Impact of previous entrepreneurial experience on start-up evaluation & success

Sirius Araya Alfons

Dissertation written under the supervision of Prof. Rand Gerges-Yammine

Dissertation submitted in partial fulfilment of requirements for the MSc in Management with Major in Entrepreneurship and Innovation, at Universidade Católica Portuguesa and for the MSc in Management at ESCP Business School, 13/05/2022.

Abstract

Title: Impact of previous entrepreneurial experience on start-up evaluation & success

Author: Sirius Araya Alfons

In this paper, a sample of 819 companies was tested for four different hypotheses. This dataset was collected and provided by Early Metrics. Throughout the literature, it is evident that several determinants influence start-up success. How exactly entrepreneurial experience contributes to this is not entirely clear, as there is also different literature contradicting each other.

The effects of entrepreneurial experience on success were tested using several multiple regressions. We can conclude that the dataset used does not provide enough evidence that entrepreneurial experience affects the Early Metrics positioning. As a result, hypothesis (H1) entrepreneurial experience has a small but positive effect on start-up evaluation, is rejected. However, it must be said that such an effect cannot be excluded in general.

The second hypothesis "(H2) Industry experience has a positive effect on start-up success" was examined and no significance could be shown in our dataset. Hypothesis (H3) that there is no significant difference between experienced and non-experienced founders in terms of team size, was analyzed and it can be concluded that we accept hypothesis H3. Due to the existing limitations within our dataset, no reliable statement can be made about the effect of entrepreneurial experience on yearly revenue.

Some indicators and findings of this paper give an impetus for further research in this field, which is currently not characterized by a clear consensus. Therefore, it is important that academia continues to add to this field and also makes the implications for theory and practice accessible.

Key Words

Entrepreneurship | Experience | Entrepreneurial Experience | Early Metrics | Industry Experience | Success | Evaluation |

Résumé

Titre: Impact de l'expérience entrepreneuriale antérieure sur l'évaluation et le succès de la création d'entreprise

Auteur: Sirius Araya Alfons

Dans cet article, un échantillon de 819 entreprises a été testé pour quatre hypothèses différentes. Cet ensemble de données a été collecté et fourni par Early Metrics. Dans toute la littérature, il est évident que plusieurs facteurs déterminants influencent le succès des start-ups. La façon dont l'expérience entrepreneuriale y contribue exactement n'est pas tout à fait claire, car il existe également différentes publications qui se contredisent.

Les effets de l'expérience entrepreneuriale sur le succès ont été testés au moyen de plusieurs régressions multiples. Nous pouvons conclure que l'ensemble de données utilisé ne fournit pas suffisamment de preuves que l'expérience entrepreneuriale a un effet sur le positionnement dans les métriques précoces. Par conséquent, l'hypothèse (H1) selon laquelle l'expérience entrepreneuriale a un effet faible mais positif sur l'évaluation de la start-up, est rejetée. Toutefois, il faut dire qu'un tel effet ne peut être exclu en général.

La deuxième hypothèse "(H2) L'expérience industrielle a un effet positif sur le succès de la start-up" a été examinée et aucune signification n'a pu être montrée dans notre ensemble de données. Par conséquent, l'hypothèse (H2) est rejetée. L'hypothèse (H3) selon laquelle il n'y a pas de différence significative entre les fondateurs expérimentés et non expérimentés en termes de taille d'équipe, a été analysée et on peut conclure que nous acceptons l'hypothèse H3 et qu'il n'y a pas de différence significative entre les fondateurs expérimentés et non expérimentés en termes de taille d'équipe. L'hypothèse (H4) indique qu'"il existe une différence entre les entrepreneurs expérimentés et non expérimentés en termes de revenus annuels". En raison des limitations existantes dans notre ensemble de données, aucune déclaration fiable ne peut être faite concernant l'effet de l'expérience entrepreneuriale sur le revenu annuel.

Certains indicateurs et résultats de cet article donnent une impulsion pour des recherches plus approfondies dans ce domaine, qui n'est actuellement pas caractérisé par un consensus clair. Il est donc important que le monde universitaire continue à enrichir ce domaine et à rendre accessibles les implications pour la théorie et la pratique. Des études à plus grande échelle dans ce domaine peuvent produire des résultats importants et pertinents.

Mots clés

Entrepreneuriat | Expérience | Expérience entrepreneuriale | Métriques précoces | Expérience dans l'industrie | Succès | Évaluation |

Resumo

Título: Impacto da experiência empresarial anterior na avaliação e sucesso de start-ups

Autor: Sirius Araya Alfons

Neste artigo, foi testada uma amostra de 819 empresas para quatro hipóteses diferentes. Este conjunto de dados foi recolhido e fornecido pela Early Metrics. Ao longo da literatura, é evidente que existem vários fatores determinantes que influenciam o sucesso. A forma exata como a experiência empresarial contribui para tal não é inteiramente clara, uma vez que também a literatura existente apresenta resultados contraditórios.

Os efeitos da experiência empresarial no sucesso foram testados por meio de várias regressões. Podemos concluir que o conjunto de dados utilizado não fornece provas suficientes de que a experiência empresarial tenha um efeito sobre o posicionamento da Early Metrics. Como resultado, a hipótese (H1) de experiência empresarial tem um efeito pequeno mas positivo na avaliação inicial, é rejeitada. Contudo, deve dizer-se que tal efeito não pode ser excluído em geral.

A segunda hipótese "(H2) A experiência da indústria tem um efeito positivo no sucesso do arranque" foi examinada e não pôde ser demonstrado qualquer significado no conjunto de dados analisados. A hipótese (H3) de que não há diferença significativa entre fundadores experientes e não experientes em termos de dimensão da equipa foi analisada e pode concluir-se que aceitamos a hipótese H3. Devido às limitações existentes nos dados considerados, não pode ser feita nenhuma declaração fiável sobre o efeito da experiência empresarial nas receitas anuais.

Alguns indicadores e conclusões deste documento poderão motivar uma maior investigação neste campo, que atualmente não se caracteriza por ser consensual. Por conseguinte, é importante que a academia continue a desenvolver esforços neste campo e, também, a tornar as implicações para a teoria e para a prática acessíveis.

Palavras-chave

Empreendedorismo | Experiência | Experiência Empreendedora | Métricas Precoce | Experiência Industrial | Sucesso | Avaliação |

Table of Contents

Table of Figures

Introduction

The field of entrepreneurship remains a rather unexplored one in which there are still some gaps. One reason for this is that it is difficult to measure intangible attributes such as skills, experience, and human capital. However, this paper will investigate how experience, especially entrepreneurial experience, affects start-ups. That is, whether there is a relationship between novice or habitual entrepreneurs and the outcome of start-ups. Habitual entrepreneurs differ from serial entrepreneurs, who start one venture after the other, and portfolio entrepreneurs, who run several businesses at the same time (Carbonara et al., 2020).

Most individuals who are self-employed, do not persist in this type of employment throughout their careers, since switching between self-employment, dependent employment, and other employment such as training or unemployment is common in today's working lives (Koch et al., 2021). Therefore, it is important to contribute to the general understanding of entrepreneurship and the factors that influence success.

This thesis was created in cooperation with Early Metrics, which conducts start-up valuations and research to support a dynamic economy. Operating as an independent rating agency for start-ups, Early Metrics created a scientific methodology to reliably rate start-ups through qualitative and quantitative metrics. Moreover, they are able to identify upcoming technology trends.

This methodology allows Early Metrics to provide venture funds and corporate managers with the appropriate set of innovative tools to discover and partner with the best-suited start-ups.

Early Metrics was founded in 2014 and employs over 50 people and has offices in Paris and London. They have evaluated over 3500 European and international start-ups for hundreds of clients, among them many CAC40 and FTSE100 companies.

Early Metrics' methodology consists of several steps including assessment criteria, interviews with founders, proprietary ranking, benchmarking, and growth tracking. Their ratings and methodology have a proven track record as in the 2 years following Early Metrics' valuation, more than 83% of start-ups ranked in the top quintile experienced rapid growth and only 33% of start-ups ranked in the last quintile experienced rapid growth.

Literature Review

Effect of Previous Entrepreneurial Experience on Different Dimensions

Various effects of past entrepreneurial experience are presented in the literature. There is no clear consensus on whether different types of experience affect future ventures or, if so, how large it is or what areas they affect. In addition, often, a lack of existing literature or data is reported. These barriers make it more challenging to formulate a cl ear hypothesis or reach an unambiguous conclusion.

The following subsections describe the effects of existing industry or entrepreneurial experience on different business dimensions. Once again, it becomes clear that the results are not conclusive and are limited by the barriers mentioned above.

New Venture Evaluation

It is argued by scholars that entrepreneurs learn important lessons from their professional experiences that can enrich their entrepreneurial reasoning. Various barriers to learning and applying the knowledge gained from experience can constrain the impact of experience. Due to the lack of available data, the empirical evidence examining the role of experience on entrepreneurs' expectations in new venture creation is inconsistent. Yet, evidenc e suggests that the dominant view is that experience improves the valuation of new ventures, determining whether experience improves entrepreneurial judgment and the valuation of new ventures could have significant practical and policy implications.

