STUDYING THE CHARACTERISTICS AND EFFICIENCY OF VENTURE-CAPITAL FUNDED STARTUPS

By

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ABSTRACT

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Every year more than 500,000 startups are created and less than 1,000 of those receive venture capital funding. Increasing the number of successful startups can lead to more jobs in the economy and improve innovation across industries. Previous research has attempted to determine characteristics of successful startups and has found that Human Capital, Structural Capital, and Social Capital have the most impact on the success of a startup. This thesis examines the quantitative characteristics of successful startups by calculating efficiency scores of startups using Data Envelopment Analysis (DEA). This thesis also uses the Boston Consulting Group Matrix as an additional tool of analysis to relate other characteristics of startups with their efficiency scores. Two Case Studies are also performed on one of the most efficient startups and one of the least efficient startups in the sample. The results of this thesis show that the most startups are relatively inefficient, however, the highest performing startups focus on human and structural capital rather than social capital. Entrepreneurs, investors, and others in the startup industry can learn from this thesis which variables impact startup efficiency and which industry impacts efficiency the most.

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Chapter 1
Introduction to the Startup and Venture Capital Ecosystem

Most startups fail within the first three years. Every year more than 500,000 startups are created and less than 1,000 of those receive venture capital funding (Libres, 2017). After venture capital funding, only a handful of startups end up reaching an Initial Public Offering (IPO). Startups can fail for a variety of reasons such as bad product-market fit, poor team management, little team experience, and lack of capital. Increasing the number of successful startups can lead to more jobs in the economy and improve innovation across industries. However, failed startups can lead to wasted opportunity costs for entrepreneurs and financial losses to themselves and investors.

Previous research has attempted to determine characteristics of successful startups by using semi-structured interviews, surveys, and case studies. These studies have found that human capital, structural capital, and social capital are the most influential on the success of a startup. However, most of the previous literature used small sample sizes, limited qualitative analysis, and have been outdated by the rapidly moving tech industry. This thesis will analyze characteristics of successful startups using Data Envelopment Analysis (DEA), Boston Consulting Group (BCG) Matrix Analysis, and Case Studies. Finding characteristics of successful startups can help entrepreneurs adapt their startups to become more successful in a highly competitive market and investors to know what to look for when investing in a startup.

This thesis explores characteristics of successful startups in three phases. In the first phase, this thesis calculates an output-oriented DEA efficiency scores for all startups in the sample. The sample consists of startups that are between 3-5 years old, have received at least one investment, have publicly available information, and are in the San Francisco Bay Area / Silicon Valley area. We assume that the goals of the startups in the sample are to grow rapidly, become profitable, and either merge, be acquired, or IPO in the future. To quantify human capital, structural capital, and social capital, this thesis includes the following input variables for the DEA Model: Number of Founders, Number of Current Employees, and Acquisition Score. Statyon and Mangematin (2016) and Rea (1989) show that human capital is the strongest indicator for a startup's success. This thesis uses the Number of Founders as a proxy for human capital and the Number of Employees as a proxy for structural (organizational) capital. The Acquisition Score also reflect the structural capital of a startup and is explained in section 3.2. For the output variables, this thesis uses the following outputs: Monthly Internet Hits, Estimated Annual Revenue, Total Amount of Funding Received, Number of Investors, and Average Funding per Investor. There are two variants of funding received. The first one is Total Amount of Funding. The second one is a combination of Number of Investors and Average Funding per investor. The second variant captures the confidence in potential success investors have on the startups and their willingness to take risk, which is not captured by the first variant. These two variants of funding received are used alternately in the DEA model.

In the second phase, this thesis relates several characteristics of startups with their DEA efficiency scores using a Boston Consulting Group (BCG) Matrix as a tool. Examples of characteristics are the number of press articles written about a startup or the number of startup conferences that a company has attended. Relating characteristics of startups with efficiency scores enables us to categorize startups and gain insight on how current and future startups can improve. In the third phase, this thesis performs in-depth case studies of two hand selected startups comparing one of the most efficient startups and one of the least efficient startups. Each case study will look beyond the DEA scores and look into the founders history, company history, and organizational style.

