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Startups' Performance: Evidence from Tunisia

Achraf Khallouli
and Rim Mouelhi

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Achraf Khallouli, Author

ESCT - Department of Quantitative Methods

University of La Manouba, Tunisia

KhallouliAchraf@gmail.com

achraf.khallouli@esc.u-manouba.tn

Pr. Rim Mouelhi, Co-Author

Full Professor, Department of Economics

ISCAE, University of La Manouba, Tunisia

mouelhirim3@gmail.com

Rym.benayed@iscae.uma.tn

ORCID

Achraf Khallouli https://orcid.org/0009-0008-8321-2573

Rim Mouelhi https://orcid.org/0000-0001-6213-3712

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Abstract

The objective of this study is to investigate the impact of intrinsic characteristics of startups, mainly, founders' characteristics (such as education, professional experience, and network) and business-related characteristics (such as product category and industry), on their performance. The study uses data from a portfolio of 51 startups belonging to a Tunisian Venture Capital firm to analyze the aforementioned impact. Performance is measured by revenue, raised funds, survival, and the firm's team assessment. The study deploys Multiple Linear Regression, Binary Logistic Regression, and Proportional Odds Logistic Regression to analyze the data. The findings contribute to the development of a framework for evidence-based investment decisions within the Venture Capital industry. The results highlight the importance of factors such as the quality of the university attended by founders, the repeat entrepreneur status, and the founder's being full-time on the startup in predicting performance.

Keywords

Venture Capital, Startups, Performance Indicators, Multiple Linear Regression, Binary Logistic Regression, Proportional Odds Logistic Regression

1. Introduction

Startups are businesses that build high-tech innovative products, with little or no operating history and intend to grow exponentially (Blank & Euchner, 2018). They have emerged as a driving force behind economic growth and innovation in various countries around the world (Colombelli & Quatraro, 2019; Fukagawa, 2018). These businesses created 2.8 trillion dollars in economic value globally between 2017 and 2019 (Startup Genome, 2020). In recent years, the venture capital (VC) industry has played a crucial role in supporting startups by providing them with capital, mentorship, and resources for growth (Metrick & Yasuda, 2021). Understanding the factors that contribute to the performance of startups has become a critical area of research, as it can inform evidence-based investment decisions within the VC industry (Gompers et al., 2020). Low survival rates of startups are very common, regardless of the market in which they are operating (Kotashev, 2022). Hence, it is crucial to measure and understand what drives their performance and their sustainability.

The research question addressed in this study is: "What are the startup-related characteristics that determine the performance of a startup?" To answer this question, the study focuses on the intrinsic characteristics of startups, mainly, the characteristics of founders and business-related characteristics and their impact on startup performance. Performance is measured by four variables: change in revenue, external investment, two-year survival, and the firm's team assessment.

We concentrate on founders at the expense of business-related characteristics due to two main reasons. The first is the amount of literature emphasizing the role of founders and portraying it as the single most important performance driver. The second is that all business-related characteristics stem from founders (Parker, 2021). It is the founders that select the startup idea, recruit the team, set the strategy, and execute.
Our work resorts to data from a portfolio of 51 startups belonging to Flat6Labs Tunisia, a Tunisian Venture Capital firm. Flat6Labs is one of the most active VC firms in Tunisia and the Middle East & North Africa region (Entreprises Magazines, 2022; Magnitt, 2022), and the dataset used in this study comprises startups that the firm invested in between 2018 and 2020. We employ Multiple Linear Regression, Binary Logistic Regression, and Proportional Odds Logistic Regression to identify the key factors that influence these startups' performance.

The methodology used in this study involves an extensive literature review to identify the most influential variables within the categories of business and founder-related characteristics. The business-related variables include the type of product, industry, and location of the startup, while the founder-related variables encompass education and sociodemographic indicators, co-founder relationships, prior experience of founders, recommendations by the Flat6Labs network, and the dedication of the entrepreneur.

The results highlight the importance of factors such as the quality of the university attended by founders, the repeat entrepreneur status, and the founder's being full-time on the startup in predicting revenue change, external investment, two-year survival, and investment team classification.

It has long been claimed that most investment professionals are using heuristics to identify the best startups (Sinyard et al., 2020; Zacharakis & Shepherd, 2007; Zhang & Cueto, 2016). Heuristics are methods, approaches, or "rules of thumb" for solving problems that do not guarantee a solution that is based on empirical evidence. They are qualified as personal experience-based rather than evidence-based or data-based (Shefrin, 2000). Future research opportunities in VC will arise from this shift from heuristics-based decision-making to data-based decision-making (Rao, 2013; Wiggers, 2023). Consequently, the findings of this study will contribute to the growing body of literature on startup performance and provide valuable insights for VC firms and investors.

2. Drivers of Startups' Performance: Literature Review

2.1. Startups' Performance

Performance is regarded as a vital component of management control (Neely et al., 1995; Slack et al., 2019). It has been proposed that traits associated with the ability to be entrepreneurial, and the business environment are closely connected to business performance (Dinh Quy, 2020). Moreover, it has been argued that all business-related characteristics stem from founders (Parker, 2021). Furthermore, it is also important for entrepreneurs to measure performance objectively, since they usually have a biased assessment of their startups (Read et al., 2009). The following sections explore how performance is perceived by three main stakeholders in a startup's ecosystem: Founders, Governments, and Venture Capital investors.

2.1.1. Founders' Perspective

There are chiefly a couple of studies that investigate startups' performance from the founders' perspective. For instance, Reis (2017) found out entrepreneurs put much emphasis on the number of clients, clients' satisfaction, meeting delivery deadlines, operational efficiency, employees' satisfaction, and attainment of objectives as the top performance indicators for healthcare startups. The findings show that non-financial indicators are the most essential for healthcare entrepreneurs. Such indicators proved to be instrumental in creating economic value regardless of the startup sector (Perramon et al., 2016). Focusing on E-commerce startups, Muntean et al. (2016) identified several crucial performance metrics such as the rate at which shoppers abandon their carts, the average revenue per visitor, and conversion rates. Other studies found additional key performance indicators, such as employment and revenue growth (Bruderl & Preisendorfer, 1998), headcount increase, return on investment, productivity (Reid & Smith, 2000), revenue, stability, founders' satisfaction (Sebora et al., 2008), and growth proxies (McKelvie & Wiklund, 2010).

Rompho (2018) carried out a survey of performance measures used by entrepreneurs across various industries. They found out that financial indicators, mainly income statement items, as well as sector/product-related metrics, are essential decision drivers.

As mentioned previously, entrepreneurs are usually biased when assessing the performance of their own ventures. As a result, it is interesting to check for other measures based on other stakeholders' perspectives (Read et al., 2009).