There is research indicating that the majority of startups fail to fulfill the entrepreneurs' expectations of performance. Industry experience has been shown to improve entrepreneurs' expectations of their start-up, whereby more industry experience results in more predictive accuracy and reduced over-optimistic bias. In addition, this effect tends to be g\stronger in high-technology industries. Overall, these findings are in line with what is known about the environment that influences entrepreneurial behavior, particularly in a highly uncertain environment. There was no evidence that start-up experience, whether industry-related or not, increases the performance expectations of entrepreneurs (Cassar, 2014).

It is described that when barriers to learning and applying acquired knowledge are overcome, work and entrepreneurial experiences can increase entrepreneurial judgment and evaluation of new ventures. However, start-up experience, as seen, cannot improve performance expectations. These results provide insights into the expectations of entrepreneurs and their judgment. Having realistic expectations is crucial because, as described by the author, this determines business survival and failure and, thus, success.

Survival and Sales

While previous research has presented arguments that the industry and start-up experience of the founding team ought to have a beneficial effect on the performance of the new venture, there has been a lack of solid empirical evidence. Beyond that, theoretical evidence suggests that the link between founder team experience and startup performance may be more complex than previous empirical research indicates. A study examined the impact of the experience on the survival and turnover of 223 new ventures in a representative sample of Swedish firms. The results show that founder team experience increases both survival and turnover of new firms, but that the effects are not linear and vary with firm maturity. In particular, teams of founders with previous startup experience were found to fail at a lower rate than firms without previous startup experience, with the effects almost entirely due to the difference between any startup experience and no startup experience.

Conversely, only companies that had founding teams with four or more prior startups were found to have a considerably greater turnover than companies started by teams having fewer years of experience. In contrast to much of the previous research, which has focused primarily on startup survival, this study shows that founder teams and industry experience improve startup survival and startup turnover in different ways (Delmar & Shane, 2006).

Capital Raising

This study empirically investigated the effects of serial entrepreneurship on key elements of capital raising. The main finding is that the contracts in venture capital funded startups founded by serial entrepreneurs are more beneficial to the start-up. This is evident in several ways: founders retain greater control over the board and undergo less equity dilution in their agreements with venture capitalists. In addition, these entrepreneurs are likelier to retain their position as chief executive officers. Similarly, startups are able to receive high valuations, albeit this finding is limited to businesses started by previously successful entrepreneurs. Finally, serial founders who were before unsuccessful also tend to obtain better agreements than novice entrepreneurs, highlighting the value of entrepreneurial experience. These findings also remain consistent also after accounting for the likelihood that serial entrepreneurs received support from investors of their previous businesses. Previous experience and entrepreneurial learnings play a role in contracting between entrepreneurs and firms (Nahata, 2019).

Career Patterns & Success

The recent paper by Koch et al. argues that there is little literature on the relationship between career patterns and success. The career patterns were divided into four categories, depending on the length of self-employment in relation to the rest of work life. More specifically, different career patterns of the self-employed are measured by objective and subjective success. This is done using data from the German Household Panel (SOEP). The results show that individuals who have been self-employed for a long time have higher job and life satisfaction than the other control groups. Findings that continued self-employment is associated with increased levels of career success mean that individuals should persist in self-employment to reap its benefits (Koch et al., 2021).

The paper above mainly describes the effect of the length of self-employment on success. However, it suggests that there may be a link between entrepreneurial experience and success in new start-ups.

Opportunities, Resources & Success

Alsos et al. studied the effects of entrepreneurial abilities and their impact on start-up success. More specifically, they examined the abilities of novice, serial, and portfolio entrepreneurs to identify opportunities and commit resources and whether this affects the performance of new businesses. Overall, the findings suggest that serial and portfolio entrepreneurs have access to more resources and opportunities than novice entrepreneurs. In this paper, performance is measured by the new venture's achieved sales and employment and was tested utilizing a multivariate regression analysis. The results show that more novel business ideas and new entrants generated significantly less revenue in the first year of operations than less novel and acquisitive entrants. The findings also suggest that both serial and portfolio entrepreneurs have significantly higher sales than novice entrepreneurs (Alsos et al., 2006).

It is shown that there is a connection between entrepreneurial abilities and start-up success, but not how entrepreneurial experience plays into this. Uncovering this is one of the objectives of this paper.

Professional Experience

The paper's aim from Kurczewska et al. is to examine the relationship between education and professional experience and their impact on an entrepreneur's success. In this context, success is defined as an entrepreneur who has been running a business for at least 36 consecutive months and has a net income. A regression was utilized to assess the effects on successful entrepreneurs and salary workers with previous entrepreneurial experience. The findings show a link between education, professional experience, and their impact on entrepreneurial success. It shows a complementary effect of education and experience on success. However, the term "experience" is also professional experience and not exclusively entrepreneurial experience (Kurczewska et al., 2020).

The paper by Parker examines the effect of entrepreneurial learning. Two contradictory hypotheses are tested. First, whether serial entrepreneurs steadily improve with experience or whether serial entrepreneurs perform better after a bad period (and worse after a reasonable period). It was evaluated by data from the Panel Study of Income Dynamics (PSID), which tracks the performance of a sample of American serial entrepreneurs. The results show that serial entrepreneurs derive temporary benefits from a period of entrepreneurship that eventually fades away. This implies that an entrepreneurial venture carries benefits that spill over from one venture to subsequent ones, even if those entrepreneurs performed poorly in their first ventures (Parker, 2013).

Entrepreneurial Skills

Carbonara et al. analyzes 4000 Vietnamese manufacturing firms over ten years. Moreover, the relation between individual skills, the quality of their business, and the likelihood of being a habitual entrepreneur. The findings show that companies run by habitual entrepreneurs stay in business longer in contrast to novice entrepreneurs. However, high-quality companies run by novice entrepreneurs with high entrepreneurial skills are least likely to leave the market in the control group (Carbonara et al., 2020). Like the previously presented papers, the research suggests that there might be a positive relation between serial entrepreneurship and success but also shows that entrepreneurial skills and the quality of a business are important factors for success.

Using a large longitudinal dataset with matched employer/employee data, Rocha et al. identified about 220,000 individuals who had their first entrepreneurial experience, of whom over 35,000 became serial entrepreneurs. The relationship between whether previously acquired entrepreneurial experience improves the survival of serial entrepreneurs was investigated. The results confirm that serial entrepreneurs, on average, have a more significant person-specific effect than non-serial entrepreneurs (Rocha et al., 2015).

Productivity Advantage

The National Bureau of Economic Research has found that serial founders achieve higher sales and productivity than their novice counterparts. Shaw & Sørensen analyzed in-depth panel tracking data on founders from Denmark from 2001to 2013 and found that serial founders have higher sales by 67% and open businesses that are larger in terms of seed equity and employees, making them 39% more efficient and productive than new founders. Serial entrepreneurs who own a portfolio of overlapping ongoing businesses do particularly well. The study also shows that women serial entrepreneurs perform as well as male serial entrepreneurs compared to new founders of their own gender. Furthermore, on average, the second-founded firm stays longer in business than newly founded first star-ups (Shaw & Sørensen, 2017). It is interesting to see here that the results regarding the portfolio entrepreneurs are similar to those of Carbonara et al..

Human Capital

The study examines whether the background of founders affects the survival of start-ups in the first years. Entrepreneurial human capital-related abilities prior to entry are identified.

The study found that having more human capital, which is more common among serial founders, plays a critical role in improving survivability, whereas more generic types of human capital can assist novice founders in mastering the critical first few years after launching (Baptista et al., 2007).

The most striking finding, however, is that "entrepreneurial experience in itself does not seem to play a significant role in enhancing survival probability, but firms started by portfolio entrepreneurs [..] do have a significantly higher probability of survival" (Baptista et al., 29). These results confirm and refute the previous literature presented. On the one hand, they show that portfolio entrepreneurs perform better than novice entrepreneurs. On the other hand, it is claimed that entrepreneurial experience has no significant impact on firms' survival. This thesis will contribute to these different findings.

Research Question & Hypotheses

Problem Statement

Through the presented literature, we see that several determinants influence start-up success. How exactly entrepreneurial experience contributes to this is not yet entirely clear, as there is also other literature on this which contradicts each other. Therefore, the author believes there is a gap in the literature, which can be explained in more detail. Thus, the research question is as follows: What is the impact of previous entrepreneurial experience on start-up success and evaluation? This should provide more clarity and enable companies, investors, and scholars to evaluate start-up companies better. This thesis could thus add to academia in this way and be used in practice or as a starting point for further research.

Hypotheses

Based on the literature review, the hypotheses developed so far are: How does entrepreneurial experience of founders affect new start-ups, or are other factors decisive for success or failure? translating into

(H1) entrepreneurial experience has a small but positive effect on start-up evaluation.