The rest of this thesis is broken down into 4 chapters which include the review of previous literature, methodology and data, empirical results, and the conclusion. In Chapter 2, this thesis covers the previous literature of startups. Previous research of startups have tested various characteristics of successful startups, created startup stage models to measure startup progress, and have used different methods to predict future company success. In Chapter 3, this thesis covers the methodology that are used to create the results. This chapter serves as an introduction to each of the analyses: Data Envelopment Analysis (DEA), Boston Consulting Group (BCG) Matrix Analysis, and Case Studies. It covers the basic analysis and how the respective technique is applied to startups in this thesis. In Chapter 4, this thesis discusses the sample and presents empirical results. The findings are broken down into DEA, BCG Matrix Analysis, and the Case Studies. Data Envelopment Analysis is a foundation for the BCG Matrix Analysis and the Case Studies. The BCG Matrix Analysis provides a big picture of how different startup characteristics compared to startups' efficiency scores. The Case Studies then looks in-depth into successful startups and un-successful startups to get a complete understanding of different characteristics. Finally, Chapter 5 concludes by summarizing the findings and implications of this thesis and mentions ideas for future research in this field.

Chapter 2

Previous Research on Startup Characteristics and Success

Most of the previous studies of startups and entrepreneurs have tested characteristics of successful startups which fall into the three major areas: Human Capital, Social Capital, and Structural Capital. Human Capital is made up of the characteristic of the entrepreneurs and their team such as Entrepreneurial Motivation, Team Composition, and the Number of Founders. Social Capital refers to the network around the startup team and includes other factors such as Reputation, Business Relationships, and Alliances. Finally, Structural Capital is the processes used to go from a startup's current state to their desired state using organizational decision-making and resource allocation. These studies have found that characteristics in these three areas are highly correlated with startup success. Previous research has also measured startup progress by creating startup stage models. A startup stage model shows various stages that a startup must go through to eventually become successful. Finally, startup success is not permanent, so several studies have used different variables to predict long-term success from initial success.

2.1 Human Capital

When a company is first started, its main assets is often human capital because the startup often has little funding and connections compared to a well-established company. Reis (2017, p. 28) states that "a startup is greater than the sum of its parts; it is an acutely human enterprise." Human Capital, such as entrepreneurial traits in founders, was highly correlated with success of startups in previous studies. Previous research has also tested Human Capital characteristics such as Team Composition, Number of Founders, Skill Sets, and Entrepreneurial Motivation.

Statyon and Mangematin (2016) found that the dynamic in Team Composition is important. In order to build a product or service and scale fast, the initial founder needs to know the initial members well and trust them. They also found that strategic leadership, innovative spirit, and team cohesiveness were some of the more important subjective characteristics in Human Capital. Xiao and Zhao (2012) found that characteristics of human capital like Team Complementation and Entrepreneur Personal Charisma are important factors in startup success. Romans (2013) found that many venture capitalists also look for a balanced team, which includes a visionary, technologist, and a sales person previously worked together when investing in startups. This agrees with the findings of Statyon and Mangematin (2016) of team composition and team dynamic.

Rea (1989) focused on entrepreneurial characteristics such as Family Self-Employment, Management Experience, and Education. He found that family self-employment has been linked to entrepreneurial values and motives. He also found that a higher degree of education of an entrepreneur has been linked to higher startup success rates. He concluded that four years of education, family business background, and age are the best indicators for startup success.

Human Capital has been found to be one of the most important factors in a startup's success. It is a startup's main resource at the beginning. These studies have identified aspects of Human Capital that are linked to success, but most of the variables used were not quantifiable.

2.2 Structural Capital

Another area that most of startup research has studied is the effects of Structural Capital. Startups are unique compared to well-established firms in the market because they must have product and organizational emergence in order to be successful. Reis (2017) found that startups use different kinds of innovation such as scientific discoveries, repurposing an existing technology, or creating a new business model to achieve product emergence. Some studies, such as Xiao and Zhao (2012), have looked into specific organization techniques while other studies, such as Statyon and Mangematin (2016), have looked at product and organizational emergence timelines.

Xiao and Zhao (2012) found that organizational decision-making influences strategy for innovation and resource allocation. A shared vision and atmosphere for democracy are important to create organizational emergence. They also found that startups should focus on market innovation and product innovation to sustain competitiveness in the market which agrees with the findings of Reis (2017). Statyon and Mangematin (2016) found that Entrepreneurs in the Computer and Technology Industry set ambitious self-constructed timeline intervals for products and set the activities required to achieve those timelines in order to be successful. They found that many other industries could copy practices used from the computer and technology industry.

Structural Capital is important for a startup to grow efficiently and scale beyond a few members to a well-established company. These studies give insight on how organizational and product emergence is important for a startup to succeed, but do not contain quantifiable measurements that can be used.

