfield_sensing_detection,
    data = quantumdataset)

Residuals:
    Min      1Q  Median      3Q     Max
-2.0711 -0.3604  0.1405  0.3960  1.3790

Coefficients:
                             Estimate Std. Error t value Pr(>|t|)
(Intercept)                -5.028e+01  1.073e+02  -0.469   0.6408
launch_year                -3.191e-03  4.156e-02  -0.077   0.9390
seed_year                   3.322e-02  5.130e-02   0.648   0.5195
rounds                      2.609e-02  4.984e-02   0.523   0.6024
public_funding             -5.331e-01  2.012e-01  -2.650   0.0101 *
university_backed          -2.842e-01  2.123e-01  -1.339   0.1853
patents                     2.116e-02  8.690e-03   2.435   0.0176 *
founder_serial             -1.692e-01  1.868e-01  -0.906   0.3682
rev_model_saas             -9.822e-02  2.907e-01  -0.338   0.7366
rev_model_manufacturing     5.280e-01  3.225e-01   1.637   0.1064
signal_completeness        -4.632e-03  2.956e-02  -0.157   0.8760
signal_team_strength        8.433e-02  8.129e-03  10.373 2.03e-15 ***
signal_growth_rate          6.132e-03  3.874e-03   1.583   0.1183
signal_timing               4.549e-04  3.445e-03   0.132   0.8953
subfield_software_apps      5.246e-01  2.833e-01   1.852   0.0686 .
subfield_comm_crypto        2.695e-01  3.173e-01   0.849   0.3988
subfield_sensing_detection  2.104e-02  2.452e-01   0.086   0.9319
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.7013 on 65 degrees of freedom
  (227 observations deleted due to missingness)
Multiple R-squared:  0.8162,    Adjusted R-squared:  0.7709
F-statistic: 18.04 on 16 and 65 DF,  p-value: < 2.2e-16
```

OLS regression with log_valuation as dependent variable, including all independent variables, estimated with robust standard errors:

```
t test of coefficients:

                            Estimate  Std. Error t value  Pr(>|t|)    
(Intercept)              -5.0281e+01  1.3177e+02 -0.3816  0.704026    
launch_year              -3.1907e-03  4.5147e-02 -0.0707  0.943874    
seed_year                 3.3224e-02  6.5868e-02  0.5044  0.615687    
rounds                    2.6092e-02  5.2529e-02  0.4967  0.621061    
public_funding           -5.3315e-01  2.1558e-01 -2.4730  0.016021 *  
university_backed        -2.8418e-01  1.9754e-01 -1.4386  0.155064    
patents                   2.1164e-02  7.2197e-03  2.9314  0.004654 ** 
founder_serial           -1.6925e-01  1.8957e-01 -0.8928  0.375270    
rev_model_saas           -9.8216e-02  3.1968e-01 -0.3072  0.759653    
rev_model_manufacturing   5.2798e-01  3.4760e-01  1.5189  0.133633    
signal_completeness      -4.6317e-03  2.9776e-02 -0.1556  0.876868    
signal_team_strength      8.4328e-02  1.2546e-02  6.7217 5.367e-09 ***
signal_growth_rate        6.1316e-03  3.9779e-03  1.5414  0.128072    
signal_timing             4.5492e-04  3.8286e-03  0.1188  0.905784    
subfield_software_apps    5.2459e-01  3.6408e-01  1.4409  0.154425    
subfield_comm_crypto      2.6950e-01  3.6094e-01  0.7467  0.457960    
subfield_sensing_detection 2.1036e-02  2.3527e-01  0.0894  0.929032    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Multicollinearity analysis for valuation regressions:

```
               launch_year                  seed_year                     rounds 
                  1.880427                   2.270989                   2.931572 
            public_funding          university_backed                    patents 
                  1.461294                   1.823396                   1.930880 
            founder_serial             rev_model_saas    rev_model_manufacturing 
                  1.259273                   3.446334                   3.898621 
       signal_completeness       signal_team_strength         signal_growth_rate 
                  1.674589                   2.267594                   1.642458 
             signal_timing     subfield_software_apps       subfield_comm_crypto 
                  1.613702                   2.548214                   1.797493 
subfield_sensing_detection 
                  1.498195 
```

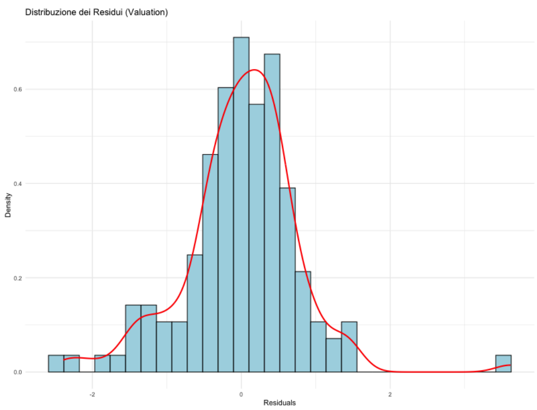
OLS regression with log_valuation as dependent variable, including only statistically significant independent variables:

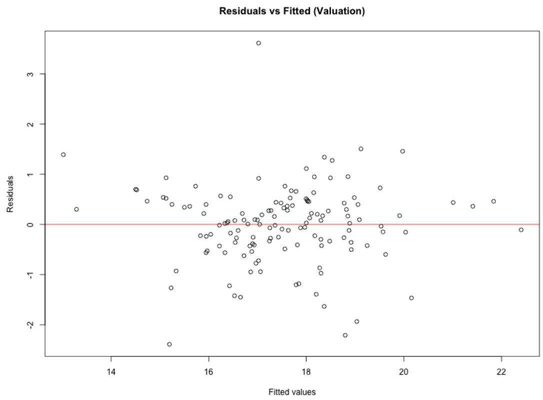
```
Call:
lm(formula = log_valuation ~ public_funding + patents + signal_team_strength,
    data = quantumdataset)

Residuals:
    Min      1Q  Median      3Q     Max
-2.3909 -0.3661  0.0436  0.4303  3.6159

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)
(Intercept)          11.52287    0.35490  32.468  < 2e-16 ***
public_funding       -0.60186    0.14703  -4.093 7.36e-05 ***
patents               0.02292    0.00320   7.163 4.97e-11 ***
signal_team_strength  0.07723    0.00488  15.827  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.7782 on 132 degrees of freedom
  (173 observations deleted due to missingness)
Multiple R-squared:  0.7978,	Adjusted R-squared:  0.7932
F-statistic: 173.6 on 3 and 132 DF,  p-value: < 2.2e-16
```

Breusch-Pagan test, Shapiro-Wilk test, Durbin-Watson test for valuation regressions:

```
 === Analisi per il modello: valuation ===

Breusch-Pagan test:

	studentized Breusch-Pagan test

data:  modello
BP = 24.143, df = 3, p-value = 2.332e-05


Shapiro-Wilk test (normalità residui):

	Shapiro-Wilk normality test

data:  residuals(modello)
W = 0.98672, p-value = 0.06827


Durbin-Watson test:

	Durbin-Watson test

data:  modello
DW = 1.9888, p-value = 0.4684
alternative hypothesis: true autocorrelation is greater than 0
```

“Residual distributions” and “Residual vs Fitted” for valuation regressions:




OLS regression with log_valuation as dependent variable, including only statistically significant independent variables, estimated with robust standard errors:

```
t test of coefficients:

                     Estimate Std. Error t value  Pr(>|t|)    
(Intercept)        11.5228719  0.4114102 28.0082 < 2.2e-16 ***
public_funding     -0.6018616  0.1564619 -3.8467 0.0001855 ***
patents             0.0229215  0.0024405  9.3922 2.317e-16 ***
signal_team_strength 0.0772314 0.0056656 13.6317 < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

**OLS regression results: *log_employees***

OLS regression with log_employees as dependent variable, including all independent variables:

```
Call:
lm(formula = log_employees ~ launch_year + seed_year + rounds +
    public_funding + university_backed + patents + founder_serial +
    rev_model_saas + rev_model_manufacturing + signal_completeness +
    signal_team_strength + signal_growth_rate + signal_timing +
    subfield_software_apps + subfield_comm_crypto + subfield_sensing_detection,
    data = quantumdataset)

Residuals:
     Min       1Q   Median       3Q      Max
-1.22110 -0.23321 -0.01733  0.23800  0.91084

Coefficients:
                            Estimate Std. Error t value Pr(>|t|)
(Intercept)               -7.3324123 60.1826868  -0.122 0.903351
launch_year                0.0019514  0.0266110   0.073 0.941735
seed_year                  0.0006661  0.0302844   0.022 0.982509
rounds                     0.0285602  0.0288527   0.990 0.325383
public_funding            -0.1112442  0.1193243  -0.932 0.354142
university_backed         -0.0321288  0.1246337  -0.258 0.797269
patents                    0.0137286  0.0055822   2.459 0.016193 *
founder_serial            -0.0543920  0.1120166  -0.486 0.628668
rev_model_saas            -0.0166930  0.1838945  -0.091 0.927910
rev_model_manufacturing    0.0528815  0.2073957   0.255 0.799428
signal_completeness        0.0374488  0.0172706   2.168 0.033261 *
signal_team_strength       0.0236293  0.0038251   6.177 2.97e-08 ***
signal_growth_rate         0.0081244  0.0023294   3.488 0.000813 ***
signal_timing             -0.0010799  0.0019607  -0.551 0.583398
subfield_software_apps     0.0564802  0.1820125   0.310 0.757175
subfield_comm_crypto       0.0109902  0.1852902   0.059 0.952858
subfield_sensing_detection -0.2941868  0.1508179  -1.951 0.054790 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4642 on 76 degrees of freedom
  (216 observations deleted due to missingness)
Multiple R-squared:  0.7301,    Adjusted R-squared:  0.6732
F-statistic: 12.85 on 16 and 76 DF,  p-value: 1.311e-15
```

OLS regression with log_employees as dependent variable, including all independent variables, estimated with robust standard errors