Secondly, how does industry experience of founder(s) affect new start-ups or are other factors decisive for success or failure? translating into

(H2) industry experience has a positive effect on start-up success.

Thirdly, are there differences between new entrepreneurs and habitual entrepreneurs in terms of number of employees employed? translating into

(H3) There is no significant difference between experienced and non-experienced founders in terms of team size.

And finally, are there differences between new entrepreneurs and habitual entrepreneurs in terms of yearly revenue? translating into

(H4) there is a difference between experienced and non-experienced entrepreneurs in terms of yearly revenue.

Methodology

Methodological Approach

The research objective was to establish a cause-and-effect relationship and see how entrepreneurial experience and other factors can affect success. Secondary quantitative data was used to investigate such associations. The targeted method was a multiple regression based on secondary data mixed with findings from existing literature to examine correlations. The secondary data was collected in 2021 by Early Metrics and describes 819 companies, mainly in Europe, some of their financial KPIs and data about their founding team. Based on these data, the hypotheses are tested, analyzed, and conclusions and remarks are drawn.

Using multiple regression analysis, researchers can assess the magnitude of the relationship between an outcome (dependent variable) and multiple predictor variables, along with the significance of each predictor variable to the relationship, while often statistically eliminating the effect of other predictor variables. Moreover, the author believes that this methodological approach is the most appropriate as other authors have also used it in this field, such as Shaw & Sørensen, 2017 or Celestino & Barreira, 2004.

Data Collection

As mentioned above, the data was provided by Early Metrics. They perform independent start-up ratings, start-up valuations, and tech trends analysis. The data were collected using a scoring product filled out by entrepreneurs in a survey. In 2021, the data were collected and origins from entrepreneurs who are in contact with Early Metrics.

The dataset consists of 843 companies and their respective financial and non-financial key figures. Prior to analyzing the collected data, the data set was checked for missing data and outliers. Of this total, 819 companies remained after the data were adjusted for errors and omissions. There were missing entries in key metrics or deficient ones, such as negative seven employees in one case, which are factors that reduced the dataset.

Data Analysis

The original dataset consists of descriptive variables such as country of incorporation, date of incorporation, maturity, investor type, and business model. The financial key figures in the dataset are number of employees, number of offices, yearly revenue - if available, contribution of international business to revenue, funding rounds, and total funds since launch. In addition, there are other non-quantitative, non-accounting metrics such as total number of founders or operational partners and how many of those previously have been entrepreneurs, founders, or operational partners with industry experience, and the positioning in the Early Metrics scorecard. The mentioned variables will be presented in more detail in the following section.

In order to have a more robust multiple regression analysis, the variables industry and entrepreneurship experience were set in relation to the number of founders in order to obtain a percentage. In addition, the variable Early Metrics positioning, which contains descriptive values, was transformed to generate a ranking on a scale of 1 to 5.

Microsoft Excel was used to analyze the data, and a regression model was created using that same program. Through the multiple regression analysis, it was possible to understand how the dependent variable changes when one of the independent variables is varied and determine which affects the dependent one mathematically. Descriptive statistics were also collected to get a good overview of the individual data series. Thus, means, medians, minimum and maximum numbers, and other data can be presented, which provides a deeper insight into the dataset.

Variables

Dependent Variables

Dependent variables can theoretically be all variables, but this depends on the effect to be investigated. The effect to be investigated has an effect on a particular metric. This metric is then the dependent variable. This allows statistical modeling to discuss dependencies and dependencies.

Success

There are many different factors for success in the literature and there is no clear way to measure success. For example, these can be divided into tangible and intangible assets (Galbreath, 2004).

One of the most common measures is revenue. Revenue shows how strong the demand for a company's product is, but it does not show profitability. Profitability often used as a success indicator, is not always accurate, especially for young companies. Other metrics of success are, for example, the number of employees or offices as this can only be achieved by a capital investment which is also characterized by mostly monthly reoccurring costs (Kiviluoto, 2013).

Another success factor can be years of existence as it can be argued that sustainable business is success. Furthermore, there are emerging trends that social impact is an important success factor and rightly gets increasing attention (Lombardo et al., 2019).

Early Metrics Position

In order to have a unified success factor, the positioning in the Early Metrics Scorecard is taken. This ensures that the regression has a higher significance and controls for variations in the dataset. As mentioned before, there are advantages and disadvantages to most of the other factors that would be given in the dataset, and therefore it was decided to use the Early Metrics scorecard. Furthermore, this ranking is based on several steps, including assessment criteria, interviews with founders, proprietary ranking, benchmarking, and growth track. Their ratings and methodology have a proven track record, as in the two years following Early Metrics' valuation, more than 83% of start-ups ranked in the top quintile experienced rapid growth, and only 33% of start-ups ranked in the last quintile experienced rapid growth.

The original data is divided into five categories, ranging from "Top 20%" and "Top40%" to "Average", "Bottom 40%" and "Bottom 20%." Top 40% refers to companies that achieve a score between 20 and 40 percent and does not include all companies from the top 1 percent. This applies vice versa to the bottom 40 percent.

Key Independent Variables

In contrast to the dependent variable, independent variables indicate an effect. Thus, the impact of the independent variable can be measured or controlled for an independent variable. When controlling for an independent variable, they can be accounted for statistically to remove their impact on other independent variables.

Of all the variables mentioned above, only those that appear in the regression analysis are considered in the following. This selection is based on the author's model to create a robust and significant regression. Many different possibilities of construction with different variables were tested. The rationale was that if one variable neither increases the significance nor affects the other variables, it is omitted. Thus, the omitted variable bias can be avoided, at least within this dataset. The omitted variable bias occurs when one or more relevant variables are not included within a model, thus biasing the results (Clarke, 2005). Furthermore, variables were not included in the model if the variable's data were either largely missing or of a purely descriptive nature.

Number of founders or operational partners

This variable describes the number of founders and operating partners in absolute terms. Research might suggest that there is an optimal number of founders or even a threshold at which each additional founder harms the success of a start-up. Thus, team size was controlled because a larger founding team could benefit from more labor and more other resources, such as information, time and capital, than a smaller team. In addition, larger team sizes can complete tasks more efficiently because founding team members can specialize their activities. In addition, larger teams benefit from varying levels of novice experience, which leads to more creative problem solving (Delmar & Shane, 2006).

As we can see in Table 1, there are on average 2.28 founders per start-up in the dataset of 819 observations. These data range from a minimum of one founder up to five founders.

Number of offices

The number of offices was measured because this is usually associated with OPEX (operational expenditure) and can therefore also be an indicator of success and impact the Early Metrics positioning. However, it can be counter-argued that due to the COVID-19 pandemic, there has been a shift in the working environment, and the way to work has become more remote and hybrid.

On average, we see 1.62 offices per company with a range of four between one office location and a maximum of five. This observation is interesting as there is no company without an office, which probably shows that the term office was defined as a space for commercial work without its operational costs.

Number of employees

The number of employees in a company can have an impact on the performance of a company and thus also contribute to its success. Businesses that do not succeed in attracting and retaining employees run a greater risk of failure when compared to those that succeed (Lussier & Corman, 1996). In addition, a higher number of employees is coupled with higher operating expenses, which are usually paid on a monthly basis. As seen in the previous chapter, the number of employees can be a success objective and a measurement for it.

The evaluated data on the statistics of the number of employees show an average of 13.32 employees. The minimum number of employees is none since some companies consist only of the founding team. The maximum number was 219 employees. We can see how much the data points differ from each other with a standard deviation of 20.21 and a sample variance of 408.33 (Hoyt & Leierer, 2006).

Funding rounds since launch

The number of completed funding rounds excluding friends and family was queried in this category. The number of these is relevant insofar as a study has found that the number of funding rounds is positively related to start-up valuations (Nahata, 2019). Companies with more funding rounds are usually in a further development phase, have more employees and are partly already profitable (Davila et al., 2003).

The histogram shows that there is a right-skewed distribution, as expected. There are significantly more companies without a funding round (300) compared to those with three (127), which also represents the maximum number of funding rounds. On average, the companies surveyed have completed 1.14 funding rounds.