2.3 Social Capital

Startups often have very little connections, business relationships, alliances, or funding options, and thus Social Capital factors are a major limiting factor for most startup. Xiao and Zhao (2012) found that the bottleneck for most startups is Social Capital because they do not have a broad social network like a large corporation i.e. reputation, relationships, alliances, etc. However, they found that relationships with related organizations, incubators, investor networks, and other startups can help grow and increase their network and Social Capital. Tello, Yano, and Latham (2012) studied how entrepreneurs use their networks around them to increase their chances of their startup's survival. They found that entrepreneurs with more networks have more access to technical resources, exposure, funding resources, and additional networks. They found that incubators helped grow a startup's network and increased their Social Capital. Cohen (2013) found that it is tempting for startups to take any money they can get from investors; however, the source of the money can provide counsel, contacts, and other benefits that outweigh the money. Romans (2013) found similar results and saw that investors have years of experience in helping others, extensive networks, contacts, and an understanding of how to succeed.

Social Capital is often a limiting factor for most startups but having a good network can increase a startups resources and survival. Most of the previous research has found that larger networks benefit startups, but do not have a quantifiable measurement for this.

2.4 Startup Stage Models

Startups across different industries share a common path to become a public company, merged, or acquired. Startups move along different stages in their lifecycle that are not linked to time, but monetary or company milestones. Many studies have created startup stage models to represent these stages that can be applied to all startups; however, there is no consensus for one startup stage model. Most studies have created their own ranging between 3 and 6 startup stages. Romans (2013) found that successful venture capital backed companies raise an average of 3-7 Venture Capital (VC) funding rounds. A standard VC defined startup stage model measure the success of a startup in the following stages: Seed Stage, Startup Stage, First Stage VC Funded, Second Stage VC Funded, Third+ Stage VC Funded, and IPO. The Venture-Capital startup stage model is a common standard to measure progress through funding rounds. However, other literature has created other startup stage models to expand research areas.

Much of the previous literature divides stages by internal company goals and expansion. Gaibraith (1982) created a 5-stage model that ranges from Proof of Principle, Prototype, Start-up, Natural Growth, and Strategic Maneuvering. Martin (2018) created a startup stage model that is broken down into 4 stages: The Tinkering Period, The Blade Years, The Growth Inflection Point, and Surging Growth. The Blade Years represent a period of time after an idea has been formed, but the growth is unpredictable, and the startup's future is rocky. Martin (2018) found that if startups can make it past The Blade Years, they are likely to continue their initial success. Each startup stage model goes from idea or inception to profitability or an IPO and moving along each stage fast is an initial indicator for future business success.

For this thesis, a VC defined Startup Stage Model will be used to show progress of startups that are in the sample given the quantitative analysis. During BCG Analysis in Chapter 4.2, startups in the sample will be analyzed to see relationships between efficiency and funding rounds (VC Startup Stage Model).

2.5 Measuring Startup Success

Success for a startup means that the company is still active and is growing; however, this is only a prediction of future company success. Previous studies such as Stuart and Abetti (1987) have measured startup success objectively and subjectively in a short amount of time in order to predict future company success. Most researchers agree that after a startup passes a certain point, success is much higher than when starting the company.

Stuart and Abetti (1987) measured success using an objective and subjective outcome based on interviewed startup members. Subjectively measuring success asks if the members felt the startup was successful, and objective measures include Sales and

Employment Growth, Profitability, and other variables. Omri and Boujelbene (2018) defined success as tangible items such as Revenue, Firm Growth, and Profitability while Statyon and Mangematin (2016) looked at startup success as a combination of profitability, internationalization, product emergence and organizational emergence. Romans (2013) found that Mergers and Acquisitions are the most common exit for a startup, and the best advice for selling their startup is to focus on building a great company with strong revenue growth and happy customers and partners. Some common startup buyer hierarchies are Team Hires, Team Buys, Technology Buys, Business Assets, and Strategic Assets. Startups that focus on their revenue, organizational structure, and customers can increase their buyout or IPO value, which leads to future company success. Previous research has used semi-structured interviews and surveys to get their data. However, quantifying some of the variables for startup success and looking at a larger data set could lead to different results than the previous literature.

2.6 Previous Literature Conclusion

The previous literature has done a great job of mapping characteristics of successful startups into the three main areas: Human Capital, Structural Capital, and Social Capital. Some Human Capital characteristics that are considered in this thesis include Number of Founders, and Number of Employees. Two quantifiable ways to measure Structural Capital are the Number of Acquisitions. Larger and higher number of acquisitions is a proxy for good Structural Capital and should lead to higher outputs.