```
t test of coefficients:

                            Estimate  Std. Error t value  Pr(>|t|)    
(Intercept)              -7.33241232 87.67206985 -0.0836 0.9335669    
launch_year               0.00195141  0.02952016  0.0661 0.9474683    
seed_year                 0.00066614  0.04244418  0.0157 0.9875192    
rounds                    0.02856017  0.03333860  0.8567 0.3943205    
public_funding           -0.11124423  0.12815371 -0.8681 0.3880981    
university_backed        -0.03212883  0.12117950 -0.2651 0.7916239    
patents                   0.01372861  0.00861070  1.5944 0.1150048    
founder_serial           -0.05439203  0.12210393 -0.4455 0.6572560    
rev_model_saas           -0.01669301  0.23422381 -0.0713 0.9433705    
rev_model_manufacturing   0.05288150  0.25308247  0.2089 0.8350466    
signal_completeness       0.03744878  0.01701090  2.2015 0.0307383 *  
signal_team_strength      0.02362926  0.00362358  6.5210 6.913e-09 ***
signal_growth_rate        0.00812441  0.00226082  3.5936 0.0005767 ***
signal_timing            -0.00107990  0.00210684 -0.5126 0.6097382    
subfield_software_apps    0.05648016  0.24982092  0.2261 0.8217441    
subfield_comm_crypto      0.01099024  0.17591308  0.0625 0.9503483    
subfield_sensing_detection -0.29418684  0.15689196 -1.8751 0.0646216 .  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Multicollinearity analysis for employees regressions:

```
               launch_year                  seed_year                     rounds 
                  2.001779                   2.140137                   2.436221 
            public_funding          university_backed                    patents 
                  1.386610                   1.632095                   1.885421 
            founder_serial             rev_model_saas    rev_model_manufacturing 
                  1.183158                   3.597007                   4.248943 
       signal_completeness       signal_team_strength         signal_growth_rate 
                  1.813028                   2.082071                   1.553996 
             signal_timing     subfield_software_apps       subfield_comm_crypto 
                  1.336697                   2.809751                   1.781372 
subfield_sensing_detection 
                  1.466171 
```

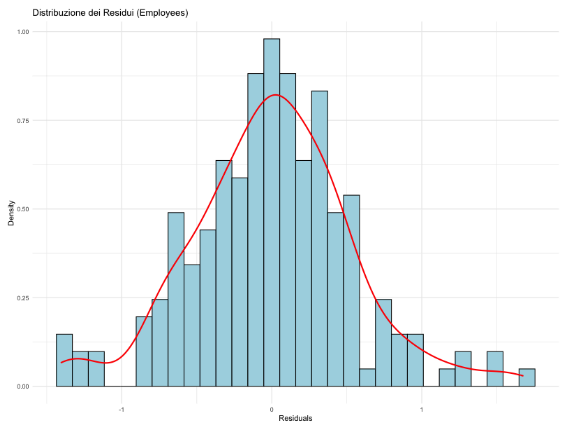
OLS regression with log_employees as dependent variable, including only statistically significant independent variables

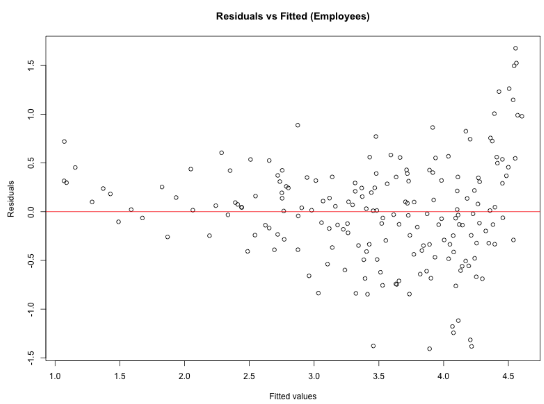
```
Call:
lm(formula = log_employees ~ signal_completeness + signal_growth_rate +
    signal_team_strength, data = quantumdataset)

Residuals:
     Min       1Q   Median       3Q      Max
-1.40654 -0.33408  0.01368  0.31690  1.67713

Coefficients:
                      Estimate Std. Error t value Pr(>|t|)
(Intercept)          -2.765313   0.815041  -3.393 0.000843 ***
signal_completeness   0.043205   0.010071   4.290 2.86e-05 ***
signal_growth_rate    0.004913   0.001511   3.252 0.001359 **
signal_team_strength  0.031295   0.002209  14.170  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.5412 on 188 degrees of freedom
  (117 observations deleted due to missingness)
Multiple R-squared:  0.7067,    Adjusted R-squared:  0.702
F-statistic:   151 on 3 and 188 DF,  p-value: < 2.2e-16
```

Breusch-Pagan test, Shapiro-Wilk test, Durbin-Watson test for employees regressions:

```
 === Analisi per il modello: employees ===

Breusch-Pagan test:

        studentized Breusch-Pagan test

data:  modello
BP = 0.65272, df = 3, p-value = 0.8843


Shapiro-Wilk test (normalità residui):

        Shapiro-Wilk normality test

data:  residuals(modello)
W = 0.94383, p-value = 2.613e-05


Durbin-Watson test:

        Durbin-Watson test

data:  modello
DW = 1.9744, p-value = 0.433
alternative hypothesis: true autocorrelation is greater than 0
```

"Residual distributions" and "Residual vs Fitted" for employees regressions:



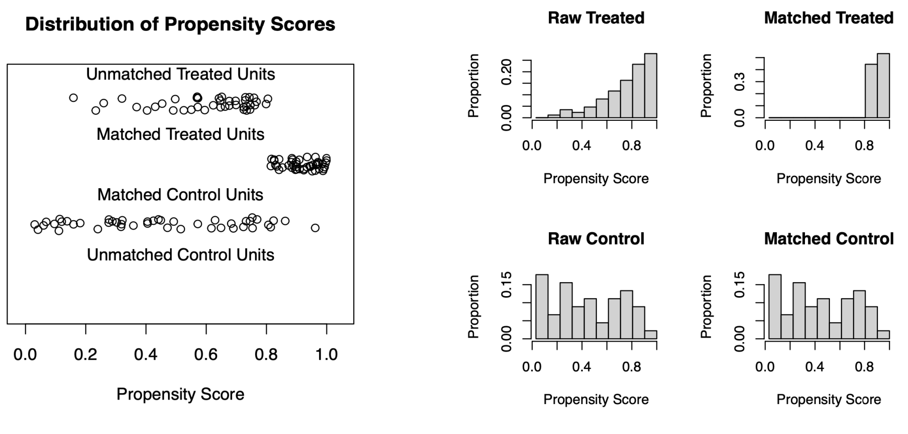



## Propensity Score Matching: *public_funding*

Balance summary for Propensity Score Matching on *public_funding*:

```
Call:
matchit(formula = ps_formula_public, data = quantum_clean_public,
    method = "nearest", ratio = 1)

Summary of Balance for All Data:
                           Means Treated Means Control Std. Mean Diff. Var. Ratio eCDF Mean eCDF Max
distance                          0.7673        0.4447          1.6278     0.5462    0.3292   0.5059
launch_year                    2016.8488     2018.2889         -0.2998     4.5882    0.0714   0.1584
seed_year                      2019.4419     2020.4667         -0.2531     2.8710    0.0530   0.1181
rounds                            6.6512        4.2000          0.6368     3.4461    0.1379   0.3674
patents                          13.1744        8.8444          0.2237     2.4390    0.0661   0.2152
university_backed                 0.4651        0.2667          0.3979          .    0.1984   0.1984
rev_model_marketplace             0.0116        0.0000          0.1085          .    0.0116   0.0116
rev_model_saas                    0.3953        0.5333         -0.2822          .    0.1380   0.1380
rev_model_manufacturing           0.7093        0.5333          0.3875          .    0.1760   0.1760
hq_europe                         0.6977        0.4444          0.5514          .    0.2532   0.2532
hq_asia                           0.0349        0.2889         -1.3843          .    0.2540   0.2540
hq_america                        0.2326        0.2000          0.0771          .    0.0326   0.0326
hq_oceania                        0.0349        0.0667         -0.1732          .    0.0318   0.0318
subfield_hardware_infra           0.4651        0.2889          0.3533          .    0.1762   0.1762
subfield_software_apps            0.2326        0.3333         -0.2385          .    0.1008   0.1008
subfield_comm_crypto              0.1279        0.2222         -0.2824          .    0.0943   0.0943
subfield_sensing_detection        0.1744        0.1556          0.0497          .    0.0189   0.0189

Summary of Balance for Matched Data:
                           Means Treated Means Control Std. Mean Diff. Var. Ratio eCDF Mean eCDF Max Std. Pair Dist.
distance                          0.9175        0.4447          2.3858     0.0445    0.5372   0.9333          2.3858
launch_year                    2015.6889     2018.2889         -0.5413     4.8166    0.1144   0.2667          0.8467
seed_year                      2018.2889     2020.4667         -0.5379     3.8027    0.1085   0.2667          0.8782
rounds                            8.6444        4.2000          1.1546     4.1983    0.2486   0.6889          1.3047
patents                          16.7333        8.8444          0.4077     3.2198    0.1270   0.3778          0.8027
university_backed                 0.5778        0.2667          0.6237          .    0.3111   0.3111          1.2475
rev_model_marketplace             0.0222        0.0000          0.2073          .    0.0222   0.0222          0.2073
rev_model_saas                    0.3778        0.5333         -0.3182          .    0.1556   0.1556          1.1363
rev_model_manufacturing           0.7556        0.5333          0.4894          .    0.2222   0.2222          1.0766
hq_europe                         0.7778        0.4444          0.7258          .    0.3333   0.3333          1.5000
hq_asia                           0.0000        0.2889         -1.5745          .    0.2889   0.2889          1.5745
hq_america                        0.2000        0.2000          0.0000          .    0.0000   0.0000          0.3556
hq_oceania                        0.0222        0.0667         -0.2422          .    0.0444   0.0444          0.4844
subfield_hardware_infra           0.5556        0.2889          0.5346          .    0.2667   0.2667          1.2475
subfield_software_apps            0.1778        0.3333         -0.3682          .    0.1556   0.1556          0.9994
subfield_comm_crypto              0.1111        0.2222         -0.3327          .    0.1111   0.1111          0.8650
subfield_sensing_detection        0.1556        0.1556          0.0000          .    0.0000   0.0000          0.2667

Sample Sizes:
          Control Treated
All            45      86
Matched        45      45
Unmatched       0      41
Discarded       0       0
```