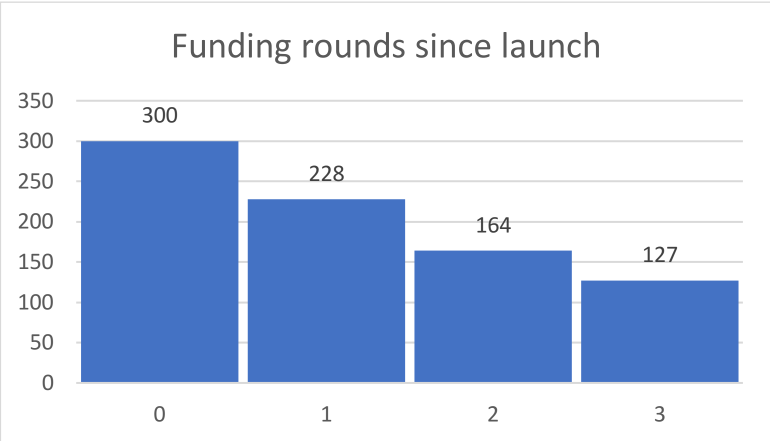

Table 1: Funding rounds since launch

Total amount of funds raised, including equity and debt

This metric is very closely related to the previous one, which will be discussed in detail later. In response to the question "Since launch, what is the total amount of funds raised, including equity and debt?", 112 companies or 13.7% of our dataset raised zero funds. The range goes from 0 to 84 million euros. On average, the companies raised 1.8 million euros, but this value should be viewed with caution as the standard deviation is 5.5 million, which is the average distance of all measured values of a characteristic from the average.

Months since company incorporation

This value indicates the number of months since the company was established up to the reporting date of February 1, 2022. On average, this is slightly more than six years within the dataset. It was controlled for the length of existence as this also influences other independent variables.

As the company ages, the impact of the founding team's experience decreases. Start-ups begin as ideas and are subsequently formed by entrepreneurs into new organizations. Converting firms from ideas to organizations shows that the contribution of knowledge to new business performance decreases as the age of the firm increases. At the beginning stages of growth, founder knowledge is instrumental in almost all performance factors. Determining if a firm survives depends mainly on how the founders know how to gain control over resources. In the later stages of firm development, with employee growth and assets acquired, these variables significantly impact performance. Hence, the relative impact of the founder's industry and start-up experience on firm performance decreases with the age of the firm (Delmar & Shane, 2006).

Yearly revenue

It was found that there is a correlation between sales and industry and entrepreneurial experience, so this was also controlled for as a variable "yearly revenue". This measure does not indicate the profitability or cost structure of the company but of the revenue volume since it only represents the total volume of goods and services of a company per year (Delmar & Shane, 2006).

It is examined whether this measure results in an impact on the Early Metrics positioning. The average turnover is 1.39 million euros, which can be considered quite a high value, but also because of the standard deviation with a value of just over 11 million. 278 companies (34%) have no turnover yet, which is not surprising in the given sample as start-ups are evaluated, which are often still in the ideation phase. The highest value is achieved by a company with 276 in annual revenue.

Adjusted Variables

Percentage of founders previously being entrepreneurs

This is one of the most critical variables in the dataset. However, it has been adjusted for greater meaningfulness. The raw data indicate the number of founders with previous entrepreneurial experience. Entrepreneurial experience is counted as any experience regardless of the length. The number of founders with experience in this area is also limited to the total number of founders. Therefore, if there are four founders and two of them have experienced it is more than if there is only one serial or portfolio entrepreneur, but in percentage terms, it is once 50% and in the latter 100%. In this conclusion, the percentage value of founders with entrepreneurial experience was taken instead of the absolute number.

The experience of a founding team is likely to promote the growth of a new company's survival and sales for several reasons. First, a large part of the knowledge relevant to the start-up is acquired through hands-on activities. Entrepreneurial experience imparts knowledge about organizational routines and skills developed from previous activities. Entrepreneurs with experience have often learned how to structure a new venture successfully due to prior exposure to the issues of hiring new employees, raising funds, developing a new product, and other efforts involved in starting a new venture. Consequently, founding experience adds a special kind of human capital that is not easily obtained in other ways. In addition, founding expertise imparts the knowledge of what roles are needed in organizations and by whom those roles should be fulfilled. Understanding the proper roles and accountabilities of organizational members is often difficult to develop without starting a new business and defining the new organizational roles and responsibilities that are needed. Entrepreneurial experience can also help founders understand what activities require their attention to be better equipped to launch a new venture than inexperienced founders. Finally, entrepreneurial experience links the founder to a network of employees, suppliers, investors, and customers. Since connections are vital to business operations, the early absence of these ties to stakeholders can hinder new ventures. Founding experience transmits these social ties from previous ventures. In addition, founding experience gives legitimacy to important stakeholders within a new venture, making it easier to obtain resources and organize the new venture's operations. Experienced start-ups often know what needs to be done to successfully organize a new venture because they have faced similar problems before (Delmar & Shane, 2006).

On average, 67% of the founders and operational partners in our data sample have entrepreneurship experience. In our entire dataset, there are 1868 founders divided among 819 companies. More than half of the companies are in the last quintile, which means that they each have a share of 80-100% of founding partners with experience in entrepreneurship.

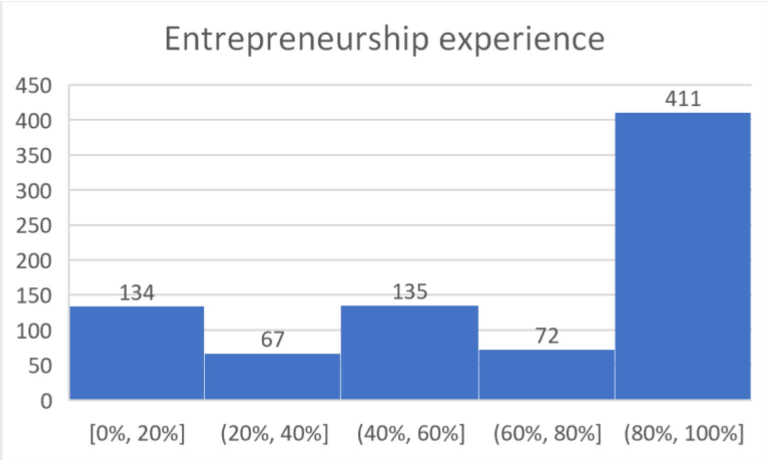

Table 2: Percentage of founding partners with entrepreneurial experience

Percentage of founders with industry experience

Founding experience is likely to improve a new company's survival and revenue for several factors. To begin with, a team of founders with broader industry experience is more likely to understand and meet customer demands in the respective industry since information like this is in most industries hard to acquire. A founding team develops a comprehensive understanding of what should be offered as a product or service by working with consumers and gaining an understanding of the advantages and disadvantages of various business propositions, as well as the existing gaps to meet customer needs. Industry knowledge may apply to manufacturing-related activities, market gaps, technological advancements, products, or services, making a company more competitive. Given that a founding team with industry experience has acquired this knowledge, companies founded by experienced teams are more likely to survive and generate higher revenues than new companies. Finally, operating in an industry builds social connections with vendors and retailers over time.

Moreover, as people start a business in the same industry in which they previously worked, the social ties from their previous environment can carry over to a new business. These connections are essential in gaining the trust and support of suppliers and vendors. In addition, these relationships, as well as the status of the individuals with whom these relationships are established, give the new venture's key stakeholders legitimacy, facilitating the acquisition of new resources. Hence, start-up teams with greater levels of experience are more likely to gain advantages over other novice teams in the growth of their new business (Delmar & Shane, 2006).

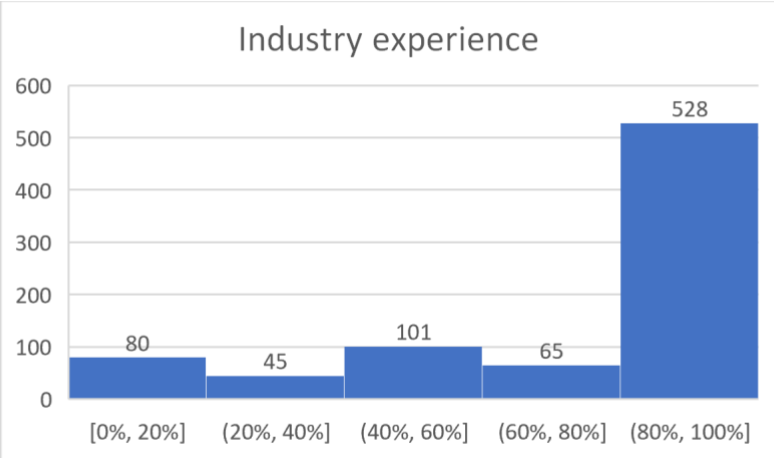

Table 3: Percentage of founding partners with industry experience

Maturity

The variable maturity is specified descriptively in the original dataset and is divided into five levels. More precisely, these were divided into "Idea", "Development", "Early Stage – Post-Revenue", "Early Stage - Pre-Revenue", "Expansion", "Late Stage" and given respective numbers from 1 to 6 to quantify the varying maturity to see the effects on the Early Metric positioning.

It was controlled for this variable since founders of new ventures have steep learning curves as they develop new ventures. Such learnings imply that as new ventures grow, the impact of experience decreases. Hence, the degree of the performance gap between experienced and inexperienced firms decreases as the firms mature. In particular, their activities become increasingly sophisticated and complex so that the performance of new firms is not so much linked to the founding team's experience and is more likely to be the result of other factors. Moreover, as firms grow, work begins to be shared among organizational members, and the founder's share of work and influence decreases. Subsequently, as firms age, these characteristics influence a smaller share of firm activities.