Since startups often have limited networks, the majority of their Social Capital comes from their investors' network. A well-established venture capital firm with numerous investments can provide more help than a first-time angel investor. These variables provide quantifiable measurements that have been limited in previous research.

Research in this field has been limited to surveys, case studies, interviews, and regression analysis. Using Data Envelopment Analysis technique to analyze startups can provide a different perspective. In addition, some of the previous research may be outdated in the rapidly evolving startup world and conducting research on recent startups may shed a new light to understand success or failure of startups.

Chapter 3

Methodology behind the Analysis

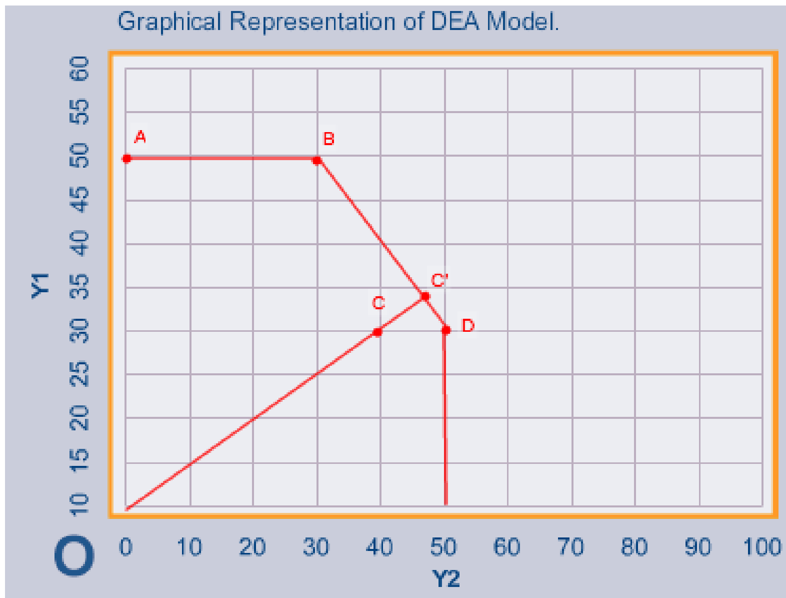
This thesis analyzes startups in the sample using three techniques: Data Envelopment Analysis, Boston Consulting Group Matrix Analysis, and Case Studies. This chapter gives an introduction to the basic foundations of each method, how they relate to this thesis, and how each will be performed.

3.1 Data Envelopment Analysis

A basic efficiency score of a company that has one input and one output can be measured by dividing its output by its input. However, when there are multiple inputs and outputs, Data Envelopment Analysis can calculate the efficiency scores. Data Envelopment Analysis (DEA) is a linear programming model that measures the efficiency of Decision-Making Units (DMUs) with respect to their multiple inputs and outputs. The reciprocal of the dual LP formulation efficiency scores ranges from 0 to 1, where an efficiency score of 1 is the most efficient in the set. DMUs that are inefficient receive efficiency scores less than 1. This thesis uses the reciprocal of the dual LP formulation for DEA following other previous economic DEA research published.

While performing DEA, an efficient frontier is created which is a subset of the perfectly efficient DMUs in the set. DEA calculates an efficient frontier of DMUs while calculating relative efficiency scores for inefficient DMUs. DEA can be used with an output-oriented approach or an input-oriented approach to produce the most efficient outputs by adjusting their outputs, given the available inputs or the most efficient inputs by adjusting their inputs to produce the predetermined level of outputs. This thesis uses an output orientation to determine how startups could possible utilize their inputs to maximize their outputs.

Figure 1: DEA Graphical Representation



To represent the DEA in a graphical example, Figure 1 illustrates a DEA model with an output-oriented approach. Efficient DMUs will be on the frontier and inefficient DMUs will be under the frontier. DMUs A, B, and D are all on the efficient frontier so they will have a relative efficiency score of 1. Since DMU C is not efficient in Figure 1, the score is calculated by OC/OC', which is less than 1. Let's say DMU C's efficiency score equals 0.7, therefore it is currently 70% efficient compared to its efficient peers given that it is only producing 70% of the observed maximum. It also can be seen that in order for DMU C to be efficient they must roughly increase output Y2 by 7 and output Y1 by 4. DMU B and DMU D are efficient peers for DMU C. This example is similar to a production possibilities frontier given two outputs and one input, however, in this thesis there will be multiple inputs and outputs so we cannot graph it in two-dimensions.