2.1.2. Government Perspective

Either on the American level or elsewhere in the world, there are major discrepancies in how governments define what a startup is. As a matter of fact, a comparative analysis of angel tax credit (ATC) programs from 1988 to 2018 in 31 American states reveals deep variations in startups' definitions. For instance, age caps vary from three to 12 years, employment caps from 25 to 100 employees, revenue caps from $150,000 to $20 million, investment caps from $1 to $10 million, and asset caps from $2.5 to $50 million. Despite the discrepancies, one might infer that for the American government, revenue, employment, investment, and assets are good indicators of startups' performance (Denes et al., 2019).

On the tax authorities' level, there are discrepancies in financial reporting practices between traditional companies and startups. For startups, there is always a focus on income statement items and capital gains (Granlund & Taipaleenmäki, 2005).

In Tunisia, the National Startup Act facilitated the launch and development of Tunisian startups. This framework integrates various measures that benefit entrepreneurs, investors, and startups. Comparable to American legislation, the act puts emphasis on employment, investment, and revenue as key performance indicators (Startup Act, 2018).

2.1.3. *Venture Capital Investors' Perspective*

Venture Capital firms are financial intermediaries that fund early-stage and emerging companies that might otherwise struggle to attract capital. These companies are usually risky to invest in, but have the potential for scalability. As a result, VC firms can realize significant capital gains by funding them (Gompers & Lerner, 2001). The ultimate goal of a VC firm is to maximize its capital gains by exiting firms through either a merger & acquisition transaction or an initial public offering (IPO). This puts additional pressure on VC professionals when selecting, supporting, and exiting investees.

Venture Capitalists usually encourage entrepreneurs to report performance indicators that limit agency costs. These indicators are mainly financial such as return on investment, capital budgeting variances, and internal profit targets. They do hold entrepreneurs accountable to shareholders and assure the alignment of their interests (Simons, 1995). VC firms have a corrective role as well vis-à-vis entrepreneurs by imposing key performance indicators that help in realizing capital gains but might get dismissed by entrepreneurs (Rompho, 2018). Overall, venture capitalists' goal is growth whether in revenue, investment, assets, or employees (Davila et al., 2003; Jeong et al., 2020). This growth is supposed to increase the investor's cash-on-cash return and net Internal Rate of Return, the two single most important performance indicators for a venture capitalist (Gompers et al., 2020; Metrick & Yasuda, 2021).

As VC firms aspire for returns, there is a need to understand the determinants of firms' performance at the early stage. To answer this question, Gompers et al. (2020) asked 885 investment professionals at 681 venture capital firms which of their activities helped drive their capital gains the most. The activities include deal flow (defined as the rate at which investment opportunities are presented to VC firms), selection of investees (i.e., the investment decision), or post-investment portfolio support. A majority of VCs reported that each of the three contributed, with the investment decision being the most important of the three.

Comparable research such as SØRENSEN (2007) also claims that the investment decision is a more influential driver of returns than portfolio support at a 60/40 dichotomy. Moreover, earlier research such as CHAN (1983) and Douglas & Shepherd (2000) concluded that a VC firm's selection process, or in other words, its ability to pick winners, is instrumental in generating significant returns. A couple of other research is in line with the aforementioned claim (Amit et al., 1998; Bottazzi & Da Rin, 2002; Roure & Keeley, 1990; Zacharakis & Shepherd, 2007).

As expounded previously, the venture capital investors' perspective relies on relatively objective performance indicators compared to the others. Being the least biased, a deeper investigation of VC firms and their decision-making process is carried out in the following sections.

2.2. Drivers of Startup's Performance - What makes a successful venture?

2.2.1. Generic Characteristics

The majority of research on the decision-making processes of venture capitalists resulted in lists of generic criteria that venture capitalists claim to follow when assessing new investment opportunities (Landström & Mason, 2014). These criteria are both business and founder-related. The aforementioned was salient since the early days of venture capital research, mainly during the eighties. One of the first studies on the matter is Tyebjee & Bruno (1984) who put forward four decision variables: market potential, management, competition, and product feasibility after surveying 41 Venture Capitalists. Macmillan et al. (1985) as well, aggregated 27 criteria used by investment professionals into six classes: the entrepreneur's personality, track record, product features, market, financial projections, and the startup's team. They discovered that six out of the top ten factors are entrepreneur and team related. In general, and as mentioned by Landström & Mason (2014), early research (before the nineties) came to the conclusion that the entrepreneur, as well as the team, are the most crucial decision-making factors in picking the best-performing startups.

As expounded in Table 1, Franke et al. (2008) carried out an exhaustive literature review of the research into investment decision criteria before the 2000s. The table reveals that VC firms regularly rank founder-related criteria among their top three evaluation criteria, despite the fact that results are relatively heterogeneous.

Table 1 : Investment Decision Criteria before the 2000s

Author(s)	Sample	Method	Evaluation criteria by rank order of importance
Wells (1974)	8 VCs	Personal interviews	(1) Management commitment (2) Product (3) Market
Poindexter (1976)	97 VCs	Mail survey	(1) Quality of management (2) Expected rate of return (3) Expected risk
Johnson (1979)	49 VCs	Mail survey	(1) Management (2) Policy/strategy (3) Financial criteria

Tyebjee and Bruno (1981)	46 VCs	Phone interviews	(1) Management skills and history (2) Market size/growth (3) Rate of return
MacMillan et al. (1985)	102 VCs	Mail survey	(1) Capability for sustained intense effort (2) Familiarity with the target market (3) Expected rate of return
Goslin and Barge (1986)	30 VCs	Mail survey	(1) Management experience (2) Marketing experience (3) Complementary skills in team
Robinson (1987)	53 VCs	Mail survey	(1) Personal motivation (2) Organizational/managerial skills (3) Executive/managerial experience
Rea (1989)	18 VCs	Mail survey	(1) Market (2) Product (3) Team credibility
Dixon (1991)	30 VCs	Personal interviews	(1) Managerial experience in the sector (2) Market sector (3) Marketing skills of management team
Muzyka et al. (1996)	73 VCs	Personal, standardized interviews	(1) Leadership potential of lead entrepreneur (2) Leadership potential of management team (3) Recognized industry expertise in team
Bachher and Guild (1996)	40 VCs	Personal interviews	(1) General characteristics of the entrepreneur(s) (2) Target market (3) Offering (product/service)
Shrader, Steier, McDougall, and Oviatt (1997)	214 new ventures with IPO	Interviews, publicly available documents	(1) Technical education (2) New venture experience (3) Focus strategy
Shepherd (1999)	66 VCs	Conjoint experiment (personal/mail)	(1) Industry-related competence (2) Educational capability (3) Competitive rivalry