Additionally, routines are created. For example, routines for invoicing, checking inventory, purchasing, budgeting, evaluating investments, selecting employees, are becoming routines. Thus, as organizations develop, the decision-making of founders is gradually replaced by organizational routines (Delmar & Shane, 2006).

The following figure illustrates the stage the companies are in. We see that slightly more than a quarter (25.9%) of the companies are in the first category, which means that they are still in the idea phase, which is not surprising since the sample focuses on start-ups. The largest part with 56.3% is in stages 3 and 4 which represent early-stage post- & pre-revenue.

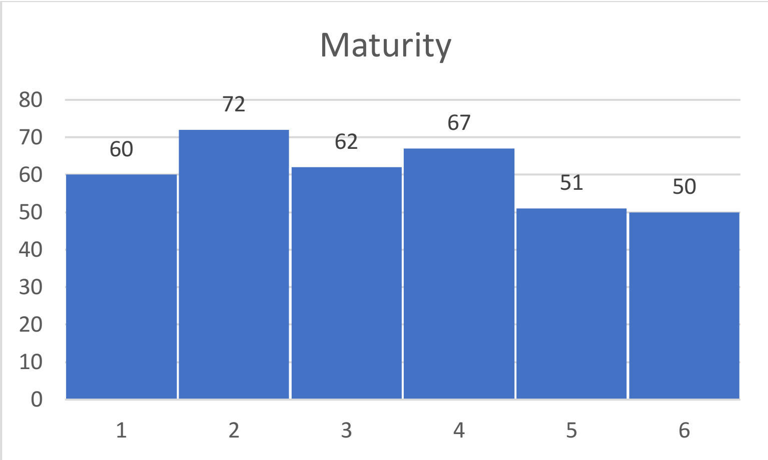

Table 4: Maturity of the firms ranked 1-6

Analysis

Model Construction

A multiple linear regression was built to analyze the effect of the above-described independent variables on the Early Metrics positioning.

As mentioned above, these variables would be the most accurate in describing the positioning, given the limitations of the dataset. The positioning indicates success within the given data, making it suitable for the analysis. In order to test the effects of entrepreneurial and industry experience, we chose these as independent testing variables alongside other controlling ones.

By including certain control variables in the regression, we aim to clean the regression from possible correlations of the positioning with those variables, which would lead us to falsely overstate and misinterpret the significance of the effect of experience.

Thus, the model is built as follows, where the variables X_1 to X_{10} represent the ten independent variables, β represents the corresponding coefficient, and subsequently Y stands for the Early Metrics positioning:

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + \beta_9 X_9 + \beta_{10} X_{10} + \varepsilon$$

The model was calculated with a 95% confidence interval, which means that the results are significant or not at the 5% level. Moreover, this means that there is a 5% chance that the null hypothesis was incorrectly rejected.

Correlation

The correlation matrix between every variable is displayed in the table below. This table aims to understand if there is a multicollinearity problem in the model. Multicollinearity is the linear relationship between two or more variables. Moreover, it is a data problem that can significantly affect the reliability of model parameter estimates. Usually, multicollinearity is observed when variables correlate close to or above 70%. It can be observed that no values have a correlation coefficient close to the threshold of 0.7, meaning that there is not a correlation problem within the model.

The second purpose of this table is to display linear relations between the variables. In the first column, the correlation of the independent variables with the dependent, EM position, is shown. It is also evident that all independent variables have a high correlation with our observed variable except for the variable percentage of founders who were entrepreneurs, all of which have a correlation above 10%. It can be observed that Maturity has a high positive correlation of 57.2%, which is the highest in the matrix. However, this is not a problem since the correlation between the dependent, and independent variables is not an indicator of multicollinearity, but only the independent variables themselves should be independent. The second highest positive value is between the total amount of funds raised and number of employees, which is interesting to see that they have a 40% correlation. In contrast, the correlation between number of employees and number of offices is only 28.7% and thus much lower. This is an excellent example to show that correlation does not mean causality (Alin, 2010).

	EM position	*Number of founders or operational partners*	*Percentage of founders previously being entrepreneurs*	*Percentage of founders with industry experience*	*Number of offices*	*Number of employees*	*Funding rounds since launch*	*Total amount of funds raised, including equity and debt? (in €)*	*Months since company incorporation*	*Yearly revenue*	*Maturity*
EM position	1										
Number of founders or operational partners	0,115	1									
Percentage of founders previously being entrepreneurs	0,022	-0,230	1								
Percentage of founders with industry experience	0,099	-0,273	0,283	1							
Number of offices	0,380	0,057	0,028	0,075	1						
Number of employees	0,403	0,107	-0,035	0,056	0,287	1					
Funding rounds since launch	0,298	-0,015	-0,010	0,000	0,123	0,252	1				
Total amount of funds raised, including equity and debt? (in €)	0,257	0,060	-0,015	-0,001	0,135	0,404	0,260	1			
Months since company incorporation	0,180	-0,139	0,079	0,150	0,081	0,226	0,259	0,211	1		
Yearly revenue	0,150	0,030	0,022	0,044	0,079	0,109	0,017	0,087	0,028	1	
Maturity	0,572	0,028	-0,001	0,109	0,202	0,267	0,110	0,106	0,198	0,003	1

Table 5: Correlation Matrix

Regression Statistics

As we can see in the table below, we have the regression statistics of the applied model. The Multiple-R-value stands for the correlation coefficient and says how strong the linear relationship is. The Multiple-R is also the square root of R-Square, which is the value underneath.

The R-squared measure is an estimate of the coefficient of determination. This is the fraction of the variability in the response variable that can be explained by the underlying variables and indicates how many points lie on the regression line. In this regression, 49.36% of the variation in the y values around the mean is explained by the x values. Stated another way, 49.36% of the values fit the model. Moreover, the independent variables can explain 49.36% of the variation in the Early Metrics positioning.

The adjusted R-squared expresses the R-squared value adjusted for the number of predictor variables in the model. It measures the robustness of a regression model. Hence, a higher R-squared means that the model fits better, while a lower R-squared indicates that the model does not fit too well. In our model, our adjusted R-square explains 48.73%. This value represents the fraction of variation in the dependent variable explained by the regression model and has revealed a considerably good value. It suggests that the model explains almost half of the variation in the dependent variable and therefore explains most of the variation of the Early Metrics positioning.

The standard error indicates how far the observed values deviate on average from the regression line. In the utilized model, the observed values deviate on average by 1.03 units from the regression line. It thus indicates how accurate the regression model is on average when using the units of the response variable (Hoyt & Leierer, 2006).

Regression Statistics	
Multiple R	0,70255761
R Square	0,493587195
Adjusted R Square	0,48731971
Standard Error	1,029056391
Observations	819

Table 6: Regression Statistics

Analysis of Variance

The F-value is the variation between sample means or the variation within samples. It is calculated as the mean square (MS) of the regression divided by the MS of the residual. This is equal to 83.4 divided by 1.06, yielding 78.75. Through the execution of an F-Test, which shows overall significance, it is possible to perceive that for a 5% significance level, it can be stated that the data sample provides sufficient evidence to conclude that the regression model fits the data better than a model with no independent variables.

The variable "Significance F" is the most important in the analysis of variance since it shows whether or not the regression model as a whole is statistically significant. In this case, the *p* value is less than 0.05, with a value of 2,84E-112. This indicates that the explanatory variables combined have a statistically significant association with the Early Metrics positioning.

	df	*SS*	*MS*	*F*	*Significance F*
Regression	10	833,967095	83,3967095	78,7536276	2,843E-112
Residual	808	855,637301	1,05895706		
Total	818	1689,6044			

Table 7: ANOVA Results

Results

Coefficients

In a linear regression, size of the coefficient of the independent variable indicates how much it affects the dependent variable. The direction of the effect is indicated by the sign of the coefficient. In a regression with multiple independent variables, as in this case, the coefficient shows the amount by which the dependent variable increases when the independent variable increases by one unit, keeping all other variables constant.

The following table shows all the coefficients of the variables and their other values. The most important is the *p* value which indicates the significance, the t-Stat, the coefficient divided by its standard error, and the coefficient itself, which describes the impact on the dependent variable.

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0,315	0,175	1,797	0,073	-0,029	0,659
Number of founders or operational partners	0,118	0,037	3,225	0,001	0,046	0,189
Percentage of founders previously being entrepreneurs	0,122	0,102	1,204	0,229	-0,077	0,322
Percentage of founders with industry experience	0,168	0,118	1,421	0,156	-0,064	0,399
Number of offices	0,314	0,041	7,600	0,000	0,233	0,395
Number of employees	0,009	0,002	4,372	0,000	0,005	0,013
Funding rounds since launch	0,232	0,036	6,489	0,000	0,162	0,302
Total amount of funds raised, including equity and debt? (in €)	0,000	0,000	2,601	0,009	0,000	0,000
Months since company incorporation	-0,001	0,001	-0,653	0,514	-0,002	0,001
Yearly revenue	0,000	0,000	4,123	0,000	0,000	0,000
Maturity	0,423	0,024	17,517	0,000	0,375	0,470

Table 8: Regression Results Coefficients

Intercept

The intercept gives the mean value when all independent variables are zero. In this regression, 0,32 would be the average Early Metrics score when all other variables are zero. However, since the Early Metrics positioning only has values between 1 and 5, the intercept is not very meaningful. Among other things because variables like number of founders would be zero, which is not possible. Furthermore, the value is not significant as the p value is above the confidence level of 0.05.