Date Envelopment Analysis for this thesis is calculated using a program called DEAP. The algorithm used to compute efficiency score for each DMU can be represented mathematically in Equation (1). Let X be a matrix of the inputs of all DMUs and Y is matrix of the outputs. In each matrix, each row is an input or output and each column is a DMU. These matrices, X and Y, are used to create an efficient frontier *T = {(X, Y) | outputs Y can be produced from inputs X}* for a sample of DMUs. Let x_j and y_j be an input and output column vector for DMU *j*. The production technology exhibits Variable Returns to Scale, i.e., it does not require that each DMU must operate at the optimal scale or a proportional change for inputs must result in a proportional change in outputs. This is represented by $e\lambda = 1$ in Equation (1) where *e* is a row vector of one for all DMUs and λ is a column vector of DMU weights when constructing efficient frontier to evaluate DMU *j*.

Equation 1: DEA LP Formulation

$$\begin{gathered} Max\ [\Theta_j]^{-1} s.t. \\ X\lambda\ \leq x_j \\ \Theta_j Y_j - Y\lambda\ \leq 0 \\ \lambda\ \geq 0 \\ e\lambda = 1\ (VRS) \end{gathered}$$

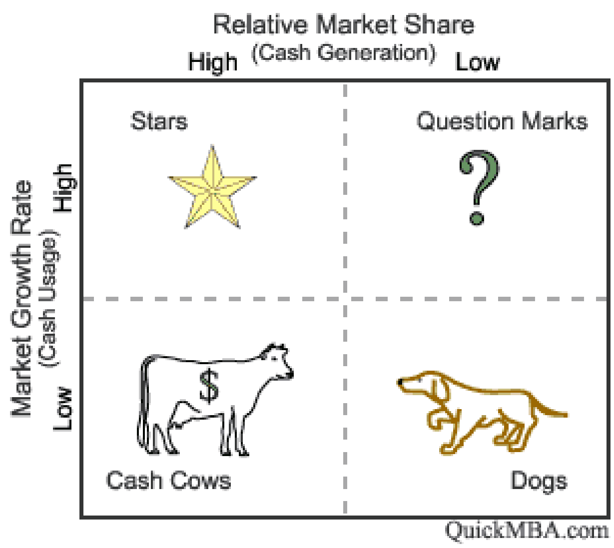
In this thesis, startups will be considered Decision-Making Units using an output-oriented Data Envelopment Analysis. To measure inputs for each startup, this thesis uses the following qualitative inputs: Number of Founders, Number of Employees, and Acquisition Score. To measure outputs for each startup, this thesis uses the following qualitative outputs: Estimated Revenue, Monthly Traffic, and Total Amount of Funding in the first model and Number of Investors and Average Fund with the first two output measures in the second model. Two models are used to show the difference between efficiency scores if a startup is just looking to just get money, measured by the total amount of funding, or for a larger and powerful investor network, measured by number of investors and average amount per investor. Since there are multiple inputs and outputs for each startup, we can use DEA to calculate the efficiency scores for each one.

The DEA model for this thesis does not factor in social capital for a startup given the data is categorical. However, further analysis will be conducted on social capital in the BCG Analysis section. DEA allows a startup efficiency frontier to be formed with the most efficient startups and identifies efficient peers for which inefficient startups can learn from. Inefficient Startups will have efficient peers that are the most similar to their inputs and outputs which can help understanding how these startups can improve. The results of the DEA performed in this thesis are discussed in Chapter 4 Section 2.

3.2 Boston Consulting Group Matrix

The BCG Matrix was originally created by Boston Consulting Group to analyze the quality of a company's product portfolio and its potential to grow. The original matrix analyzes a company's product by using a grid with relative market share on the X axis and market growth on the Y axis which was then divided into a 2x2 grid. Analyzing a company along these two axes provides insights on opportunities and problems for a company. Figure 2 displays the original BCG matrix where the four quadrants are: Stars, Cash Cows, Question Marks, and Dogs. Stars have rapid growth and dominant market share; these products are great and can only become an issue if the market stops growing since they require a large burn rate. Cash Cows have a high dominant position and low market growth which allows them to make income while not costing much. Dogs have low market share and low growth; the products are making a loss or very low profit which may need to divest. Problem Childs have low market share and high market growth; it can be the case for a new product on the market but is bad for well-established companies.