Source: Franke et al. (2008)

2.2.2. Business-related Characteristics

Since the 2000s, few studies have concluded that business-related characteristics are either the most influential or more influential than founder-related ones in determining the performance of a startup (Prohorovs, 2019). These studies include Hellmann & Puri (2000), who, upon relying on a sample of 173 Silicon Valley startups, claimed that the most influential factor behind raising venture capital is the degree of innovation in the product. In the same direction, Leleux (2007) used VC funding as a proxy for performance. They concluded that the top three determinants of performance are 1- Market penetration stage 2- The expected return on investment/capital gains and 3- The startup's future funding needs. Kaplan et al. (2009) analyzed the IPO prospectuses of 50 VC-backed startups and concluded that business-related characteristics such as product, technology, and business model have been consistent during the lifetime of the venture. On the opposite, the entrepreneur/team was more prone to change. Consequently, business-related characteristics may be more explanatory of a startup's performance in the long run. With the rise of machine learning methods, Krishna et al. (2016) used classification methods on a database of 11,000 startups to determine performance predictors. Performance was measured by the company status (i.e., active or inactive). Having used more than 30 classifiers and more than 70 explanatory variables, the paper finds out that the key predictor of performance is the startup's ability to raise funds.

Recently, Ross et al. (2021) performed a machine learning algorithm using publicly available data from 1,000,886 companies on Crunchbase and from the United States Patent and Trademark Office (USPTO) and highlighted the importance of company-related variables in determining if the startup will succeed in a scenario of IPO or acquisition, will remain private, or will fail. The factors that turned out to be the most instrumental in this study are the presence of the startup on LinkedIn, the company category, and the number of acquisitions made.

As mentioned earlier, there haven't been many studies where business-related characteristics turned out to be either the most or relatively influential criteria in determining performance. On the other hand, much of the research resulted in the founder or team-related characteristics being the influential ones, as explained in the following section.

2.2.3. Founder-related Characteristics

Since the early 2000s, research in VC decision-making has concentrated on the role of founder-related characteristics in determining the startup's fate. For instance, Rauch & Frese (2000) carried out an exhaustive literature review on the relationship between entrepreneurial success and the entrepreneur's personality. Findings put forward that factors such as locus of control, innovation, entrepreneurial orientation, low-risk appetite, need for achievement, strategy & planning, skill set, and tough conditions can explain the venture's success. Experiment-wise, entrepreneurial success can be assessed by VC professionals using ex-ante performance if the conjoint analysis is used. In this context, Franke et al. (2008) performed a choice-based conjoint analysis on 51 VC professionals assessing 20 hypothetical founding teams. Findings reveal that industry experience, educational background, and leadership experience are the top three team characteristics that determine expected capital gains in venture capitalists' opinions.

Some research starting from the 2010s was more focused on understanding the impact of very specific founder-related variables on performance while controlling for other variables. For example, starting from the popular motto "success breeds success", Gompers et al. (2010) assembled a sample of 9,790 startups to study whether a founder's entrepreneurial history can explain his startup's performance. Having measured performance by the success of the startup in offering its shares publicly, evidence emerged that entrepreneurs in their second or later ventures have a higher probability of success compared to their first-time counterparts. This is even accentuated when the previous entrepreneurial endeavor was successful. Within the same paradigm, Hvide & Panos (2014) set out to test whether the theoretical tradition that argues that risk-tolerant individuals are more likely to become entrepreneurs, but less likely to succeed, is supported by empirical evidence. Hvide & Panos (2014) measure risk by first, common stock participation and second, by personal leverage. On the other hand, sales and return on assets served as proxies for performance. Relying on a database of 400,000 individuals, evidence in favor of the aforementioned tradition emerges.

Another seminal quantitative study on performance determinants is Streletzki & Schulte (2014), which resorts to a sample of 64 German startups to explain their VC firms' ex-post internal rate of return. Using a couple of independent variables related to education, functional experience, and specific experience, they conclude that education in Marketing or Finance and previous experience within a startup are the main performance drivers. On the same note, Gompers et al. (2020) interviewed 885 venture capitalists to find out what they considered instrumental in a founding team. Over two-thirds of investment professionals claimed that founders' execution capacity is the most important factor, just before industry experience. Passion, entrepreneurial experience, and teamwork fill out the rest of the ranking.

The authors of the papers in this literature review largely concur that, either from the perspective of investors or on a quantitative ground, a startup's founders are the main performance driver in the early stages of its development. Therefore, investors must develop models for founders' assessments that help them in their investment decision-making. It's been documented that VC firms rarely use such decision aids, despite their ability to improve their returns. It is believed that data-based modeling in VC can improve accuracy and consistency, reduce biases, and cut down over-reliance on heuristics (Shepherd & Zacharakis, 2002).

Table 2 provides a detailed account of the main quantitative studies that revolve around VC decision-making criteria.

Table 2 : Main Most Recent Quantitative Studies around VC Decision-Making Criteria

Article	Sample	Performance Proxy	Independent variables	Method	Findings
Nikolaus Franke et al. (2008)	51 VC professionals assessing 20 hypothetical founding teams	Predicted Ex-ante return on investment	industry experience, leadership experience, managerial skills, and engineering/technological skills, level of education, type of job experience (start-up vs. large firm), age, and mutual acquaintance within the team	Choice-based conjoint analysis method (Exploded logit)	Findings indicate that industry experience, educational background, and leadership experience are the three most important team characteristics.
Gompers et al. (2010)	9,790 startups: 8,753 are first-time startups and 1,037 are second-time startups	The startup going public (dummy variable)	- The entrepreneur's track record is measured by whether he has previously started a VC-backed company or not. (dummy variable) - The entrepreneur's success or not in his previous venture	Logistic regression	Entrepreneurs in second or later ventures have a higher probability of succeeding compared to first-time entrepreneurs. This is accentuated when the previous entrepreneurial endeavor was successful.
Hvide (2014)	400,000 individuals	Sales and return on assets	Risk measured by common stock participation and personal leverage	Linear probability models	Risk-tolerant individuals are more likely to become entrepreneurs, but less likely to succeed.