Visual diagnostics of Propensity Score Matching on *public_funding*:

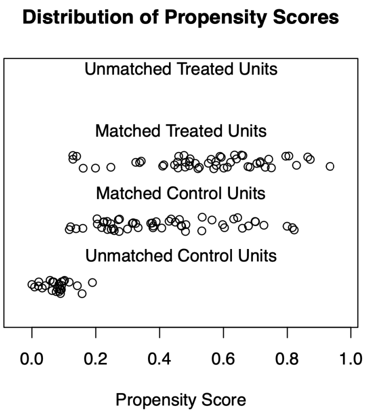


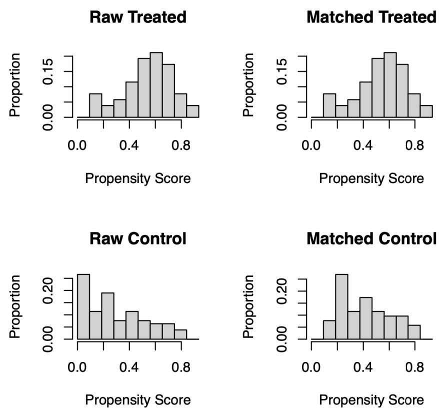
## Propensity Score Matching: *university_backed*

Balance summary for Propensity Score Matching on *university_backed*:

```
Call:
matchit(formula = ps_formula_univ, data = quantum_clean_univ,
    method = "nearest", ratio = 1)

Summary of Balance for All Data:
                          Means Treated Means Control Std. Mean Diff. Var. Ratio eCDF Mean eCDF Max
distance                         0.5460        0.2988          1.2607     0.7609    0.2958   0.5358
launch_year                   2017.1731     2017.4557         -0.0631     1.2855    0.0228   0.0725
seed_year                     2020.1538     2019.5570          0.1573     1.2090    0.0492   0.1261
rounds                           6.8077        5.1519          0.4394     1.3568    0.0922   0.3717
patents                         12.5769       11.1013          0.0715     1.9183    0.0252   0.0791
public_funding                   0.7692        0.5823          0.4437          .    0.1870   0.1870
rev_model_marketplace            0.0000        0.0127         -0.1458          .    0.0127   0.0127
rev_model_saas                   0.2692        0.5570         -0.6487          .    0.2877   0.2877
rev_model_manufacturing          0.8077        0.5443          0.6683          .    0.2634   0.2634
hq_europe                        0.7692        0.5063          0.6240          .    0.2629   0.2629
hq_asia                          0.0385        0.1772         -0.7215          .    0.1388   0.1388
hq_america                       0.1538        0.2658         -0.3104          .    0.1120   0.1120
hq_oceania                       0.0385        0.0506         -0.0633          .    0.0122   0.0122
subfield_hardware_infra          0.5000        0.3418          0.3165          .    0.1582   0.1582
subfield_software_apps           0.2308        0.2911         -0.1433          .    0.0604   0.0604
subfield_comm_crypto             0.0769        0.2152         -0.5189          .    0.1383   0.1383
subfield_sensing_detection       0.1923        0.1519          0.1025          .    0.0404   0.0404

Summary of Balance for Matched Data:
                          Means Treated Means Control Std. Mean Diff. Var. Ratio eCDF Mean eCDF Max Std. Pair Dist.
distance                         0.5460        0.4132          0.6772     1.0313    0.1538   0.3846          0.6781
launch_year                   2017.1731     2018.0000         -0.1846     1.6194    0.0346   0.1346          0.8457
seed_year                     2020.1538     2020.2885         -0.0355     1.5745    0.0226   0.0577          0.9170
rounds                           6.8077        5.4808          0.3522     1.0696    0.0817   0.3654          0.9034
patents                         12.5769        8.9231          0.1770     2.7654    0.0374   0.1154          0.7191
public_funding                   0.7692        0.6538          0.2739          .    0.1154   0.1154          1.0042
rev_model_marketplace            0.0000        0.0000          0.0000          .    0.0000   0.0000          0.0000
rev_model_saas                   0.2692        0.3846         -0.2601          .    0.1154   0.1154          0.6937
rev_model_manufacturing          0.8077        0.6923          0.2928          .    0.1154   0.1154          0.7807
hq_europe                        0.7692        0.6731          0.2282          .    0.0962   0.0962          0.8672
hq_asia                          0.0385        0.0769         -0.2000          .    0.0385   0.0385          0.6000
hq_america                       0.1538        0.1923         -0.1066          .    0.0385   0.0385          0.8528
hq_oceania                       0.0385        0.0577         -0.1000          .    0.0192   0.0192          0.5000
subfield_hardware_infra          0.5000        0.4231          0.1538          .    0.0769   0.0769          0.8462
subfield_software_apps           0.2308        0.2885         -0.1369          .    0.0577   0.0577          0.9585
subfield_comm_crypto             0.0769        0.1154         -0.1443          .    0.0385   0.0385          0.5774
subfield_sensing_detection       0.1923        0.1731          0.0488          .    0.0192   0.0192          0.7319

Sample Sizes:
          Control Treated
All            79      52
Matched        52      52
Unmatched      27       0
Discarded       0       0
```

Visual diagnostics of Propensity Score Matching on *university_backed*:



**Exploratory analyses per subfield**

Descriptive statistics of total funding by subfield:

```
# A tibble: 4 × 7
  subfield              n avg_funding median_funding sd_funding min_funding max_funding
  <chr>             <int>       <dbl>          <dbl>      <dbl>       <dbl>       <dbl>
1 comm_crypto          46        8.96           2.34       18.0        0           82.7
2 hardware_infra       95       64.0           15.6       174.         0         1498.
3 sensing_detection    36        8.85           2.80       21.2        0.31       116.
4 software_apps        82       33.0            2.66      118.         0          955.
```

ANOVA results for funding differences across subfields:

```
             Df Sum Sq Mean Sq F value   Pr(>F)
subfield      3   87.1  29.040   12.25 1.64e-07 ***
Residuals   255  604.7   2.372
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

OLS regression output for subfield and log-transformed funding:

```
Call:
lm(formula = log_total_funding ~ subfield, data = quantumdataset)

Residuals:
    Min      1Q  Median      3Q     Max
-2.7597 -1.2561 -0.2015  0.9348  5.1985

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)
(Intercept)                 1.4253     0.2271   6.277 1.47e-09 ***
subfieldhardware_infra      1.3343     0.2766   4.824 2.43e-06 ***
subfieldsensing_detection   0.1080     0.3427   0.315    0.753
subfieldsoftware_apps       0.2384     0.2837   0.840    0.401
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.54 on 255 degrees of freedom
Multiple R-squared:  0.1259,    Adjusted R-squared:  0.1156
F-statistic: 12.25 on 3 and 255 DF,  p-value: 1.642e-07
```

Tukey post-hoc test results for subfield differences in *log_total_funding*:

```
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = log_total_funding ~ subfield, data = quantumdataset)

$subfield
                                       diff        lwr        upr     p adj
hardware_infra-comm_crypto        1.3343446  0.6189958  2.0496935 0.0000144
sensing_detection-comm_crypto     0.1079738 -0.7782140  0.9941617 0.9891463
software_apps-comm_crypto         0.2384310 -0.4951840  0.9720459 0.8350863
sensing_detection-hardware_infra -1.2263708 -2.0057909 -0.4469507 0.0003652
software_apps-hardware_infra     -1.0959137 -1.6962117 -0.4956156 0.0000229
software_apps-sensing_detection   0.1304571 -0.6657606  0.9266749 0.9743881
```

**Exploratory analyses per region**

Descriptive statistics of total funding by region:

```
# A tibble: 4 × 7
  region      n avg_funding median_funding sd_funding min_funding max_funding
  <chr>   <int>       <dbl>          <dbl>      <dbl>       <dbl>       <dbl>
1 america    66        73.1           3.42      228.         0          1498.
2 asia       30        28.1           5.5        66.9        0           338.
3 europe    155        22.5           5.07       57.6        0           588.
4 oceania     8        44.7          43.0        40.5        1.16        116.
```

ANOVA results for funding differences across regions:

```
                Df Sum Sq Mean Sq F value Pr(>F)
region           3   12.1   4.021   1.508  0.213
Residuals      255  679.8   2.666
```

OLS regression output for region and log-transformed funding:

```
Call:
lm(formula = log_total_funding ~ region, data = quantumdataset)

Residuals:
    Min      1Q  Median      3Q     Max 
-2.4226 -1.3274 -0.2892  1.1211  5.2774 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)    2.03513    0.20098  10.126   <2e-16 ***
regionasia    -0.07379    0.35952  -0.205   0.8375    
regioneurope  -0.09539    0.23998  -0.397   0.6913    
regionoceania  1.15754    0.61125   1.894   0.0594 .  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.633 on 255 degrees of freedom
Multiple R-squared:  0.01743,	Adjusted R-squared:  0.005874 
F-statistic: 1.508 on 3 and 255 DF,  p-value: 0.2129
```

Tukey post-hoc test results for region differences in *log_funding*:

```
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = log_total_funding ~ region, data = quantumdataset)