Figure 2: BCG Matrix



This thesis borrows the BCG matrix technique to analyze startups. Specifically, the modified BCG matrices measure different variables and group them into categories to find new insights and possible opportunities for startups. In a modified BCG Matrix, one axis will have startup efficiency scores calculated from DEA, and the other axis will be related startup characteristic. Since the DEA model does not include categorical variables or dummy variables, BCG Matrix analysis includes these other related factors to have a more complete picture of the startups in the sample. Several other modified BCG Matrices are used in this thesis to analyze variables such as incubator status, founding date, IPO status, For Profit, and Location. The results of the modified BCG Matrices appear in Chapter 4 Section 3.

3.3 Case Studies

After Data Envelopment Analysis and Boston Consulting Group Matrix Analysis, this thesis conducts Case Studies on two select startups to gain more in-depth understanding of startups' performance that could lead to success or failure. The first Case Study will look into one of the most efficient startups in the sample. The second Case Study will be of one of the least efficient startups in the sample. By conducting Case Studies on these startups, entrepreneurs, investors, and others will have a greater understanding of why these startups fell into these categories and how to improve upon them. In each Case Study, this thesis will review the company's founder history, investor history, and recent new articles in order to find what made them successful or not. After conducting a Case Study on a startup, this thesis provides lessons from that startup that future entrepreneurs can use in their own business.

Chapter 4

Analysis of Startups in San Francisco Bay Area and Silicon Valley

This chapter applies the methodologies discussed in Chapter 3 to a sample of startups in the San Francisco Bay Area and Silicon Valley. Section 4.1 discusses how the data was captured, transformed, and used to produce the results. The results of the Data Envelopment Analysis are covered in Section 4.2. This section explores what is different between the most efficient startups and the rest. Boston Consulting Group analysis is covered in Section 4.3. Several other social capital factors that were not included in the DEA model are compared with startup efficiency scores to categorize the startups. Finally, Section 4.4 presents two case studies of one the most efficient startups and one of the least efficient startups.

4.1 Data

For startup information including quantitative and qualitative metrics, this thesis uses Crunchbase, Owler, SimilarWeb, and LinkedIn as data sources. These websites provide the most up to date and accurate information for startup companies around the world. These websites are constantly updated with the most up to date information for these private companies. Crunchbase provides the majority of the data used for this thesis and is an online database for startup information across the world. Owler provides estimated revenues, number of competitors, and other information not on Crunchbase. SimilarWeb provides information on startup's monthly website traffic, app traffic, and technology stack. Finally, LinkedIn provided more information on startup founders, company information, and more qualitative information used in the Case Studies.

This thesis analyzes startups that are three to five years old as of the date of recording, May 23, 2019. Specifically, this thesis conducted research on startups that were founded between January 1st, 2014 to January 1st, 2016. These startups must also have publicly available information on Crunchbase and must have received at least one Venture Capital (VC) investment. From the 3,889 startups in the United States that met this criterion, this thesis selects 757 startups (31% of the US startups); all were founded in the San Francisco Bay Area and Silicon Valley. This thesis focuses on startups in this particular region for a number of reasons. First, this region is the biggest hub for new startups in the US since computer revolution in the 1950's. Second, it represents some of the leading startups in the country. Third, startups in this region are typically more developed and have access to more resources than other places in the United States. Fourth, by focusing on one small area, it reduces possible effects of different laws, cultures, and economies.

For each of the startups in the sample, the number of founders, the number of employees, the number of acquisitions, the number of investors, the total amount of funding received, the monthly website hits, and the estimated revenue were recorded. The number of founders represents the number of people that created the company and have the most impact on culture and human capital. The number of employees represents the number of people currently working for a startup at the point of recording and represents structural (organizational) captial. The number of employees appears on Crunchbase as interval, i.e. 1-10, 101-250, etc. and is converted into a single number to be used in this thesis. This thesis uses the average value of each interval for the number of employees for the startup. For example, suppose a DMU is reported to have employees between 11 and 50 persons, this thesis uses 30.5 persons as the number of employees.

The number of acquisitions refers to the number of other startups that the recorded startup acquired. Since DEA in general cannot handle zero values, this thesis follows Mohamud and Said (2011) by converting the observed number of acquisitions for DMU *i* into the acquisition score as follows:

$$\text{Acquisitions score}_i = \frac{9*(X_i - X_{min})}{X_{max} - X_{min}} + 1$$

Where X_i is the observed number of acquisitions for DMU *i*, X_{min} is the smallest number of acquisitions for all DMUs in the sample, and X_{max} is the largest number of acquisitions for all DMUs in the sample. Acquisitions score takes a value between 1 and 10. Number of founders, number of employees, and acquisitions score are three inputs used in this thesis' DEA model.