J.G. Streletzki & R. Schulte (2014)	64 VC-backed German startups	Ex-post internal rate of return	Education, functional experience, and specific experience while controlling for biotech companies and the exit year	Multiple Linear Regression	Education in Marketing or Finance as well as previous experience within a startup are the main performance drivers.
Greg Ross et al. (2021)	1,000,886 companies, 141,430 investors	Exit potential	Average time between funding rounds, number of female/male founders, number of patents, number of employee degrees, Number of degrees from top 50 schools, number of acquisitions, type of investors, number of company events, state and country code, industry category, the length of the company description, whether the company has a web domain, email, LinkedIn, Facebook, and Twitter.	Deep Learning, XGBoost, Random Forests, and K-Nearest Neighbors	Findings indicate that whether the startup has a LinkedIn account or not, the company's industry category, and the number of acquisitions made by the startup are the most important business characteristics in determining the potential success or failure of the startup.

Source: Authors' Elaboration using Existing Literature

3. Drivers of Startups' Performance: Empirical Evidence

This section investigates the potential determinants of performance using a dataset of startups that the firm invested in between 2018 and 2021. It is important to mention that the choice was made to consider the venture capital perspective over other stakeholders' perspectives due to its relatively greater importance and the availability of data. It is important to note that data on this issue is almost unavailable in Tunisia, in particular for the lack of VC firms in the first place as well as confidentiality reasons. We took advantage of the collaboration with Flat6labs, the only operational venture capital firm in Tunisia during the years of study. The firm provided us with very detailed information on the characteristics of their portfolio of startups, which turned out to be instrumental for the conduct of this study[1].

The small sample size is certainly limiting this work and does not allow for the extrapolation of results to all startups. However, the use of this data allowed to conduct one of the first analyses on this issue in Tunisia and may provide insights into an underexplored area.
As proxies for the startup performance, we use change in revenue, external investment, two-year survival, and the firm's team assessment. Business-related variables include the type of product, industry, and location of the startup. Founder-related variables encompass education and sociodemographic indicators, co-founder relationships, prior experience, recommendations by the Flat6Labs network, and the dedication of the entrepreneur.

3.1 Variables' Definitions and Measurement

3.1.1 Startups' Performance (Dependent Variables)

In order to explain startups' performance using business & founder-related variables, there is a need to operationally define performance. Based on the aforementioned literature review,

[1] The sample is composed of startups selected by Flat6Labs between 2018 and 2021, which may introduce selection bias. Yet , we are unable to test for the presence of this bias or correct for it, as we do not have access to the characteristics of startups that were not chosen by Flat6Labs.

performance is defined following four dimensions: revenue, investment, survival, and the venture capitalist's own judgment. These performance variables are detailed below.

Table 3 : Startups' Performance Variables

Variable	Measurement	Unit	Type
Change in Revenue	Change in revenue is the difference between the startup's revenue post-investment and pre-investment.	Thousands of Tunisian dinars	Continuous
External Investment	The variable measures the amount of equity/mezzanine funds raised by the startup during the year following its receipt of Flat6Labs' funding.	Thousands of Tunisian dinars	Continuous
Two-year Survival	The variable indicates whether a startup survived during the two years following Flat6Labs' investment (1) or not (0).	Yes/No	Categorical
Investment Team Classification	This variable indicates the class that the investment team believes the startup belongs to. The variable counts five ordinal classes based on how good the startup is perceived by the Flat6Labs' team.[2]	0 to 4	Ordinal

Source: Authors' Elaboration

Evaluating a startup's revenue performance, using the "change in revenue", also known as year-over-year (YOY) revenue growth, turned out to be a more reliable alternative compared to relying on the growth rate of revenue or the Internal Rate of Return (IRR). This is because both revenue growth rate and IRR have limitations that may not provide significant results, as explained below.[3]

Firstly, the revenue growth rate can be biased as it may be skewed by the size of the initial revenue base. Startups with low initial revenues may experience higher growth rates simply because they are starting from a smaller base, which may not necessarily indicate better performance compared to startups with higher revenues and lower growth rates. In contrast, YOY revenue growth computes the change in revenue from one year to another, providing a more meaningful measure of actual revenue growth over time without being influenced by the initial revenue base . This approach avoids the issue of extreme or undefined growth rates when initial revenues are zero, making it a more robust metric for assessing performance.

Startups with low initial revenues typically have more room for growth, and even relatively small absolute revenue increases can result in high growth rates in percentage terms. On the other hand, startups with higher initial revenues may have already captured a larger market share, making it harder for them to sustain the same high percentage growth rates over time. As a result, comparing startups based on their revenue growth rates can be misleading, as it may not accurately reflect their relative performance or potential for future success.

The same applies to the IRR, which is a financial metric used to evaluate the profitability of an investment. It can also be subject to similar biases when used as a measure to assess a startup's

[2] The pillars of this classification will be explained in section 4.4 of this chapter.

[3] Despite running regressions on both variables, IRR and growth rate, we did not find any statistically significant results.

performance. While IRR is commonly used to assess the financial viability of an investment, including in the context of startups, it has limitations that should be considered. The IRR method does not take into account the project size or scale, which can lead to misleading results when comparing projects of different sizes. A larger startup with higher cash flows may have a lower IRR compared to a smaller startup with lower cash flows, but it may still result in a more profitable exit for a venture capitalist due to the higher absolute cash flows.

Using the “change in revenue” from year to year can be a better alternative to evaluating a startup's performance compared to using the growth rate of revenue or the IRR, as it has certain advantages and similarities with the concept of Net Present Value. “Change in revenue” is similar in spirit to the concept of Net Present Value (NPV) as it considers the changes in revenue over time. NPV is a financial metric that takes into account the time value of money and assesses the value of an investment by comparing the present value of expected cash flows with the initial investment. Similarly, “change in revenue” captures the changes in revenue from one year to another, which can be interpreted as the “cash flows” generated by the startup, and provides a measure of the increase or decrease in value over time.

On another level, the recourse to the amount of external investment raised by a startup can provide insights into its performance in multiple ways. Firstly, a higher amount of external investment may suggest higher growth potential. Investors are typically attracted to startups that show promise in terms of their business models, innovative products or services, and potential for scalability in the market. Therefore, a startup that has successfully raised a significant amount of external investment may be perceived as having strong growth prospects. This can be indicative of its performance, as it reflects the level of confidence that investors have in the startup's business idea and potential for success. Secondly, the amount of external investment raised can serve as market validation for a startup. When investors are willing to invest a substantial amount of capital into a startup, it may signal that the startup has generated interest and confidence from the market. This can be interpreted as a positive sign that the startup's business idea, value proposition, and market traction are resonating with potential customers and investors. Market validation through external investment can provide credibility to the startup and enhance its reputation, which can positively impact its overall performance by attracting further investment, customers, and partnerships.

Similarly, the two-year survival of a startup can be considered an indicator of its performance, as it reflects the startup's ability to overcome challenges and sustain its business operations during the initial critical period. It can demonstrate resilience, viability, and investor confidence, indicating that the startup has effectively executed its business plan, generated revenue, managed expenses, and met or exceeded investor expectations.