$region
                       diff        lwr       upr     p adj
asia-america    -0.07378771 -1.0035207 0.8559453 0.9969349
europe-america  -0.09538980 -0.7159923 0.5252128 0.9786845
oceania-america  1.15754259 -0.4231744 2.7382596 0.2332881
europe-asia     -0.02160208 -0.8638009 0.8205967 0.9998950
oceania-asia     1.23133031 -0.4487940 2.9114546 0.2326338
oceania-europe   1.25293239 -0.2779372 2.7838020 0.1505925
```

# Appendix C – Interview transcripts

*All interviews were conducted in Italian. To preserve the accuracy and authenticity of the interviewees' statements, the transcripts are presented in their original language.*

**Interview 1: Luca Adinolfi**

FP: Le prime due domande sono molto trasversali: dal punto di vista dell'investimento, cosa distingue una startup deep-tech, come nel quantum computing, da una startup che opera in altri settori? Poi, negli ultimi anni ha notato un cambiamento nel modo in cui il mercato valuta le startup nel quantum computing rispetto ad altri settori deep-tech?

LA: Per quanto riguarda il quantum computing, noi come Lumen non facciamo questo tipo di investimento. Sicuramente curiamo l'asset class del venture capital, ma questa industry non la facciamo per diversi ordini di motivi.
Forse è sbagliato da un punto di vista tecnico, ma da un punto di vista pratico, bisogna dircelo, già il venture capital è un'asset class estremamente nuova e tu, venture capitalist, devi convincere degli investitori che, nel nostro caso, sono fondi vigilati, banche, casse di previdenza e, generalmente, soggetti abbastanza complessi da convincere. Ma perché? Non perché siano difficili, ma perché il venture capital non ha track record. Generalmente sugli alternativi, quindi su private equity e venture capital tu come valuteresti un investimento, un team? La classica domanda è "mi dà il track record dei fondi precedenti?" o "Cosa hai saputo fare di rendimento nei fondi precedenti?". E il venture capital non ha tanti numeri, non ha tanto di questo track record, semplicemente non perché sia andato male, ma perché è un asset class molto giovane.
Riguardo alla tua industry [il quantum computing], mi viene da dire che ci sia una grandissima complessità nel comprenderla, quindi si aggiunge una complessità ulteriore a un'asset class che è appena nata. Metterci dentro anche un'industry complessa da leggere, difficile da comprendere, è un mix che produce una fatica enorme nei confronti dei nostri investitori. Quindi: l'asset class è difficile, non comprendo bene il business, avrei bisogno di industry expert o di professionisti in quella materia, [l'investitore

pensa] “non lo faccio”. È una cosa che noi seguiamo. Oltretutto, farlo nello stadio di investimento che fa Lumen Ventures, cioè il seed, aumenta ancora la complessità, perché un business del genere su un seed round rischi di fare un write-off totale dell'investimento. E questo è chiaramente comprensibile per un asset class come il venture capital, però complica ancora di più le cose.

FP: La ringrazio assolutamente per questi insight. Specificatamente, invece, sul tema della qualità percepita del team, quali sono gli elementi chiave che le permettono di valutarla?

LA: Su questo, sfondi una porta apert perché la nostra investment thesis è proprio people-driven. Noi siamo 100% team-driven. La nostra due diligence, quando attiviamo la fase di investimento che, in un fondo vigilato, è abbastanza complessa e va dall'analyst fino al partner, passando per comitato di investimento e consiglio di amministrazione, vede prima il team.
Noi cerchiamo una diversità nel team, quindi cerchiamo team che siano complementari. Questo per noi è fondamentale, quindi tendiamo a scartare prima di tutto (non perché sia sbagliato, ma perché non rientra nella nostra tesi di investimento) i primi team. Quindi, noi facciamo esclusivamente second-time team. Per essere “second-time” non per forza devi aver fatto una exit o essere uno startupper seriale, sebbene chiaramente questa sia l'accezione principale, ma va bene anche una grande esperienza in una grande corporate o in più corporate. Di base, non prendiamo team all'esordio. Questo per calmierare ovviamente il rischio, perché ai nostri investitori piace così.
Detto questo, cerchiamo di complementarità. Noi abbiamo un focus particolare sull'Italia. Noi possiamo fare e faremo anche investimenti esteri, ma che abbiano comunque un po’ di “italianità”. Ci piace dire che noi facciamo investimenti che abbiano sempre il tricolore all'interno del proprio progetto, che significa anche società straniere che portano la sede in Italia, founder italiani che vogliono rientrare, eccetera. Devono avere un passaporto italiano e una sede stabile in Italia. Sicuramente, poi, ci piace molto la diversità, cioè i team devono essere complementari anche riguardo gender, age, provenienza accademica. Tendiamo ad evitare di fare degli investimenti, come spesso capita, di due colleghi piuttosto che due soggetti provenienti dalla stessa

accademia, stessa università, stessa corporate. Per noi, quello non è motivo di no-go, ma la consideriamo una red flag. In due diligence, comunque, la guardiamo.

FP: Perfetto, la ringrazio, anche perché ha anticipato una mia domanda, che sarebbe stata: “dà più peso alla complementarità interna delle competenze o al profilo di uno o due key founders?”.

LA: Tendiamo ad avere un'accezione un po’ più ampia del termine “team”: non devono essere necessariamente i founder, ma founder più la prima linea di persone chiave dell'azienda. Se due provengano dalla stessa corporate, ma, sotto, a valle, ci sono 4/5 del team che provengono da realtà completamente differenti non è più una red flag. L'importante è che ci sia una certa complementarità nella struttura, ecco.

FP: Lei ha detto che non investite in deep-tech o, quantomeno, ci sono pochi investimenti al proposito. In questo riguardo, l'approccio che ha Lumen quando analizza una startup deep-tech o di quantum computing, rispetto a settori meno R&D-intensive, come cambia?

LA: Ci sarebbe bisogno di un grandissimo supporto. Facendo un passo indietro, il deep-tech in Italia gode di un buon posizionamento e ci sono altri fondi che hanno preso quella nicchia. Noi ci occupiamo di altro e non l'abbiamo mai fatto anche per questo un investimento del genere. Noi, comunque, amiamo definirci industry-agnostic, nel senso che facciamo 3/4 industrie abbastanza bene, ma vediamo tutto volentieri. Questo significa che il deep-tech noi lo vediamo e, in casi eccezionali, nessuno ci vieta di non poterlo fare. Non è che abbiamo un accordo di investimento con le banche, che ci dicono “non lo puoi fare”. Anzi, ci piace anche come esercizio interno, in quanto fondo di investimento, guardarlo. Fa bene guardare anche in altre industrie. La cosa che non abbiamo internamente e che fondi che seguono questa industria hanno è la professionalità. Quindi, noi dovremmo ogni volta, in fase di due diligence, di origination, eccetera, farci affiancare da un industry expert, perché la comprensione di alcune materie che sono all'interno di startup di genere deep-tech è veramente complessa e gli studi, le esperienze del nostro team non sono di fatto predisposte ad accettare una cosa del genere. Quindi, è davvero difficile comprenderla la cosa. Ti dovresti fidare troppo del team non arrivando a una comprensione totale, ti dovresti fidare di quello che dicono. Ma per noi quello è un investimento e dobbiamo comprendere perfettamente quello che stiamo facendo. Se non lo capiamo, non lo facciamo. Perché non facciamo investimenti “spray and pray”, non è che abbiamo 100 partecipate come, magari, possono fare altri fondi americani che mettono un ticket un po’ di qua, un po’ di là, dopodiché si aspettano 7/8 anni. Noi questo non lo possiamo fare. Noi dobbiamo portare rendimento immediato perché [il venture capital] è un’asset class che sta nascendo e non possiamo permettercelo. Detto questo, se dovessimo riassumere la risposta, la cosa più difficile è la comprensione del business.

FP: Mi collego a questa cosa che ha detto. Quindi, nel caso di team scientifici, quanto incide la capacità comunicativa rispetto alle credenziali tecnico-accademiche?
Lei dice “se non ce lo fanno capire loro quello che veramente vogliono fare, è difficile che ci investiamo perché ci dovremmo fare affiancare da industry experts”, quindi se dei founders sono bravi a comunicare, potreste considerare un investimento in deep-tech?

LA: Lo consideriamo. Noi abbiamo un advisory board abbastanza variegato ed è da lì, ma non solo, che peschiamo la maggior parte degli esperti che poi ci supportano. Ci sono varie professionalità nella due diligence, quindi non è tanto quello, quanto il problema di reperire una professionalità in grado di fare una diligence tecnica e approfondita e spiegarcelo.
Un'altra cosa che non ci fa fare un investimento del genere è la duration. Gli investimenti in deep-tech hanno bisogno di veramente tanto, tanto tempo. Quindi, un altro tema che, in qualche modo, aggrava la situazione è questo. Generalmente, quando si costituisce un fondo, o almeno per noi è stato così, si fissa una durata di massimo 10 anni. O lo facciamo subito un investimento in deep-tech o, arrivati al quarto/quinto anno, che per noi è la fine della fase di investimento del fondo, non lo valuteremo. Avremmo bisogno di troppo tempo per maturare una possibile exit e, a quel punto, non ci conviene tenere un fondo aperto esclusivamente per una startup deep-tech.

FP: Ora volevo passare alle domande che riguardano le implicazioni strategiche degli investimenti pubblici. Infatti, come le ho anticipato, sorprendentemente, dalla mia statistica, per quante limitazioni possa avere, è emerso l'essere pubblicamente finanziati influenza negativamente la valutazione. Ciò mi ha colpito, anche perché ci sono parecchi programmi in Europa, negli Stati Uniti e in Asia che investono in questi settori.

In Europa, per esempio l'European Investment Fund, l’acceleratore dell'European Innovation Council, eccetera. Mi conferma anche lei che il vedere che una startup è pubblicamente finanziata scoraggia l'investimento di un investitore privato di venture capital?

LA: La metterei al contrario. Non vuol dire che laddove c'è la parte pubblica sono bravi lato nostro [di investitori privati] ad abbassare la valutazione. La metterei in questo modo: che un investitore pubblico ha una mole di responsabilità, seppur già noi siamo soggetti vigilati da Banca d'Italia, dai nostri investitori, dalle banche, eccetera, ancora superiore. Quindi, ti direi che tante volte non entrano su attività estremamente speculative ed estremamente tirate nelle valutazioni, anche come tema di responsabilità. Un soggetto pubblico ha un duplice scopo: deve fare sicuramente rendimento, perché è un soggetto che viene definito a mercato, una società di gestione del risparmio, ma ha uno scopo anche di ecosistema. Un soggetto pubblico non può dire un soggetto pubblico “faccio solamente le cose che mi interessano e dove faccio rendimento”. Deve farlo certamente, ma ha anche uno scopo proprio di sistema. Deve tendere a fare anche delle startup che abbiano un impatto, magari sul paese, sull'innovazione di una parte di filiera, sulle supply chain. Non esclusivamente di rendimento.
Un fondo privato non deve rendere conto a nessuno, se non alle regole del mercato e ai propri investitori. Non ha lo scopo di fare innovazione per il paese. Noi dobbiamo fare rendimento per i nostri investitori, seppur poi implicitamente c'è anche quella parte lì. Mi viene da dire, perciò, che vada letta al contrario [la domanda che mi hai posto].