Number of founders or operational partners

The corresponding p value, which is 0.001, is lower than the significance level and therefore statistically significant. Now the coefficient determines how high the impact on the dependent variable is. With a value of 0.118, we see that when the number of founders increases by one level, in this case, one founder, it positively impacts positioning by 0.118 points to the higher level.

It is important to note that the maximum number of founders in our dataset is five. It can be assumed that above a certain number of founders, the effect decreases or can even go into the negative if there are too many founders. In the limit of one to five founders, this is not the case, as the model shows.

Percentage of founders previously being entrepreneurs

Based on the literature review, the regression examined our initial hypothesis that (H1) entrepreneurial experience has a small but positive effect on start-up success. The result shows that if there is a slope in the variable "Percentage of founders with entrepreneurial experience," this would influence the positioning by 0.12 points. However, the *p* value with a value of 0.229 is above our significance level of 0.05 and thus not significant.

Therefore, we can conclude that the dataset used does not provide enough evidence that this variable affects the dependent variable. As a result, hypothesis (H1) is rejected. However, it must be said that such an effect cannot be excluded in general. It is therefore interesting for future research, which can build on it as this can be a relevant observation.

Percentage of founders with industry experience

The second hypothesis, "(H2) Industry experience has a positive effect on start-up success," was examined through this variable. There is much more literature suggesting and proving that industry experience positively affects start-up evaluation and success. However, no significance could be shown in our dataset with a *p* value of 0.156. Subsequently, the hypothesis (H2) is rejected. On the other hand, the variable had a positive coefficient of 0.168, which would suggest that it has a positive effect on the Early Metrics positioning.

However, in other regressions (see appendix) performed, this value is slightly below the significance level and shows a positive impact. However, this regression was not used because the adjusted R-square was only 29.35%, and other variables were insignificant.

Number of offices

The number of offices has an impact on the positioning. The corresponding p value is significantly below the significance level. Therefore, it can be said that if the number of offices increases by one, there is an increase in the Early Metrics positioning of plus 0.314, which represents one-third of a category and thus a considerable value. Thus, this metric has the second-highest impact of all independent variables in the regression.

In the regression where effects on the size of the team (see appendix) were tested, a significant impact is also seen. However, this is not surprising, as it indicates that when the number of offices increases by one, the number of employees increases by a rounded 4. This makes sense since, in most cases, when a new office is opened, it is also staffed.

Number of employees

If we look at the number of employees and their effect on the dependent variable, we see that it has a negligible impact with a value of 0.01. This is a small number in absolute terms but can be interpreted as follows: If the number of employees increases by one unit, i.e., one employee, then the evaluation increases by 0.01 points. It should be noted that this is multiplied by the number of employees so that a company with ten employees would achieve a significantly more significant effect than a company with only one. Companies with as many as 100 employees see an impact in positioning by an absolute position. This result is statistically significant at the 5% level and consistent with the last variable of the number of offices having a significant impact. Since we tested for multicollinearity, there is no problem with keeping both variables in the regression.

A point of interest in this variable is the regression regarding team size, which can be found in the appendix and represents the number of employees as a dependent variable. The regression has an adjusted R-square of 27,8%. This value represents the fraction of variation in the dependent variable explained by the regression model. It suggests that the model explains almost a third of the variation in the dependent variable. The overall regression is also statistically significant, with an F-value of 7.9E-54.

In conjunction with the hypothesis (H3) that there is no significant difference between experienced and non-experienced founders in terms of team size, we can analyze this effect through the regression. Since the *p* value of the variable "percentage of founders with entrepreneurial experience" is not significant, it can be concluded that we accept hypothesis H3 and that there is no significant difference between experienced and non-experienced founders in terms of team size. However, in this regression, the limitation that it explains only about 30% of the dependent variable must be mentioned.

Funding rounds since launch

The number of funding rounds is usually also an indicator of the success and maturity of a company. However, the correlation between the number of funding rounds and maturity is only 11%, so it is not very strong.

With a *p* value of 1.5E-10, the coefficient is clearly below the significance level. It can be concluded that each completed funding round has a positive impact of 0.23 on the dependent variable. Thus, this is the third most influential independent variable.

Total amount of funds raised, including equity and debt?

One may assume that the total amount of funds raised is strongly correlated with the previous variable, funding rounds. In the correlation matrix of the regression we see that these two values have a correlation of only 26% and thus can be tested for multicollinearity and this is not proven.

The *p* value also indicated that our result was significant (0.01). The associated coefficient is marginal with a value of 0.00000002. However, this must be considered with caution because the unit of the independent variable is euros. Thus, the coefficient is the factor by which the positioning is affected when one euro is raised more. For example, if one million euros is raised, this has a much larger effect of 0.019.

Months since company incorporation

This value measures the number of months since the company was founded, with a cut-off date of February 1, 2022. It is evident that the coefficient is not significant due to the excessively high *p* value and therefore has no effect on the dependent variable in our model.

Yearly revenue

The influence of annual revenue is positive on the positioning of Early Metrics, and it is also significant with a *p* value of 7.1E-09. The coefficient, similar to the variable "total funds raised", has the unit euro and is therefore very low (0.000000014). As before, if this value is multiplied by one million euros in annual revenue, we arrive at an effect of 0.014.

The interesting thing about this variable is the regression (see appendix) in which the variable was specified as a dependent. This was done to test (H4) "there is a difference between experienced and non-experienced entrepreneurs in terms of yearly revenue".

The value of the significant F is only just below the significance level of 0.05 at 0.049. In addition, the adjusted R-square is not very meaningful at 0.01 or only one percent, respectively. Furthermore, the independent variable of entrepreneurial experience is insignificant. Due to all these limitations, no reliable statement can be made about the effect of entrepreneurial experience on yearly revenue, and therefore hypothesis (H4) is rejected.

Maturity

At first glance, this variable seems to be very highly related to "months since company incorporation", but in the correlation matrix, we see a correlation of merely 19.8%. This is due to the fact that despite the similar name, these two variables measure different things. One variable represents a time, while the other variable, maturity, indicates the stage a company is in. This is not always related to the time of existence, as some companies develop faster than others within the same timeframe.

Given the p value and the coefficient, it can be concluded that the level of maturity with a value of 0.42 has the greatest significant influence on the Early Metrics positioning. This is understandable since more advanced companies allow better and simpler predictions than companies that are still in the ideation phase, for example. In addition, companies with a higher maturity have already passed some critical phases.

Limitations

Like all empirical research, this study was based on several assumptions and exposed multiple limitations that added several biases to the analysis, which need to be considered when interpreting the results obtained.

As we have seen in the literature, there is a difference between novice, serial, and portfolio entrepreneurs. A distinction is only made between entrepreneurs with or without experience in the dataset discussed. Concerning those who already have experience, it was not possible to distinguish whether they are serial or portfolio entrepreneurs. Consequently, it was also impossible to distinguish whether they were successful or unsuccessful in their previous ventures.

Another factor that affects this variable and is a limitation to the study conducted is the quantification of experience. On the one hand, for entrepreneurial and on the other hand for industry experience. However, for the latter, we have a minimum threshold of five years which is a minimum standard. For entrepreneurial experience, however, we do not have a quantification factor and therefore do not know how much experience is available in this area when an entrepreneur states that he has experience.

Another limitation is that it was impossible to set up a representative study due to the low number of data records available. Therefore, it was impossible to control a specific region or industry, as much more data would be needed. However, most of the data sets come from Europe, with the United Kingdom leading the way. However, this has not been sufficient to collect specific results for a country or continent.

Furthermore, with regard to the available data, this survey only shows data from one year, as it was only introduced last year (2021). Data from one year cannot, therefore, be used to control for a period of time or to identify a trend. However, this also gives an outlook for further years and can therefore, serve as a cornerstone for further research.

Moreover, Early Metrics positioning was given as a success determinant. It must be said that the company has an excellent track record of successfully evaluated companies, and its success of it is the validation of the choice to take this metric. However, this success factor is also somewhat limited as it is biased and not purely financial KPIs such as revenue. On the other hand, the EM positioning is accurate to a very high percentage but not 100% reliable, which means that not 100% of the evaluation of EM is correct.

There are limitations in the regression itself, which were partly described in the previous chapter. On the one hand, there are the different significance levels of the coefficients and the regressions themselves. On the other hand, the model only explains half of the dependent variable.