Moreover, the Investment Team Classification variable determines the class that the investment team believes the startup belongs to. It is important to put emphasis on the fact that this classification is based on heuristics, team experience, and common practices. It is also ex-post, as it is established after at least one year after Flat6Labs first investment in the startup. The investment team classification, which refers to a venture capital firm's heuristic assessment of a startup's potential, can be considered an indicator of a startup's performance.
The investment team at Flat6Labs employs a comprehensive five-class scale ranging from 0 to 4 to evaluate the potential of a startup. This scale takes into consideration critical variables that are grouped into specific pillar variables, with each pillar being assigned a specific coefficient. The pillar variables and their corresponding evaluation criteria include:

- Founding Team: the pillar is scored based on a weighted average of various factors such as the technical background of the founding team, their business background, market familiarity, adaptability, personal engagement and harmony, personality and ability to handle investor relations, management skills and leadership, and the complementarity of the startup's team.

- Product: the pillar is scored based on a weighted average of factors such as the proprietary nature of the technology, market acceptance of the product, its development stage (fully fledged, Minimum Viable Product or prototype), user experience in terms of simplicity and intuitiveness, and uniqueness of the value proposition.

- Market: the pillar is scored based on a weighted average of factors such as the potential of the target market, the competitiveness of the market, the scalability of the business model, sensitivity to external factors, and market timing.

- Traction: the pillar is scored based on a weighted average of factors such as attraction and awareness of the startup's product, acquisition and conversion of customers, retention, scale and growth potential, and product-market fit.

- Investment: the pillar is scored based on a weighted average of factors such as whether the startup has received investment from external investors, assessment of investors' engagement, and whether the startup was able to secure follow-on funding from Flat6Labs or not.

These pillars of variables have corresponding coefficients of 30%, 15%, 20%, 25%, and 10%, respectively. To calculate the final score for each startup, each variable within a pillar is assigned a score ranging from 0 to 1, with values of 0, 0.25, 0.5, 0.75, and 1. These scores are subjectively determined by the investment team based on their expertise, intuition, and common sense. Although not entirely based on a scientific approach, this classification system serves as the main decision-making tool within the Flat6Labs investment team.

VC firms often use the investment team classification as a proxy for the startup's ability to execute its business plan, make strategic decisions, and navigate market challenges. A higher investment team classification may indicate that the startup has a team with a track record of success or relevant expertise, or that there is a market potential for the startup idea which can positively impact its performance. However, it's important to note that the investment team classification is a subjective assessment and may not always accurately predict a startup's actual performance.

3.1.2 Business & Founder-related Characteristics (Independent Variables)

To predict the performance of startups, various indicators related to both the business and the founders are taken into consideration. The extensive literature review has enabled the identification of the most influential variables within each category. The business-related variables include the type of product the startup is working on, the industry it operates in, and its location. On the other hand, founder-related variables include education and sociodemographic indicators, co-founder relationships, prior experience of the founders, recommendations by the Flat6Labs network, and the dedication of the entrepreneur. Below, we provide a detailed description of these important business and founder-related variables.

Table 4 : Startups' Business and Founder-related Variables

Variable	Measurement	Unit	Type
Product Category	The variable indicates whether the product consists of a software component only (0) or both a hardware and software component (1)[4]	N/A	Categorical
Industry (Services or Manufacturing)	The variable indicates whether the business operates in a services-related (1) or a manufacturing-related (0) industry.	N/A	Categorical
Location	The variable indicates whether the business is located in an inside (1) or an outside city (0).	N/A	Categorical
Number of Years of Education	The variable indicates the number of years of education of the founder of the startup after the baccalaureate.	Years	Continuous
Technical Knowledge	The variable indicates whether the founder has technical knowledge or background about the startup-related technology (1) or not (0).	Yes/No	Categorical
Business Knowledge	The variable indicates whether the founder has business knowledge or background (1) or not (0).	Yes/No	Categorical
University Category - Excellent	The variable indicates whether the university attended by the founder is excellent (1) or not (0).	Yes/No	Categorical
University Category - Good	The variable indicates whether the university attended by the founder is good (1) or not (0).	Yes/No	Categorical
Marital Status	The variable indicates whether the founder is married (1) or not (0).	Yes/No	Categorical
Kids	The variable indicates whether the founder has kids (1) or not (0).	Yes/No	Categorical
Diaspora	The variable indicates whether the founder has lived abroad (1) or not (0) before launching their startup.	Yes/No	Categorical
Female Founder	The variable indicates whether the founder is a female (1) or not (0).	Yes/No	Categorical
Age	The variable indicates the age of the founder.	Years	Continuous
Number of Co-founders	The variable indicates the number of co-founders in the startup.	People	Continuous
Same Nationality	The variable indicates whether the founder and the co-founders have the same nationality (1) or not (0).	Yes/No	Categorical
Family Related	The variable indicates whether the founder and the co-founders are related by blood (1) or not (0).	Yes/No	Categorical
Past Accelerator	The variable indicates whether a startup has gone through an acceleration program before Flat6Labs (1) or not (0).	Yes/No	Categorical

[4] The variable distinguishes between products with only a software component (0) and those with both hardware and software (1), used to assess scalability. Investors often view software as more scalable due to lower variable costs, whereas hardware introduces additional production and logistical challenges, making it less scalable.

Repeat Founders	The variable indicates whether the founder had any previous experiences with launching startups (1) or not (0).	Yes/No	Categorical
Past Working Experience	The variable indicates whether the founder had any previous working experiences (1) or not (0).	Yes/No	Categorical
Recommended to Flat6Labs	This variable indicates whether Flat6Labs received a recommendation from someone within their network or ecosystem to include a startup in their acceleration program.	Yes/No	Categorical
Full Activity	The variable indicates whether the founder is fully dedicated to the startup by working full-time on it (1) or not (0).	Yes/No	Categorical

Source: Authors' Elaboration

3.2 Summary Statistics

The data of 51 Tunisian startups were collected directly from their founders through primary research. All of these startups were at pre-seed or seed stage at the time of Flat6Labs investment. Most of the time, Flat6Labs is their first institutional investor, providing them with tickets ranging from 150,000 dinars to 300,000 dinars.

A significant proportion of the startups are in the early revenue stage (72.5%), while the remainder are in the pre-revenue or near-profit stage. With regard to product development, the majority of the startups have fully developed products (90.2%), while others are in the Minimum Viable Product or iteration phases. In terms of market penetration, only a small fraction of startups (15.7%) are in the growth phase, while the rest are in either the market testing (49%) or product market fit (35.3%) phase. The startups operate in a diverse range of sectors, with EdTech, Entertainment, HealthTech, and logistics being the most frequent ones. The startups are geographically dispersed, and they demonstrate gender diversity among their employees, with 52.8% being female.