There will be two models with different output measures. Model A contains three outputs: Total Amount of Funding, Estimated Revenue, and Monthly Hits. Model B has four outputs: Number of Investors, Average Funding per Investor, Estimated Revenue, and Monthly Hits. Both models differ in how startups raise money. Model A only focuses on the amount of money raised regardless of number of investors involved. In contrast, Model B not only captures the investor network, but also the average money that investors give to startups on average. Assuming that the investor network is positively related to the number of investors; the higher number of investors, the larger the investor network and the larger their social capital is.

The Number of Investors refers to the total number of venture capital investors that funded a startup in the sample. The Total Amount of Funding is the total amount of money that a startup has received from investors during funding rounds. The Average Amount per Investor is the Total Amount of Funding divided by the Number of Investors which shows the strength of the average investor. The monthly website hits refer to the amount of traffic the startup's website received for the month before the data was collected. This shows how many active people visit the startup and potentially use their product. This metric is recorded by a third-party analyst and it is nearly impossible for a company to boost this statistic significantly. Finally, the estimated revenue refers to the Owler estimated revenue for a given startup in the sample. One caveat of the study is that most of the startups do not post their financials online because they are private companies. The Owler estimated revenue is the most accurate way for measuring revenue. All these variables comprise the outputs for the Data Envelopment Analysis in a quantifiable and useable way that accurately represent the startups.

After recording the data of the startups in the sample, outlier analysis was performed to achieve the 757 startups that are used in the DEA Analysis. Removing the extreme values in the dataset leads to a better model fit and overall higher accuracy. Startups were chosen for removal by containing an attribute or DEA result that is extreme when compared to the rest of the dataset. These outliers could be truly efficient startups or be because some of the data is inaccurate, however they negatively affect the rest of the model. Of 792 startups that met the original requirements, 35 startups were removed. Both Model A and Model B use the same sample of 757 startups in the San Francisco Bay Area.

4.2 Data Envelopment Analysis

Table 1 presents descriptive statistics of input and output variables used in the DEA models. As previously discussed, this thesis computes output-oriented DEA efficiency scores for all startups in the sample using two models: Model A and Model B. Both models include three inputs: Number of Founders, Number of Employees, and Acquisition Score. Model A includes three outputs: Total Amount of Funding, Estimated Revenue, and Monthly Hits. Model B replaces Total Amount of Funding in Model A with Average Funding per Investor and Number of Investors. Hence, Model B includes four outputs. Table 2 presents summary efficiency results from both models. Figure 3 shows a scatterplot of the startups with their efficiency score from Model A and Model B to gain a better understanding of the distribution from both models.

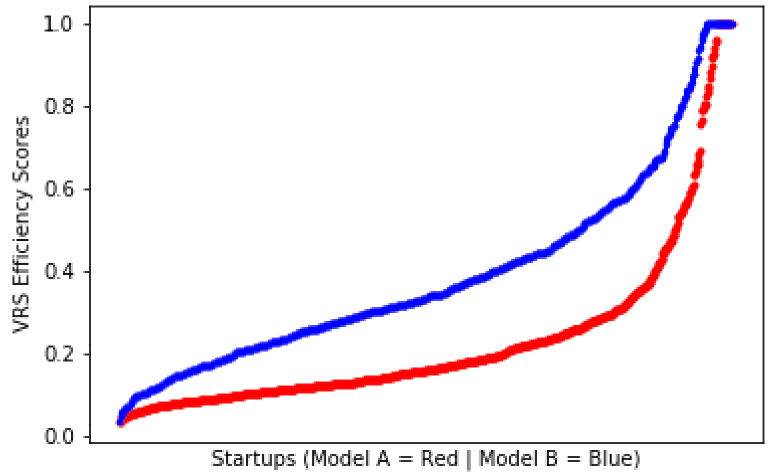
Table 1: Summary Statistics of Input and Output Measures (N = 757)