Oggi, rispetto a tre anni fa, le valutazioni sono tornate a delle cose normali, quasi basse. 3/4 anni fa, pre e durante il Covid, c'erano state delle valutazioni, soprattutto sul fintech, totalmente fuori misura. In qualche modo, oggi si è tornati a delle cose normali, ma anche sui top del mercato. Ci sono aziende che hanno delle valutazioni alte e sono a un livello di round veramente molto avanzato in termini di maturità, quanto un soggetto pubblico può partecipare ad operazioni del genere? Che senso avrebbe partecipare a delle cose del genere, in una fase così avanzata di investimento? Poche, molto poche. Magari, il risultato della tua statistica viene da quello. Immedesimandomi in un soggetto pubblico, preferirei finanziare una startup nel deep-tech appena nata, facendo del bene anche al mio paese, creando un ecosistema. In sintesi, le tesi di investimento tra un

soggetto pubblico e uno privato sono simili, ma il soggetto pubblico ha un add-on, cioè deve fare sistema.

FP: Tornando un po' più focus sul quantum computing, nonostante quanto detto da lei prima, in una startup di questo settore, ritiene che il capitale pubblico sia necessario in fase iniziale? O al contrario, è evitabile?

LA: No, non è necessario. È un elemento che può essere interessante per la startup. Tieni conto che, generalmente, un investitore pubblico è un investitore abbastanza passivo, quindi è raro che partecipi in maniera intensiva al business, alla vita della startup, ai consigli di amministrazione, che aiuti la supporti nelle attività commerciali, di sviluppo, eccetera. Ti dà denaro, a volte anche tanto, però subisce passivamente gli eventi, cosa che è un po' diversa in un contesto privato. Noi [privati] viviamo le startup. Esse sono le nostre aziende e, in qualche modo, supportiamo i team. Noi metà giornata la dedichiamo a lavorare per loro e con loro. A distanza o in presenza, ci troviamo sempre a lavorare con loro. Quindi se mi chiedi "è necessario?", ti rispondo che no, non è necessario.
Ora ti do un altro punto di vista, ci sono round di investimento esclusivamente privati, mentre alcune volte è necessario il soggetto privato a un investimento pubblico per delle regole di alcuni investitori pubblici. Non entriamo nel merito anche per questione di riservatezza, ma spesso e volentieri la componente pubblica ha bisogno di una componente privata di co-investimento per poter fare round. Ti do una market practice: generalmente, il 30% di quello che investe un soggetto pubblico deve essere privato a round. Quindi, è vero il contrario: tante volte, per un investimento pubblico, è necessario il capitale privato, altrimenti loro non possono proprio investire.

FP: Ok, grazie mille. Il suo approccio in una startup che ha chiuso un round di finanziamento pubblico o ha preso parte a un programma pubblico qual è? La ritiene una cosa neutra o in qualche modo influisce, positivamente o negativamente che sia, nell'investimento?

LA: Da un punto di vista tecnico, neutra. Noi facciamo il nostro percorso e la nostra due diligence ugualmente, quindi dal punto di vista tecnico no. Però, se, per esempio, una startup fintech è validata da un fondo pubblico che fa solo fintech, in termini di bias, ti senti un po' più confident: l'hanno già vista. Da un punto di vista reputazionale, quindi, se c'è un soggetto pubblico, ti direi di sì perché la due diligence parte di un soggetto pubblico, lato reputazionale, è molto approfondita. Se [una startup] è stata validata al mercato, su un mercato italiano, ti direi che si tratta di un giudizio positivo. Il fatto che ci sia un soggetto pubblico, anche se in Italia non ne abbiamo tantissimi, può essere un elemento positivo in termini di valutazione, validazione, reputation, standing. Su contesti esteri, però, non viene prezzato questo valore. Fondi stranieri che devono investire su una startup già investita da un soggetto pubblico italiano non prezzano questa cosa in nessun modo, né negativamente né positivamente. C'è un approccio diverso.

**Interview 2: Arianna Tibuzzi**

FP: I dati mostrano che la posizione geografica conta meno nella determinazione del funding. Lei condivide questa impressione? O ritiene che il "bias geografico" esista ancora in qualche forma?

AT: Può essere vero. In America è sicuramente più facile raccogliere cifre elevate, anche nel quantum, sin dai round iniziali. Però ti confermo che c'è una certa uniformità nella valutazione delle pre-money nel quantum, cosa che non succede in altri settori. Negli Stati Uniti si danno molte cose per scontate, anche nello spazio. In Europa no. Ma sul quantum ti do ragione: è un settore talmente strategico che ormai è diventato globale. Il valore è riconosciuto da tutti, indistintamente. È una tecnologia abilitante con la "A" maiuscola, con un impatto potenzialmente dirompente, come lo è stato Internet. Per questo motivo tutti vogliono esserci: Europa, Asia, Stati Uniti. Da almeno due anni c'è un bel movimento anche in Italia sul quantum computing. Si inizia ad essere un po' più scettici, ma il valore potenziale rimane enorme.

FP: Mi collego a quanto mi stava dicendo. Focalizzandomi sull'Europa, quando ho visualizzato che non ci sono differenze significative negli investimenti, valutazioni ecc., a livello geografico, la prima cosa che mi è venuta in mente è stata: l'Europa ha effettivamente una possibilità nel quantum computing in più rispetto ad altri settori, come l'AI, dove è un po' rimasta indietro?

AT: Sì, sicuramente. Abbiamo scienziati che sono tra i key opinion leader, anche diversi brevetti depositati. Il quantum è comunque un tema su cui l'Europa e anche l'Italia stessa possono dire la loro, tranquillamente a livello degli Stati Uniti. Quindi sì, concordo con te che rispetto all'AI ci troviamo un po' più uniformi, proprio a livello di conoscenze e a livello di contributo che ci si aspetta rispetto ad altre regioni del mondo.

FP: E quali sono, secondo lei, i principali limiti o vantaggi per una startup europea che cerca di competere a livello globale nel quantum?

AT: Il primo limite sono sicuramente gli investimenti molto alti di cui queste startup hanno bisogno. In Europa non si è troppo abituati, sin dai primissimi round, a cercare 5–6 milioni, mentre negli Stati Uniti è normalissimo che un seed round sia di sei milioni. Normalmente, [in Europa] una cifra del genere si aggira più su quello che viene chiamato "serie A". Però, purtroppo, nel campo dei quantum hardware, i seed devono essere importanti e quindi questa è sicuramente una difficoltà in più perché i nostri investitori non sono abituati a pensare di investire una cifra così elevata quando l'azienda è ancora così rischiosa. Anche la pre-money deve essere sufficientemente alta, altrimenti con 5 o 6 milioni di seed vai a diluire completamente i founder e non è possibile su una startup che si aspetta di fare cinque round, anche cospicui, no? Quindi uno dei problemi grandi è anche quello di trovare investitori pronti ad investire cifre importanti molto, molto early stage. E l'altro problema è la poca conoscenza tecnica da parte degli investitori. Perché negli Stati Uniti è più comune poter trovare investitori che hanno una conoscenza anche di deeptech, mentre in Europa è abbastanza raro. Noi di Obloo, per esempio, siamo tutti tecnici, abbiamo tutti una laurea in ingegneria fisica, chimica e il 70% di noi è anche un dottorato di ricerca. Io personalmente vengo da 10 anni fatti nella ricerca su microelettronica, per esempio. E quindi, un campo come il quantum, è così complesso, veramente tecnicamente complesso. Spesso gli investitori si sentono spaesati, completamente disorientati, perché hanno difficoltà a capire. Alcuni investono perché c'è il trend, però molti altri rimangono bloccati da questo scoglio del comprendere.

FP: Sì, questa difficoltà a capire il settore l'avevo riscontrata anche in un'altra intervista. Alla fine lei mi ha parlato solo di limiti, ma vantaggi per crescere una startup in Europa ce ne sono?

AT: Sicuramente c'è il tema della facilità nel mettere su laboratori, e della forza lavoro qualificata, ma mai pagata ai livelli degli Stati Uniti, un po' a basso costo diciamo. All'inizio, si può avere comunque la stessa qualità, se non più alta di quello che si trova fuori dall'Europa.
Dopodiché, il programma EIC Accelerator, che è quello della Commissione Europea dentro Horizon, quindi dentro il programma di ricerca europeo pilastro dello European Innovation Council, lo hai mai sentito? È praticamente uno strumento proprio per dare equity, fino a 15 milioni in investimento, quindi una cifra grande. Ha dei campioni di eccellenza scientifica e sicuramente diverse delle startup più visibili che abbiamo in Europa sono passate quasi tutte da lì. EIC Accelerator è un programma interessante perché fondi pubblici vengono messi a disposizione. Poi, è sempre un investimento, quindi comunque c'è equity, però sono fino a 15 milioni, uniti anche a 2,5 milioni in grant non diluitivi. È uno strumento molto attraente per chi lavora nel quantum perché si riesce ad essere molto, molto, molto competitivi. C'è una spinta fortissima, proprio strategica, da parte dell'Europa a investire nel quantum computing proprio per mantenere la leadership rispetto ad altri governi. Non dico semplicemente "prendete questi finanziamenti", ma diciamo che è sicuramente un'opportunità vera, reale, che c'è. Detto questo, rispetto ad altre geografie non trovo altri potenziali, abbiamo comunque ottime università e laboratori qui, ma ci sono anche all'estero.

FP: Perfetto. E sull'Asia ha qualche spunto oppure è un mondo troppo distante?

AT: In realtà non è mai uscita parlando con le startup che conosco nel quantum. L'Asia non è mai stata discussa, devo dire la verità. Gli Stati Uniti sì, anche il Canada, però non ho mai sentito nominare una spinta così forte dalla parte asiatica. Però, per esempio, le foundry che costruiscono i chip sono in Asia, questo sì. Per quanto riguarda la parte quantistica relativa all'hardware e quindi ai chip, sicuramente l'Europa non è ben messa perché comunque dobbiamo sempre rifarci a partner e fornitori che sono in maggioranza fuori dall'Europa. Siamo effettivamente un po' dipendenti dalle fonderie e dai semiconduttori fabbricati in Asia.

FP: Grazie mille, è stata esaustiva su tutte le domande. Torno un attimo all'inizio con due domande generali. Dal punto di vista degli investimenti, cosa distingue una startup deep-tech come nel quantum computing da una che opera in altri settori? E, negli ultimi anni, ha notato cambiamenti nel modo in cui il mercato valuta le startup quantum rispetto ad altre deep technologies e anche rispetto ad altri settori?

AT: La prima domanda riguarda un po' tutto il deep-tech. Noi come Obloo lavoriamo solo su fondi di venture capital deep-tech. Sicuramente una cosa che contraddistingue molto il deep-tech è la quantità di investimenti necessari, la dimensione dei round, il time-to-market e il time-to-exit. Questa è una grande differenza. Anche il famoso pre-seed, nel deep-tech e soprattutto nel quantum, non può essere di €100,000. Mentre in altri settori si riesce anche ad avere un Minimum Viable Product o un prototipo con €100,000, nel deep-tech devi stare sui €500,000 già a livello di pre-seed.