Beginning with the study's discrete variables, the gender distribution is skewed, with 74.5% of founders being male and only 25.5% being female. 29.4% of founders are diaspora, and the rest are not. Concerning university categories, 3 people went to excellent-class universities, 13 founders went to very good universities, 18 other founders went to good universities, 16 people went to average universities, and only one founder went to a poorly-classed university. A significant proportion of founders (72.5%) have previous working experience, while 66.7% of entrepreneurs have technical knowledge about the tech field of their startups. However, only 47.1% of the founders have business knowledge. Furthermore, only 7.8% of the entrepreneurs are repeat founders, and 27.5% of the startups have previously undergone acceleration programs other than that of Flat6Labs. Despite these challenges, the startups demonstrate strong survival rates, with 61.8% of them having survived two years after their acceleration.

Below is an examination of continuous variables.

Table 5 : Summary Statistics of Continuous Variables

	N	Mean	Standard deviation	Median	Min	Max	Skewness	Kurtosis

Number of Co-founders	51	1.961	0.958	2	1.000	4.000	0.744	-0.424
Age	51	32.641	6.349	32	22.670	54.000	0.843	1.079
Number of Years of Education after Baccalaureate	51	4.900	1.191	5	2.500	8.000	0.073	-0.286
External Investment (kTND)	51	117.523	315.345	0	0.000	1,717.300	3.468	12.718
Change in Revenue (kTND)	51	117.449	664.839	0	-93.000	4,734.410	6.565	42.605

Source: Authors' Elaboration using R

The findings reveal that the average number of co-founders in a startup is 1.961 and a median of 2, with a range from 1 to 4, indicating that half of the startups are founded by two entrepreneurs. The age of the founders ranges from 22.67 to 54, with an average age of 32.641 and a median of 32, suggesting that the majority of the founders are relatively young. The startups are youth-driven, with young people making up 70% of the founder's base. On average, founders have 4.9 years of education after the baccalaureate degree, with a median of 5 as most of them are either engineers or master's holders. The average external investment in TND is 117 523, but the distribution is highly positively skewed, indicating that most startups receive little or no investment. The startups' average change in revenue is TND 117 449, with a highly positively skewed distribution, indicating that a few startups experience substantial revenue growth, while most struggle to maintain their revenue.

3.3 Econometric Analysis & Results

Given the nature and structure of the data in our study, we have chosen to employ specific regression techniques for different variables. For the variables "Change in Revenue" and "External Investment", we will be utilizing Multiple Linear Regression. In our case, we will be examining how changes in revenue and external investment can be explained by startup-related variables.

For the variable "two-year survival", we will be using Binomial Logistic Regression. Binomial Logistic Regression is a type of regression analysis that is suited for predicting binary outcomes, such as whether a startup survives or fails within a two-year period. This technique allows us to examine the factors that influence the likelihood of a startup's survival over a specific time frame.

Lastly, for the variable "Investment Team Classification", we will be employing Ordinal Linear Regression, which is a statistical method that is suitable for modeling relationships between an ordinal dependent variable (i.e., a variable with ordered categories) and one or more independent variables. This technique will enable us to analyze how different factors relate to the classification of the investment team, which has multiple ordered categories based on startups' performance, the team's expertise, or other relevant criteria.

3.3.1 Change in Revenue & External Investment

The "Change in Revenue" and "External Investment" variables are modeled using multiple linear regression. In order to estimate the parameters, we use the Ordinary Least Squares (OLS) method. The estimation results are below.

Table 6 : Change in Revenue and External Investment Estimation Results[5]

Coefficients	Change in Revenue			External Investment		
	Estimate	Std. Error	Pr(>|t|)	Estimate	Std. Error	Pr(>|t|)
(Intercept)	1,824.62	1,285.62	0.166	272.15	517.36	0.603
Product Category	-71.40	145.11	0.626	-77.86	96.29	0.425
Industry (Services or Manufacturing)	-329.43	232.27	0.167	-15.49	130.51	0.906
Location	217.95	213.62	0.316	63.19	118.91	0.599
Number of Years of Education	-3.86	50.59	0.940	-14.64	39.77	0.715
Past Working Experience	130.46	238.84	0.589	91.74	117.56	0.442
Technical Knowledge	-4.06	200.54	0.984	55.79	142.97	0.699
Business Knowledge	143.52	147.24	0.338	-35.76	122.77	0.773
Past Accelerator	-317.01	224.17	0.168	7.23	101.84	0.944
Repeat Founders	-578.33	511.38	0.267	**478.21 *** **	166.10	0.00742
University Category - Excellent	**2,127.85 ***	1,244.02	0.098	**506.02 ***	249.11	0.051
University Category - Good	154.06	163.77	0.355	69.67	100.04	0.492
Marital Status	-124.08	207.58	0.555	177.65	115.66	0.135
Kids	190.74	228.48	0.411	-211.58	130.86	0.117
Diaspora	-70.47	202.69	0.731	-34.77	118.37	0.771
Recommended to Flat6Labs	49.05	199.02	0.807	122.19	94.58	0.207
Number of Co-founders	8.60	92.72	0.927	-33.92	51.41	0.515
Same Nationality	-372.04	336.03	0.277	-16.82	208.83	0.936
Family Related	439.31	357.06	0.228	42.50	143.48	0.769
Full Activity	168.77	206.55	0.421	83.59	111.93	0.461
Female Founder	-295.02	238.25	0.226	-29.17	116.56	0.804
Age	-47.33	33.58	0.169	-8.49	10.32	0.418

Source: Authors' Elaboration using R

In order to ensure that estimation results do not violate any of the multiple linear regression assumptions, we have tested for heteroscedasticity using the Breusch-Pagan test. For "change in revenue", we had a p-value of 0.01. Since the p-value < 0.05, we end up rejecting the null hypothesis (homoscedasticity). There was sufficient evidence to say that heteroscedasticity is

[5] p < 0.1 (*), p < 0.05 (**), p < 0.01 (***)

present in the regression model. Acknowledging the inadequacy of the ordinary least squares method to produce the best linear unbiased estimators, we used robust standard errors introduced by White (1980) which have laid the above results.

For “External Investment”, the Breusch-Pagan test of homoscedasticity in the errors accept the null hypothesis.