Due to all these limitations, the results should be interpreted with caution. However, they can serve as an indicator for further, larger-scale studies.

Conclusion

This paper tested a sample of 819 companies for four different hypotheses. This dataset was collected and provided by Early Metrics. Throughout the literature, it is evident that several determinants influence start-up success. How exactly entrepreneurial experience contributes to this is not entirely clear, as other literature also contradicts each other.

The effects of entrepreneurial experience on success were tested by means of several multiple regressions, one of which was mainly used because it was most significant and meaningful. The dependent variable was the Early Metric positioning, also specified in the dataset. Since Early Metrics has a proven track record of correctly evaluating start-ups, this indicator can serve as a reliable and conscientious success factor. However, there are also limitations as described above. Further limitations lie in the dataset itself but also in the regression performed. Due to these limitations, the results of the tested four hypotheses should be interpreted with caution.

We can conclude that the dataset used does not provide enough evidence that entrepreneurial experience affects the Early Metrics positioning. As a result, hypothesis (H1) is rejected. However, it must be said that such an effect cannot be excluded in general. Therefore, it is interesting for future research, which can build on it as this can be a relevant observation.

The second hypothesis, "(H2) Industry experience positively affects start-up success," was examined. Although there is much literature suggesting that industry experience positively affects start-up evaluation and success, no significance could be shown in our dataset with a p p value of 0.156. Subsequently, the hypothesis (H2) is rejected. On the other hand, the variable had a positive coefficient of 0.168, which would suggest that it has a positive effect on the Early Metrics positioning. Another regression showed a positive impact of industry experience. However, this regression was not used because the adjusted R-square was not significant enough.

The hypothesis (H3) that there is no significant difference between experienced and non-experienced founders in terms of team size was analyzed. Since the respective p value of the variable "percentage of founders with entrepreneurial experience" is not significant, it can be concluded that we accept hypothesis H3 and that there is no significant difference between experienced and non-experienced founders in terms of team size. However, in this regression, the limitation that it explains only about 30% of the dependent variable must be mentioned.

The last hypothesis (H4) states that "there is a difference between experienced and non-experienced entrepreneurs in terms of yearly revenue".

Due to the existing limitations within our dataset, no reliable statement can be made about the effect of entrepreneurial experience on yearly revenue; therefore, hypothesis (H4) is rejected.

In summary, it can be said that this work is subject to some limitations. However, some indicators and findings give an impetus for further research in this field, which is currently not characterized by a clear consensus. Therefore, it is crucial that academia continues to add to this field and also making the implications for theory and practice accessible. Larger-scale studies in this area can yield significant and relevant findings.

Bibliography

Alin, A. (2010). Multicollinearity. *Wiley Interdisciplinary Reviews: Computational Statistics*, *2*(3), 370–374. https://doi.org/10.1002/wics.84

Alsos, G. A., Kolvereid, L., & J. Isaksen, E. (2006). New business early performance: Differences between firms started by novice, serial, and portfolio entrepreneurs. In *Managing complexity and change in SMEs : frontiers in European research.* (pp. 35–49).

Baptista, R., Karaöz, M., & Mendonça, J. (2007). *Entrepreneurial Backgrounds, Human Capital and Start-up Success*. www.uni-jena.dewww.econ.mpg.de

Carbonara, E., Tran, H. T., & Santarelli, E. (2020). Determinants of novice, portfolio, and serial entrepreneurship: an occupational choice approach. *Small Business Economics*, *55*(1), 123–151. https://doi.org/10.1007/s11187-019-00138-9

Cassar, G. (2014). Industry and start-up experience on entrepreneur forecast performance in new firms. *Journal of Business Venturing*, *29*(1), 137–151. https://doi.org/10.1016/j.jbusvent.2012.10.002

Celestino, J., & Barreira, D. (2004). *The influence of business knowledge and work experience, as antecedents to entrepreneurial success*.

Clarke, K. A. (2005). The phantom menace: Omitted variable bias in econometric research. *Conflict Management and Peace Science*, *22*(4), 341–352. https://doi.org/10.1080/07388940500339183

Davila, A., Foster, G., & Gupta, M. (2003). Venture capital financing and the growth of start-up firms. *Journal of Business Venturing*, *18*(6), 689–708. https://doi.org/10.1016/S0883-9026(02)00127-1

Delmar, F., & Shane, S. (2006). Does experience matter? The effect of founding team experience on the survival and sales of newly founded ventures. *Strategic Organization*, *4*(3), 215–247. https://doi.org/10.1177/1476127006066596

Galbreath, J. T. (2004). *Graduate School of Business Curtin Business School Determinants of Firm Success: A Resource-Based Analysis*.

Hoyt, W. T., & Leierer, S. (2006). *Analysis and Interpretation of Findings Using Multiple Regression Techniques*.

Kiviluoto, N. (2013). Growth as evidence of firm success: Myth or reality? *Entrepreneurship and Regional Development*, *25*(7–8), 569–586. https://doi.org/10.1080/08985626.2013.814716

Koch, M., Park, S., & Zahra, S. A. (2021). Career patterns in self-employment and career success. *Journal of Business Venturing*, *36*(1). https://doi.org/10.1016/j.jbusvent.2019.105998

Kurczewska, A., Doryń, W., & Wawrzyniak, D. (2020). An everlasting battle between theoretical knowledge and practical skills? The joint impact of education and professional experience on entrepreneurial success. *Entrepreneurial Business and Economics Review*, *8*(2), 219–237. https://doi.org/10.15678/EBER.2020.080212

Lombardo, G., Mazzocchetti, A., Rapallo, I., Tayser, N., & Cincotti, S. (2019). Assessment of the economic and social impact using SROI: An application to sport companies. *Sustainability (Switzerland)*, *11*(13). https://doi.org/10.3390/su11133612

Lussier, R. N., & Corman, J. (1996). A business success versus failure prediction model for entrepreneurs with 0-10 employees. *Journal of Small Business Strategy*, *7*(1).

Nahata, R. (2019). Success is good but failure is not so bad either: Serial entrepreneurs and venture capital contracting. *Journal of Corporate Finance*, *58*, 624–649. https://doi.org/10.1016/j.jcorpfin.2019.07.006

Parker, S. C. (2013). Do serial entrepreneurs run successively better-performing businesses? *Journal of Business Venturing*, *28*(5), 652–666. https://doi.org/10.1016/j.jbusvent.2012.08.001

Rocha, V., Carneiro, A., & Amorim Varum, C. (2015). Serial entrepreneurship, learning by doing and self-selection. *International Journal of Industrial Organization*, *40*, 91–106. https://doi.org/10.1016/j.ijindorg.2015.04.001

Shaw, K. L., & Sørensen, A. (2017). *The Productivity Advantage of Serial Entrepreneurs*.

Appendix

Regression Statistics	
Multiple R	0,549
R Square	0,301
Adjusted R Square	0,294
Standard Error	1,208
Observations	819,000

ANOVA

	df	SS	MS	F	Significance F
Regression	9,000	5,090E+02	56,561	38,759	0,000
Residual	809,000	1,181E+03	1,459		
Total	818,000	1,690E+03			

	Coefficients	;tandard Erroı	t Stat	P-value	Lower 95%	Upper 95%
Intercept	1,076	0,199	5,396	0,000	0,684	1,467
Number of founders or operational partners	0,143	0,043	3,342	0,001	0,059	0,227
Percentage of founders previously being entrepreneurs	0,081	0,119	0,681	0,496	-0,153	0,315
Percentage of founders with industry experience	0,343	0,138	2,485	0,013	0,072	0,613
Number of offices	0,409	0,048	8,496	0,000	0,314	0,503
Number of employees	0,016	0,002	6,493	0,000	0,011	0,021
Funding rounds since launch	0,242	0,042	5,761	0,000	0,159	0,324
Total amount of funds raised, including equity and debt? (in €)	0,000	0,000	1,859	0,063	0,000	0,000
Months since company incorporation	0,001	0,001	1,487	0,137	0,000	0,003
Yearly revenue	0,000	0,000	2,961	0,003	0,000	0,000

Table 9: Regression Output on EM Positioning

Regression Statistics	
Multiple R	0,144
R Square	0,021
Adjusted R Square	0,010
Standard Error	10982012,079
Observations	819,000

ANOVA

	df	SS	MS	F	Significance F
Regression	9,000	2,062E+15	229069040378546,000	1,899	0,049
Residual	809,000	9,757E+16	120604589312836,000		
Total	818,000	9,963E+16			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	-1646531,656	1870589,357	-0,880	0,379	-5318312,725	2025249,413
Maturity	-271737,839	257429,174	-1,056	0,291	-777045,733	233570,055
Number of founders or operational partners	336219,279	389346,981	0,864	0,388	-428030,165	1100468,723
Percentage of founders previously being entrepreneurs	575423,351	1083895,163	0,531	0,596	-1552155,171	2703001,873
Percentage of founders with industry experience	1403923,605	1256980,890	1,117	0,264	-1063405,005	3871252,214
Number of offices	629160,926	439932,950	1,430	0,153	-234383,749	1492705,601
Number of employees	44837,959	22439,645	1,998	0,046	791,166	88884,752
Funding rounds since launch	-203592,168	381606,402	-0,534	0,594	-952647,624	545463,287
Total amount of funds raised, including equity and debt? (in €)	0,108	0,078	1,385	0,166	-0,045	0,261
Months since company incorporation	681,344	8604,059	0,079	0,937	-16207,569	17570,257