In più, il quantum, come dicevo prima, prevede un utilizzo di quello che uno sta costruendo, proprio a livello quantistico, non tra 2 o 3 anni, ma tra molti più anni. Quindi è un investimento a lungo termine che i fondi di venture capital guardano sempre con scetticismo. Tutti i fondi, penso che lo sai, sono normalmente costruiti in modo che nei primi 5 anni fanno gli investimenti, ma poi ci sono i secondi 5, quindi 5+5, in cui devono disinvestire, ossia devono arrivare a una exit su alcune del portafoglio. Ovviamente non su tutte, perché molte poi saranno liquidate, non avranno successo, però loro si aspettano un orizzonte di 5 anni più o meno per vedere la possibilità di uscire dall'azienda. E questo nel deep-tech è difficile, soprattutto nel quantum. Allora, quello che si prova per cercare di mitigare un po' questa parte è avere più modelli di business e guardare se ci sono delle possibilità di poter vendere anche una parte del prodotto. Una parte nel senso di una concezione del prodotto più bassa, che magari sia ispirata al quantum ma che non funzioni esattamente con i concetti e le regole della fisica quantistica, che ne sia ispirata, ma che però ti permette di cominciare a vendere anche tra 2 o 3 anni. E questo è fondamentale perché, a quel punto, una startup che già ha un certo fatturato riesci in modo più semplice a farla acquisire o a portarla in borsa. Una startup che resta senza fatturare per 5 o 6 anni è pesante per un investitore. Questo è molto tipico in realtà deep-tech. Per esempio, abbiamo una nostra startup che si occupa di quantum e loro hanno una tecnologia, ovviamente brevettata, che permette di realizzare nuovi chip quantistici ottici. Però non hanno pensato subito,

all'inizio, di realizzare un super-computer,  un computer quantistico, ma hanno semplicemente pensato, come primo go-to-market, di andare sul mercato con degli acceleratori di elettronica, ovvero dei chip che semplicemente si inseriscono nei computer esistenti e che accelerano la grafica come delle GPU. Questo ovviamente ha una potenza molto più importante perché all'interno ha effettivamente dei chip quantistici, però ti permette di avere a disposizione una scheda acceleratrice che puoi inserire dove vuoi e, a quel punto, non devi aspettare di creare il computer quantistico o il centro di computer quantistici. È una specie di via di mezzo che, intanto, ti permette [di andare sul mercato] mentre si sviluppa. Così, mentre si vede nel lungo termine una roadmap, intanto puoi realizzare già qualcosa che si può vendere: questo è abbastanza fondamentale. Noi lo consigliamo a tutte le nostre startup, al di là della visione ultima, di cercare nel mezzo di poter consegnare al mercato un sotto-prodotto, un prodotto che possa già essere utilizzato in anticipo rispetto a quello finale.

FP: Molto, molto interessante. Tra l'altro ha anticipato un sacco di domande che le avrei fatto e ha accorciato ulteriormente i tempi. Rispetto a quanto detto, volevo chiederle quali segnali le indicano che una startup è effettivamente pronta a scalare? Al di là della maturità tecnologica, lei ritiene sia principale questa cosa di iniziare a fatturare con un sotto-prodotto?

AT: Sì, sicuramente è importante. Molto spesso siamo noi che cerchiamo di far ragionare le nostre startup deep-tech su questa possibilità perché altrimenti non riescono proprio a trovare altri round, cioè non chiudono altri round di investimento a causa del tanto scetticismo da parte di investitori che non riescono a vedere il valore che cresce in pochi anni; vederlo a 10 anni è troppo per loro, quindi questo è importante.
Poi, per scalare, come ti diranno in tantissimi, è [fondamentale] il team. Qui forse c'è una differenza tra deep-tech e quantum, effettivamente, almeno per quello che abbiamo visto. Il deep-tech soffre un po' di più su questo tema perché i fondatori normalmente sono dei tecnici, sono veramente degli inventori, degli scienziati, dei dottorati di ricerca o dottorandi, anche qualche ricercatore. È un'eccezione trovare lo scienziato, l'inventore, che poi sia in grado anche di prendere il ruolo di CEO al 100%, che sia in grado di parlare in modo chiaro e convincente con tutti gli investitori. Questa è una parte un po' più delicata. Se non all'investimento seed, sicuramente per gli investimenti

successivi, bisogna essere sicuri di aver inserito nel team il CEO giusto, se gli inventori di prima non sono stati in grado di coprire a sufficienza questa posizione.
Però, ho notato che nel quantum ci sono due componenti. Da una parte, è un campo molto tecnico-scientifico: dunque, se l'imprenditore-scienziato porta avanti la sua azienda e diventa CEO, ciò è spesso accettato lo stesso. Cioè, non si ricerca per forza il manager o venditore, perché devi interagire con altre persone molto tecniche. Da un'altra parte, però, questi founding team hanno all'interno delle persone senior, che vengono da tanti anni di ricerca, essendo temi molto complessi. E queste tecnologie vengono sviluppate da persone che ci hanno lavorato per anni, non da qualcuno che ha fatto la tesi di laurea due anni fa; non hai l'imprenditore di 24 anni che apre la startup. Questo non l'ho visto, e credo sia una caratteristica comune. Ho parlato con tanta gente che lavora nel quantum, con tanti imprenditori, e nessuno era un ragazzino: tutti abbastanza senior. E quando dico senior, intendo più di 50 anni, cioè non 35 o 40. È interessante, visto che il campo è molto sfidante. Proprio dal punto di vista tecnico, non nasce da qualcosa che fai nel garage, ma viene da anni di sviluppo e prevede anche il coinvolgimento di persone più senior.

FP: E quali sono, secondo lei, gli elementi fondamentali che una startup quantum deve avere per essere considerata davvero pronta ad entrare sul mercato? Le parlo di roadmap, partner strategici, accesso a casi d'uso concreti: quali sono gli elementi fondamentali prima di entrare sul mercato, fermo restando che nel mercato magari ci entrerà in 5 o 6 anni [dalla sua fondazione]?

AT: È importante che ci siano dei brevetti, almeno se si parla di hardware. Anche il team e una chiara roadmap [sono elementi rilevanti]. Proprio tu mi hai parlato di roadmap ed è molto corretto perché, come ti dicevo prima, avendo questo lungo cammino verso il mercato, è importante avere chiari e scanditi i passi che devi fare per arrivare sul mercato e quali sono le milestone intermedie che permetteranno di aumentare il valore della tua startup. Ok, non vendi tra 2 anni, vendi tra 5 o 6, però fammi capire nella tua roadmap come cresce quello che stai costruendo e facendo.
I partner? Dipende se fai hardware o se il tuo algoritmo e i tuoi software hanno bisogno di hardware specifici. In quel caso allora sì, è importante mostrare che hai quelle partnership, visto che non c'è un accesso così rapido e semplice a chi può metterti a

disposizione quell’hardware quantistico. Come dicevo prima, le fonderie che fanno i chip piuttosto che chi fa dei laser particolari, chi lavora con l’ottico: devi effettivamente far vedere che sai già da chi andare per trovare quello che ti serve, perché poi, se questo non ce l'hai, significa anche che possono passare mesi e mesi di tempo per identificare il tuo network. Siccome il quantum è un campo di nicchia ancora, è fondamentale anche vedere che hai identificato i fornitori giusti e che ci hai già parlato, perché questo ti dà proprio anche una referenza, fa crescere l’idea di affidabilità e fiducia che l’investitore ha di quel team, vuol dire che si sa già muovere nel suo campo.
I casi d’uso in generale sono importanti, nel quantum non lo so. Chi investe nel quantum adesso non lo fa più puramente in modo strategico, ma per investire in quelle tecnologie che saranno molto impattanti. E poi, certo, ci sono investitori che, volendo vedere dapprima dei guadagni più rapidi, ti chiederanno sicuramente quella go-to-market che ti permette con uno o due casi d’uso di entrare sul mercato un po’ prima. Era quello che ti raccontavo dell’acceleratore [ottico della startup nel portafoglio di Obloo], per esempio.

FP: Ultima domanda. Gliela vorrei fare al riguardo dei vari “subfield”. Lei spesso mi ha parlato di quantum hardware ed, effettivamente, dalla mia analisi, i manifatturieri di computer e processori sono le startup che ricevono più finanziamenti rispetto a chi fa software e quantum communication. Secondo lei, il fatto che questi ricevano meno finanziamenti è perché il quantum computer, in sé per sé, ha più hype o, semplicemente, c’è anche qua un knowledge gap?

AT: In realtà, chi fa software è anche più vicino al mercato. A volte, gli algoritmi quantistici o sistemi di simulazione quantistici (già ne conosco diverse di queste startup) possono applicarsi anche a casi attuali senza avere il super-computer o possono appoggiarsi su degli hardware esistenti. È proprio un tema che, quando vai a vedere la roadmap di cui parlavamo, hanno bisogno di meno investimenti. Essendo software o algoritmi, non hanno bisogno di mettere su il proprio asset o di capitalizzare sull’hardware. Non hanno bisogno di andare dalla fonderia per farsi realizzare i chip, ma riescono a fare coding indipendentemente, soprattutto senza che debbano pagare persone addette alla produzione fisica.

**Interview 3: Emilia Garito**

FP: Dal punto di vista dell'investimento, cosa distingue una startup deep-tech (come nel quantum computing) da una startup che opera in altri settori? Negli ultimi anni, ha notato un cambiamento nel modo in cui il mercato valuta le startup nel quantum computing? Sono cambiate le aspettative o i criteri rispetto ad altri settori deep-tech?

EG: Allora intanto io direi di partire da che cosa significa deeptech e quando è nato questo termine. Il deep-tech c'è sempre stato. Il deep-tech è la scienza, la ricerca scientifica che diventa ricerca applicata e, quindi, che crea delle soluzioni tecnologiche particolarmente disruptive, ma soprattutto con un altissimo livello di innovazione e di unicità. Semplicemente, però, è [solamente] dal 2014 che si utilizza questo termine. È stato coniato nel 2014 perché ad un certo punto si è resa evidente la necessità di dover differenziare questo settore del deep-tech da tutto quello che veniva definito high-tech e soprattutto digitale, in quanto l'high-tech e le tecnologie digitali avevano una componente di innovazione, soprattutto nello use case, nell'applicazione, nell'utilizzo di tecnologie già disponibili, invece il deep-tech inventa di sana pianta delle tecnologie, le crea da zero. Ecco perché è fortemente connotato da una competenza che nasce all'interno della ricerca scientifica. Quindi, per andare a capire se una soluzione è effettivamente deep-tech, è chiaro che bisogna partire da questo presupposto e fare anche delle valutazioni in termini di contenuto tecnologico. Bisogna valutare il contenuto tecnologico della soluzione, cioè la capacità di creare proprietà intellettuale, dove la proprietà intellettuale non è solo il brevetto, ma anche il know-how, quello può essere poi secretato laddove esiste una soluzione tecnologica unica, originale che ha un impatto ed è industrializzabile, che sia veramente innovativa e che ha come come base una complessità di studio, di ricerca e di tecnologia. Allora, lì parliamo di deeptech.

Abbiamo anche come rilevatore dell'evidenza del fatto che si tratti di una tecnologia innovativa la proprietà intellettuale che, però, deve essere ovviamente valutata. Ma cosa vuol dire questo? Che, chiaramente, più il portafoglio brevettuale di una soluzione tecnologica è diversificato ed esteso geograficamente, più abbiamo un'evidenza quantitativa del fatto che si tratta di una soluzione unica e rilevante. Ma non basta, bisogna andare a fare delle due diligence tecnologiche avanzate basate proprio sulla valutazione del peso del contenuto tecnologico, di quanto ci sia davvero di unicità, di rilevanza all'interno della soluzione evidenziata. E questo si fa attraverso tutta una serie di analisi, anche di strumenti come ad esempio gli strumenti di IP intelligence, del patent landscape: tutta una serie di attività che ci vengono in soccorso per poter avere dei dati evidenti, sebbene poi vanno comunque interpretati e saputi interpretare. Però, [la cosa importante è] che siano dei dati che ci danno evidenza della forza tecnologica della soluzione.