We also use the Kolmogorov-Smirnov test to assess the normality of residuals for the variables “Change in Revenue” and “External Investment”. The resulting p-value for “Change in Revenue” was found to be 0.2017, indicating that there is no sufficient evidence to reject the null hypothesis of normality. As a result, we accepted the assumption of normality for residuals in the analysis of “Change in Revenue”. Similarly, for the variable “External Investment”, the obtained p-value was 0.2166, leading to the assumption of normality for residuals in this case as well. By confirming the normality of residuals, we can ensure that the assumptions of normality underlying our econometric analysis are met, providing a solid foundation for our statistical inferences and interpretations.

The results suggest that the classification of universities as “excellent” or not is a significant variable in our context, as it plays a critical role in predicting a startup's potential revenue. It is important to note that the determination of university excellency was based on the national ranking of 2010. Specifically, founders who were able to obtain a state-granted national scholarship to study abroad in German and French universities, or attend prestigious institutions such as “Institut préparatoire aux études scientifiques et techniques”, are considered part of this category. Examples of schools attended by these founders include Centrale Paris, Telecom Paris, and L'École Polytechnique. By including this variable in our analysis, we have evidence of the potential influence of the founders' educational background on the startup's performance, as attending highly ranked universities may provide graduates with valuable skills, networks, and resources that could impact their entrepreneurial endeavors.

For “External Investment”, the University Category and Repeat Founder variables are crucial in our analysis, as they strongly influence the prediction of an entrepreneur's success in raising funds for their startup. Specifically, previous entrepreneurial experience through founding ventures in the past is a significant indicator of fundraising success. Additionally, our findings suggest that startups founded by individuals who attended higher-ranked universities based on national rankings are more likely to secure funding, highlighting the potential impact of the founders' educational background on the startup's investment prospects. By including these variables in our analysis, we aim to capture the nuanced relationship between the founders' previous entrepreneurial experience, the quality of their educational background, and the startup's investment outcomes, providing valuable insights into the factors that contribute to startup success in the fundraising process.

Approximately 60% of the variability in the “change in revenue” can be explained by the model, indicating a good level of explanatory power. Similarly, approximately 66% of the variability in the “External Investment” can be explained by the model, indicating a relatively higher level of explanatory power compared to the “change in revenue”. These results highlight the importance of the selected variables in explaining the variations in revenue change and external investment and suggest that the model has some degree of predictive power in explaining these outcomes.

3.3.2 Two-year Survival

The Two-Year Survival variable predicts whether a startup survives during the two years following Flat6Labs' investment or not. As a result, “two-year survival” is modeled using logistic regression as follows. Binary logistic regression is a type of regression analysis used to model the relationship between a binary dependent variable and one or more independent variables. In binary logistic regression, the dependent variable is binary, meaning it can take on one of two values, typically 0 or 1. The goal of binary logistic regression is to estimate the probability of the dependent variable taking on the value of 1, given the values of the independent variables.

The equation for binary logistic regression is:

$$p(y=1 \mid x) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k)}}$$

Where p (y=1 | x) is the probability of the dependent variable being equal to 1 given the values of the independent variables.

The logistic regression model is fitted using maximum likelihood estimation, which seeks to find the values of coefficients that maximize the likelihood of observing the data.

The estimation results are below.

Table 7 : Two-Year Survival Estimation Results[6]

Coefficients	Two-year Survival		
	Estimate	Std. Error	Pr(>|t|)
(Intercept)	0.19	5.78	0.974
Product Category	-1.58	1.41	0.263
Industry (Services or Manufacturing)	-0.69	1.54	0.654
Location	0.25	1.55	0.871
Number of Years of Education	0.30	0.45	0.500
Past Working Experience	0.22	1.48	0.882
Technical Knowledge	-0.08	1.68	0.964
Business Knowledge	-0.51	1.26	0.684
Past Accelerator	0.33	1.51	0.828
Repeat Founders	-1.15	2.07	0.576
University Category - Excellent	21.99	2,735.24	0.994

[6] $p < 0.1$ (*), $p < 0.05$ (**), $p < 0.01$ (***)

University Category - Good	0.84	1.22	0.489
Marital Status	-1.09	1.26	0.388
Kids	0.37	1.47	0.802
Diaspora	0.99	1.39	0.475
Recommended to Flat6Labs	-1.58	1.31	0.230
Number of Co-founders	0.92	0.69	0.186
Same Nationality	-0.26	2.08	0.902
Family Related	-0.62	1.57	0.694
Full Activity	**2.91 ****	1.47	0.0473
Female Founder	-0.13	1.41	0.929
Age	-0.08	0.13	0.524

Source: Authors' Elaboration using R

"Full Activity" is the significant variable in this context. Estimation results support the claim that founders' dedication by working on a full-time basis on the development of their startup is positively correlated with the likelihood of the survival of the startup within two years of the Flat6Labs investment.

We use McFadden's R^2 as a measure of goodness of fit, as it is a widely used measure for logistic regression and compares the likelihood of the full model to that of a null model containing only the intercept. In our analysis, McFadden's R^2 is calculated as 32.75%, signifying that 32.75% of the variations in the "Two-year Survival" outcome variable are predicted by the logistic regression model under consideration

3.3.3 Investment Team Classification

To explain the "Investment Team Classification", we use the proportional odds logistic regression (Agresti, 2013) which is a type of logistic regression model used for ordinal response variables with three or more ordered categories. The proportional odds model assumes that the coefficients for the independent variables are the same for all categories of the response variable, meaning that the odds ratios comparing two adjacent categories are constant across all levels of the predictors.

To understand proportional odds logistic regression, Let y be the ordinal response variable for a dataset with n observations, taking on K ordered categories from 1 to K, and let X be a vector of p predictor variables. The proportional odds model assumes that the cumulative odds of the response variable being less than or equal to each level k are proportional across levels:

$$\mathrm{log}it(\ P(\ y \leq j \mid X)\ )\ =\ \ln(\ \frac{P(\ y \leq j \mid X)}{1 - P(\ y \leq j \mid X)}\ )\ \ = \alpha_j - \beta X$$

Where logit is the log−odds function, $P(y \leq j \mid X)$ is the cumulative probability of y taking a value less than or equal to j given X, α_j is the threshold parameter for the jth category, β is the vector of coefficients for the independent variables X, and j = 1, 2, …, K-1 where K is the total number of categories for y.

Overall, proportional odds ordinal logistic regression is a useful tool for modeling ordinal response variables and predicting the probability of an observation falling into a certain category based on one or more predictor variables.