Table 10: Regression Output on Yearly Revenue

Regression Statistics	
Multiple R	0,535
R Square	0,286
Adjusted R Square	0,278
Standard Error	17,165
Observations	819,000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	9,000	9,567E+04	10629,538	36,077	0,000
Residual	809,000	2,384E+05	294,631		
Total	818,000	3,340E+05			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	-11,669	2,896	-4,029	0,000	-17,354	-5,984
Number of founders or operational partners	1,745	0,606	2,881	0,004	0,556	2,934
Percentage of founders previously being entrepreneurs	-1,821	1,693	-1,075	0,283	-5,144	1,503
Percentage of founders with industry experience	2,614	1,964	1,331	0,184	-1,241	6,469
Number of offices	3,953	0,674	5,863	0,000	2,630	5,277
Maturity	2,045	0,396	5,162	0,000	1,267	2,823
Funding rounds since launch	2,039	0,592	3,444	0,001	0,877	3,202
Total amount of funds raised, including equity and debt? (in €)	0,000	0,000	9,634	0,000	0,000	0,000
Months since company incorporation	0,039	0,013	2,943	0,003	0,013	0,066
Yearly revenue	0,000	0,000	1,998	0,046	0,000	0,000

Table 11: Regression Output on Team Size

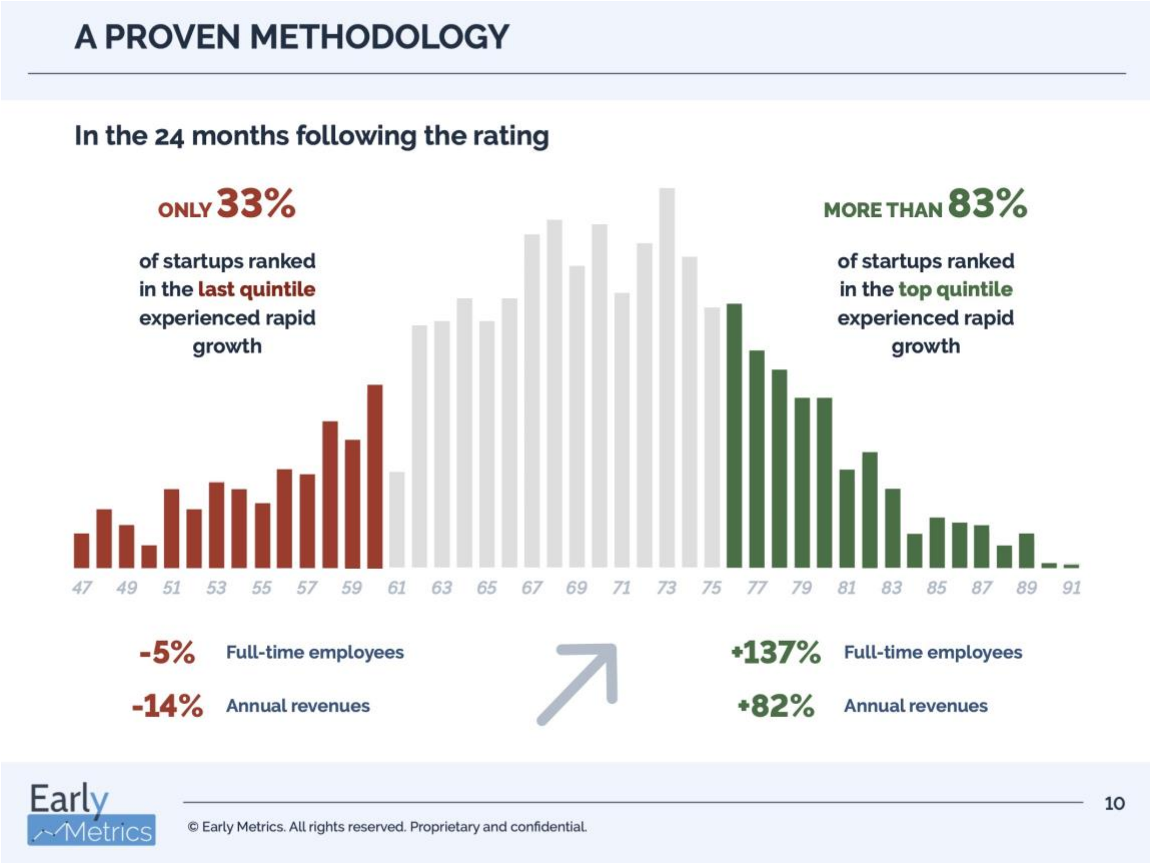

Table 12: Early Metrics Track Record

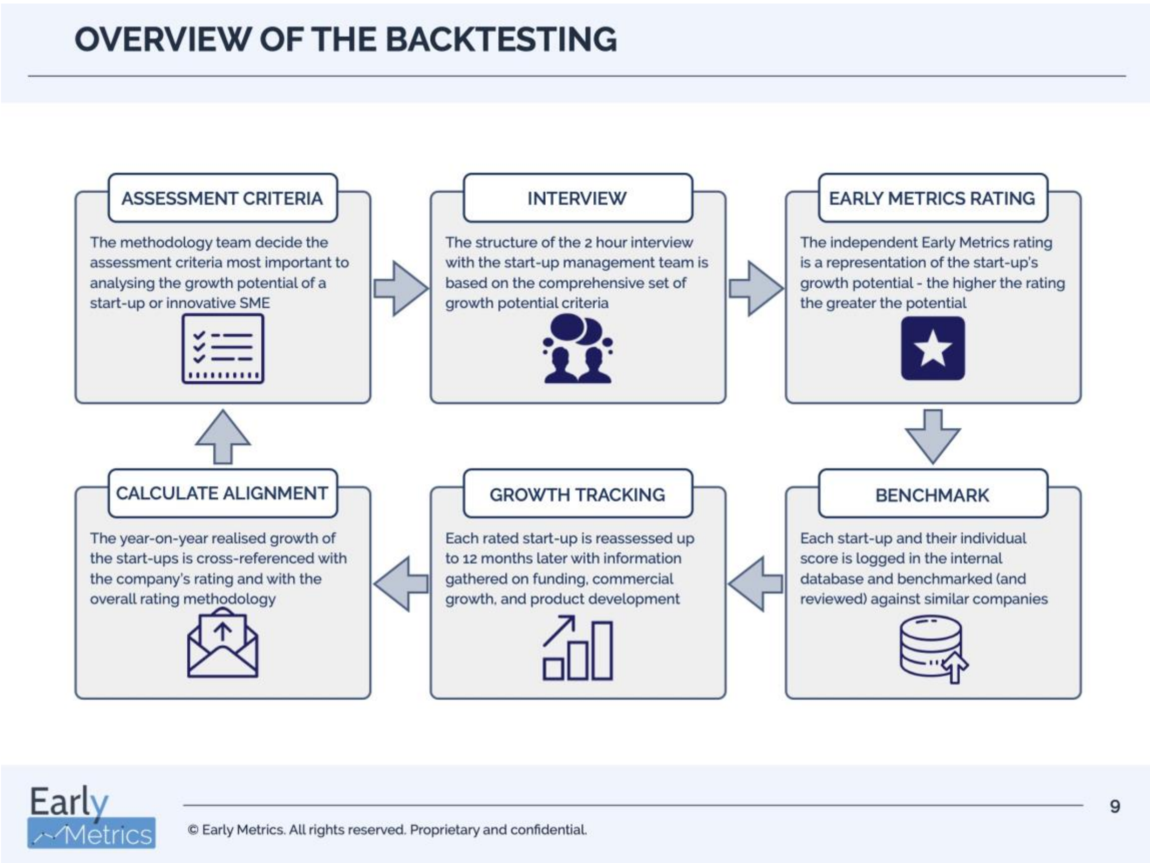

Table 13: Early Metrics Methodology

Affidavit

ESCP Europe

I, the undersigned, do hereby state that I have not plagiarised the paper enclosed and that I am the only author of all sentences within this text. Any sentence included which was written by another author was placed within quotation marks, with explicit indication of its source. I am aware that by contravening the stated ESCP Europe rules on plagiarism, I break the recognised academic principles and I expose myself to sanctions upon which the disciplinary committee will decide.

I also confirm this work has not previously been submitted during studies prior to ESCP Europe. If this work has been written during studies conducted in parallel to my time at ESCP Europe, I must state it.

I accept full responsibility for the content of this paper.

Sirius

Sirius Araya Alfons

13/05/2022