FP: Si è collegata subito al tema appunto della proprietà intellettuale. Al proposito le volevo chiedere: quanto valuta la proprietà intellettuale nel determinare il potenziale di investimento? Rappresenta tutto?

EG: Allora, i criteri in base ai quali si decide se investire o meno in una soluzione tecnologica sono ovviamente più di uno. Uno rilevante è sicuramente la capacità di fare una due diligence tecnologica e brevettuale, quindi di comprendere proprio il valore della proprietà intellettuale, che in realtà non veniva fatto [in precedenza]. Anche la Commissione Europea, nei propri programmi di investimento, è da pochi anni che ha [saputo indicare con precisione] la documentazione che le aziende devono presentare in ambito deep-tech, in maniera tale che ci sia una certa omogeneità. Prima, era un pochino la shadow. Adesso la Commissione Europea ha deciso che bisogna avere comunque dei documenti solidi come la "Freedom to Operate Analysis", pena l'esclusione dalla gara. Quindi, si sta dando maggiore rilevanza a livello proprio anche europeo, e questo effettivamente è sicuramente un elemento importante. Poi ce ne sono chiaramente altri.

Avere un forte contenuto tecnologico, una forte soluzione tecnologica che però non soddisfa un reale bisogno, una reale esigenza, è male. Un'invenzione che poi tutto sommato però non è industrializzata in termini di sostenibilità economica perché il mercato è molto, molto piccolo, è embrionale o magari è latente: anche questo è un elemento molto importante perché abbiamo visto come la storia dell'ultimo secolo ci racconta tanti di questi esempi di tecnologie super interessanti, venute però troppo in anticipo magari, oppure che si riferivano a mercati troppo piccoli e non potevano avere il successo di società, di altre tecnologie, di altre invenzioni tecnologiche che effettivamente erano una risposta puntuale ed efficace a problemi che erano stati individuati. Quindi, da una parte c'è la valutazione del contenuto tecnologico. Dall'altra parte abbiamo anche soprattutto capire se c'è un fit con il bisogno che è stato individuato e che va risolto. Tutto questo nell'ambito del quantum computing in che cosa si esprime? Nel fatto che chiaramente, in quanto il quantum computing è un mercato emergente, la proprietà intellettuale fa un gioco importante. Per cui, chi riuscirà prima a proteggere alcune soluzioni che potrebbero diventare addirittura lo standard delle applicazioni di quantum technologies del futuro, avrà ovviamente un vantaggio competitivo molto importante. Perché, essendo appunto un mercato in apertura, all'inizio è molto importante non lasciare nulla al caso e capire come proteggersi. Avere una solida proprietà intellettuale è sicuramente un elemento che pesa molto di più rispetto che in altri ambiti.

[Ora ti dico] un'altra cosa che è più specifica per il quantum dal punto di vista di un investitore di venture capital. Mentre sappiamo che il mercato del quantum computing, in quanto proprio computer quantistico, ha bisogno ancora di parecchi anni di maturazione, ci possono essere delle tecnologie già industrializzabili, che oggi sono, ad esempio, il quantum machine learning, software, algoritmi, oppure tecnologie che pensano al quantum computing, ma che possono anche avere dei mercati già esistenti, come nell'ambito dei super-computer oppure nell'ambito dei microchip fotonici. Per cui, tutte quelle che sono le tecnologie all'interno di un ambito di quantum technologies, o quantum meets, che possono avere già delle applicazioni attuali senza dover attendere la maturazione totale del settore del quantum computing, sono molto interessanti per un fondo di venture capital che ha durata di 10 anni e che, quindi, non può attendere la maturazione totale del quantum computing, ma che sulle sub-categorie, se vogliamo, di tecnologie quantistiche potrebbe investire e avere anche delle remunerazioni interessanti.

FP: Ok, perfetto. Mi ha confermato, tra l'altro, cose che avevano detto altri in precedenza. Penso sia abbastanza univoca questa cosa di voler monetizzare anche nel medio termine perché i fondi durano comunque 10 anni. Collegandomi a queste cose delle sub-categorie (quantum machine learning, software, algoritmi): per queste, rispetto a chi invece fa puramente hardware, la strategia di proprietà intellettuale viene di meno? O ha un peso strategico specifico anche in questo caso?

EG: Beh, chiaramente sì, anche se ci stanno delle regolamentazioni molto differenti tra Europa e, per esempio, l'America. [In America,] è più semplice ottenere dei brevetti di algoritmi, di machine learning o di software semplice. È più facile perché c'è una regolamentazione e una struttura di brevettazione che lo consente. In Europa, è molto più complicato e molto più difficile. Quindi, c'è una disomogeneità in questo, ed è anche un problema a livello di competitività, no? Quando si parla della sovranità tecnologica europea, sull'AI è molto più complicato averla, perché non si può brevettare quello che invece si potrebbe brevettare negli Stati Uniti. Vediamo, ad esempio, nel settore del fintech: algoritmi, metodi che hanno applicazioni in banking e fintech, che sono esclusi a livello normativo dalla possibilità della protezione in Europa. Sicuramente, per l'hardware è molto più facile perché ci sono gli strumenti per poter avere un brevetto di invenzione. Però, ci sarebbe tanto altro [da brevettare] anche nell'ambito del software e del machine learning, a partire dal metodo e l'algoritmo in sé. Poi, laddove c'è comunque un'integrazione magari tra software e hardware, dove si può pensare di usare il computer implemented invention, è ancora più forte il bisogno di protezione. Ovviamente c'è il know-how, il trade secret, che non ha limiti temporali in termini di durata di proteggibilità, ma che però ha delle caratteristiche che vanno rispettate, il fatto che effettivamente quella soluzione tecnologica o quell'algoritmo non può essere individuato e reso noto facilmente, non può essere mantenuto segreto.

FP: Quali errori o sottovalutazioni nota più spesso nelle strategie IP delle startup early-stage deep-tech?

EG: Nel deeptech c'è maggiore consapevolezza della brevettazione, della protezione, proprio perché su arriva un po' dal mondo un po' più hardware, come dalla fisica, dalla ricerca. Quindi c'è una maggiore conoscenza. Ma non tantissima a livello italiano. Qui ancora molti pensano che, tutto sommato, la proteggibilità e quindi la brevettazione non ponga dei vantaggi competitivi così rilevanti. Oppure tanti altri pensano che le cose che sviluppano non siano proteggibili, quindi neanche tentano questa strada. c'è da lavorare tanto a livello di cultura della proteggibilità e, soprattutto, della valorizzazione. Che vuol dire valorizzare una soluzione? Parte proprio dalla proteggibilità della stessa ai fini della valorizzazione, passando dalle dinamiche che dicevamo prima in relazione alle sotto-categorie [ovvero che, in Europa, c'è una cultura di brevettazione inferiore rispetto che in altre parti del mondo].

FP: Secondo la sua esperienza, perché le startup hardware-based tendono a ricevere più fondi rispetto a quelle attive in software, sensing o communication? Come se lo spiega, questa cosa che chi fa computer e processori tendono a ricevere più fondi rispetto agli altri player del settore?

EG: Questo sinceramente non sono in grado di dirtelo perché, da quello che è la mia visibilità rispetto ai finanziamenti europei, si vede abbastanza di tutto. Sicuramente si può dire che ci sono meno proposte veramente deeptech rispetto alle proposte IT, quindi, in proporzione  a quante ditte prendono finanziamenti, siccome poi i soldi quelli sono…,

FP: Ok. La spiegazione che io mi ero provato a dare era che un computer con un milione di qubit fa più notizia rispetto a chi fa, per esempio, il sistema di quantum communication. Quest'ultima è una cosa fondamentale, ma magari fa meno hype e di conseguenza potrebbe essere più difficile da piazzare sul mercato, diciamo. La spiegazione che mi ero cercato di dare era questa. Non so se lei la condivide.

EG: Non saprei. È un po' tricky, sai? Anche perché io ho fatto un'analisi di patent landscape sui brevetti di AI e sui brevetti di quantum, e alla fine siamo allo stesso posto in Europa per numero di pubblicazioni scientifiche e numeri di brevetti. Quindi, a livello di finanziamenti, dovrebbero andare di pari passo.

FP: A questo punto, le rivolgo una domanda riguardo alla distribuzione geografica dei finanziamenti. Qua io mi aspettavo che l'America fosse messa meglio, in realtà dalle mie analisi, con tutte le limitazioni che possano avere, non si è evidenziata alcuna differenza significativa tra i finanziamenti negli Stati Uniti, in Europa e in Asia. Sono quasi egualmente distribuiti. Questo lei lo riscontra?

E a tal proposito le chiedo anche: proprio per questo motivo, l'Europa ha una possibilità in più rispetto ad altri settori di colmare il gap con USA e Canada?

EG: Per me, sì. Secondo me, sull'AI più o meno abbiamo dato ormai, mentre nel quantum computing, che è molto più complesso ovviamente, perché dentro ha tante cose, tra cui la fisica quantistica, la fotonica, il laser, i materiali quantistici, potremmo creare una filiera più solida. Però, certo, ci vogliono dei grossi capitali. E poi forse ci vuole anche una focalizzazione su delle verticali applicative, non solo sul quantum computer in sé.Io punterei molto sulle telecomunicazioni e sulla fotonica, soprattutto in Europa. Però, quello è sicuro, che bisogna investire molto di più e molto velocemente lato governativo.

FP: Le faccio l'ultima domanda. In Europa esiste l'acceleratore dell'European Innovation Council, lei valuta positivamente, neutralmente o negativamente il fatto che una startup del suo portafoglio possa partecipare a questo programma?

EG: È fondamentale che partecipi. È una validazione. È una validazione importantissima. E purtroppo il numero di proposte italiane è sempre molto più basso rispetto a quello degli altri Paesi europei. Questo è un grosso problema che noi abbiamo a livello italiano. Dobbiamo aumentare il numero di proposte e la qualità delle proposte. Ed è fondamentale per due motivi. Tralascerei il fatto di avere delle risorse, che comunque è un motivo. Tu ti prendi 5-10 milioni, che è molto utile, visto che il capitale di venture capital europeo è più piccolo rispetto a quello americano. Tralasciando però la tematica del finanziamento, è importante che si ottenga quello che si chiama Seal of Excellence. Seal of Excellence significa che la Commissione Europea valuta quella tecnologia con il bollino dell'eccellenza europea. Questo ovviamente è un biglietto da visita fondamentale per farsi presentare a investitori qualificati, anche non europei. Per alcuni Paesi membri europei, addirittura, avere il Seal of Excellence consente di poter avere finanziamenti governativi extra. Non è il caso dell'Italia, perché non ha fatto questo accordo. Però molti Paesi hanno anche questo tipo di accordo con l'Europa, per cui chi ha la Seal of Excellence può ricevere finanziamenti una volta che tornano a casa dai governi di provenienza.