In general, proportional odds logistic regression models require more degrees of freedom compared to binary logistic regression models since they estimate multiple sets of regression coefficients corresponding to each threshold of the ordinal response variable. Therefore, the number of degrees of freedom required for the models to converge can be relatively high, especially when dealing with numerous predictor variables or small sample sizes, as is the case. Hence, after a lot of trial, we reduce the independent variables to include only Age, Full Activity, Kids, Diaspora, University Category – Excellent, University Category – Good and Repeat Founder.

Table 8 : Investment Team Classification Estimation Results[7]

Coefficients	Investment Team Classification		
	Estimate	**Std. Error**	**Pr(>|t|)**
Age	-0.02	0.06	0.686
Full Activity	0.44	0.69	0.519
Kids	0.25	0.73	0.731
Diaspora	0.12	0.72	0.863
University Category – Excellent	**5.75 *****	1.78	0.001
University Category – Good	0.94	0.62	0.126
Repeat Founders	0.44	1.09	0.684

Source: Authors' Elaboration using R

The "University Category – Excellent" is the only significant variable in this context. Estimation results support the fact that the quality of the university attended is instrumental in determining a startup's classification within the Flat6Labs portfolio. The startup is more likely to have a better classification if the founder attended a higher-ranked university based on national rankings.

3.4 Summary of Results

3.4.1 University Category

Alumni of prestigious universities often have access to a wide range of resources and opportunities that can be beneficial to their entrepreneurial endeavors. One of the key advantages is the expansive and high-quality network that these alumni can tap into. Many prestigious universities have large alumni networks that are made up of influential business

[7] $p < 0.1$ (*), $p < 0.05$ (**), $p < 0.01$ (***)

leaders, successful entrepreneurs, and potential investors and clients. Through their university's alumni network, entrepreneurs can make valuable connections and build relationships with people who can help them grow their businesses.

In addition to networking opportunities, prestigious universities typically offer a range of resources and support services for alumni entrepreneurs. This can include funding opportunities, accelerator programs, and access to other business resources. Many universities have established funds and programs specifically designed to support alumni entrepreneurs, providing them with seed funding and other resources to help get their businesses off the ground. These programs typically provide mentorship, coaching, and other resources to help entrepreneurs refine their ideas and strategies, and ultimately increase their chances of success.

Another significant advantage of being an alumni entrepreneur is access to university resources and facilities. These resources can include state-of-the-art research facilities, specialized equipment, and business incubators. Alumni entrepreneurs can leverage these resources to gain a competitive advantage and accelerate their business growth.

In general, having graduated from a well-respected university can offer numerous advantages to entrepreneurs. These benefits include access to a larger and better-quality group of potential investors and customers, financial and acceleration programs to support entrepreneurial endeavors, and access to university resources and facilities. These advantages can assist alumni entrepreneurs in broadening their businesses to other markets, establishing a solid foundation for growth, and enhancing their chances of achieving long-term success.

3.4.2 Full Activity

As previously discussed, wholeheartedly committing to a startup has proven to increase the likelihood of its survival during its early years.

In order to achieve long-term success and sustainability, startups require a significant amount of effort, resources, and dedication from their founders. By fully committing to their startup, founders demonstrate their willingness to invest the necessary time and energy to drive the company forward. This level of commitment also helps to build a strong foundation for the company, which can increase its chances of surviving the challenges that arise during its initial years.

3.4.3 Repeat Founders

Repeat founders often perform better than first-time founders when it comes to fundraising for several reasons:

- Experience: Repeat founders have typically gained valuable experience from their previous ventures, which can help them avoid common mistakes and make better decisions. They have already navigated the challenges of starting a company, and they know what to expect.

- Network: Repeat founders often have an established network of contacts, including investors, mentors, and industry experts. They can leverage these connections to get advice, access resources, and potential customers.

- Reputation: If the previous venture was successful, the repeat founder can benefit from the positive reputation and credibility that they have already built. This can make it easier to attract talent, investors, and customers for their new venture.

- Resilience: Repeat founders have typically experienced failure before and have developed the resilience and persistence needed to overcome obstacles and keep pushing forward.

- Learning: Repeat founders are often more open to learning from their past mistakes and using those experiences to inform their decisions and strategies for their new venture.

Overall, repeat founders have a valuable combination of experience, networks, reputation, resilience, and a willingness to learn, which can help them perform better in subsequent ventures compared to first-time founders.

4. Conclusion

The research question of this paper — "What are the startup-related characteristics that determine the performance of a startup?" — has been addressed through a comprehensive literature review and empirical research. Our findings strongly align with the existing literature, confirming that founder-related variables remain the most important factors in venture capital decision-making processes. Specifically, the quality of the university attended by founders, repeat entrepreneur status, and the founder's commitment to being full-time on the startup were found to significantly impact and predict the performance of startups.

Our findings suggest that the quality of the university can be used as a gauge for the level of knowledge and skills founders have acquired, resulting in a positive impact on the startup's performance. Moreover, the status of being a repeat entrepreneur highlights prior entrepreneurial experience, which can provide invaluable insights and expertise, ultimately contributing to the startup's success. As well, the founder's complete dedication to the startup, by committing full-time, is a sign of his strong and unyielding determination to drive the company's growth, leading to its continued existence.

These findings have significant implications for venture capital firms in making informed investment decisions. By considering these factors, venture capital firms can better evaluate the potential of startups and make data-driven investment decisions. The findings also highlight the importance of adopting data-driven approaches based on factual information rather than heuristics in the decision-making process.

However, it is important to acknowledge the limitations of this research, including the small sample size and the consideration of a single VC. Another limitation worth noting as well is the limited time span of performance variables. For instance, the "Change in Revenue", "External Investment" and "Two-year Survival" only take two years into consideration. It would have been better to have more years of performance.

Time is an essential factor in assessing the performance of startups. Startups typically operate in a dynamic and uncertain environment, and it can take time to see the full impact of their efforts. While early indicators such as user growth, revenue, and funding can provide useful insights into a startup's potential, it is essential to assess its longer-term performance to determine its ultimate success or failure. For all these reasons, our results cannot be extrapolated and generalized to the entire startup population in Tunisia.

Despite the aforementioned limitations, it is important to note that the study still provides intelligence on the determinants of startup performance in the Tunisian context. The use of a focused sample, such as the one provided by Flat6Labs, the most active investor in the country during the years of the study, allowed for a more in-depth exploration of the characteristics of early-stage startups in Tunisia. The results of this research provide valuable insights into the factors that influence the performance of startups and emphasize the importance of data-driven decision-making in venture capital investments. The findings contribute to the existing literature in the field of entrepreneurship and provide practical implications for venture capital firms in enhancing their investment strategies. Using appropriate sample size and sampling process, longer time horizons, and incorporating more variables can enhance the validity and generalizability of findings seeking to explain startups' performance.

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