Variable Name	Average	Standard Deviation	Minimum	Maximum
Input Measures				
Number of Founders	2.33	0.99	1	6
Number of Employees	49.71	74.41	6	751
Acquisition Score	1.34	1.35	1	10
Output Measures				
Total Amount of Funding (Million $)	26.39	52.21	0.03	790
Estimated Revenue (Million $)	3.94	8.76	0.00	140
Monthly Website Hits (Thousands)	155.55	816.33	0.03	12,276.32
Number of Investors	7.22	5.45	1	39
Average Amount of Funding per Investor (Million $)	4.27	8.85	0.01	124.03

Table 2: Output-Oriented Efficiency Scores

	Model A	Model B
Average	0.21	0.39
Standard Deviation	0.21	0.23
Number of Efficient Startups	21	33

Figure 3: Model A vs Model B Distribution of Efficiency Scores (Both Sorted)



On average, startups in our sample are relatively inefficient. The average efficiency scores are 0.21 for Model A and 0.39 for Model B. Model B has a larger efficient frontier than Model A containing 33 startups compared to 21 startups. In fact, Model B's efficient startup frontier is mostly comprised of Model A's frontier by sharing 19 of the same startups. As predicted by the theory, efficiency scores from Model B are higher than the corresponding scores from Model A since Model B includes more outputs. However, the distribution of efficiency scores differs between the two models which can be seen in Figure 3. In Figure 3, sorted Model A and Model B are overlapped in the same graph to show the different distribution patterns. This implies that Model B more accurately represents the sample given that some startups can go for higher amount of funding per investor, higher number of investors, or both. A rank-order correlation test was performed to compare Model A and Model B's efficiency scores which can be found in Appendix 1-E. The results show that there is a 63% correlation between both model's efficiency scores and is statistically positive at the 1% level. This implies that each model's results do not differ from each other significantly and a single model can be used to interpret the results of both. The rest of this thesis will focus on Model B, for the results of Model A please refer to Appendix 2.

Next, the efficient frontier of 33 startups in the sample is compared to the top 10 least efficient startups in the sample. Table 3 and Table 4 show the differences between the Model B's set of the efficient startup frontier and the set of the 10 least efficient startups. Comparing the two tables, the number of founders and acquisition score changes very little between the two sets implying that these variables do not affect the efficiency very much. The average number of employees is generally higher in efficient startups, 128 employees compared to 28 employees. The most efficient startups seem to have expanded their number of employees and maintained their culture and values while growing. The efficient startups outperform their least efficient counterparts greatly in output. The efficient startups have far more monthly website hits than their average or worst peers. This is a result of the startup's focusing on their product to attract customer to their website. The large variation of monthly hits in the efficient set occurs because some startups are not internet companies and their business doesn't revolve around their website. These efficient startups also received a greater number of investors and average funding per investor within the same time period. This shows that the efficient startups progressed faster with their investments than their non-efficient peers. Progressing through funding rounds and gaining more investments involves more effort to attract investor and good employees but allows the startups to have quicker expansion if properly managed.

Table 3: Model B Efficiency Frontier Descriptive Statistics

N=33	Average	Standard Deviation	Minimum	Maximum
Number of Founders	2.21	1.24	1	6
Number of Employees	122.92	196.34	6	751
Acquisition Score	1.41	1.73	1	10
Number of Investments	12.45	10.72	1	39
Monthly Website Hits (in thousands)	1484.80	3285.49	0.13	12276.32
Estimated Revenue (in millions $)	17.07	32.06	1.00	140.00
Average Funding Per Investor (in millions $)	16.77	31.03	0.14	124.03

Table 4: Model B Top 10 Least Efficient Startups Descriptive Statistics

N=10	Average	Standard Deviation	Minimum	Maximum
Number of Founders	2.30	1.34	1	5
Number of Employees	28.50	7.91	6	31
Acquisition Score	1.90	1.90	1	5.5
Number of Investments	1.10	0.32	1	2
Monthly Website Hits (in thousands)	14.36	27.55	0.13	89.66
Estimated Revenue (in millions $)	0.70	0.47	0.08	1.25
Average Funding Per Investor (in millions $)	0.70	0.95	0.05	2.50
VRS Score	0.06	0.01	0.04	0.07

After running DEAP, further analysis was performed on the acquisition score variable. Since there are only a few numbers of startups in the sample that acquired another company, another DEA model was performed to calculate efficiency scores without using acquisition score as an input. Then rank-order correlation analysis was performed; the results show that there is a 99% correlation between the efficiency scores between the two models and the result is statistically significant at the 1% level.[1] The results of the rank-correlation analysis can be found in Appendix 1-F.

Each startup in the sample is categorized under multiple industries by CrunchBase. Through Python data processing, the mean efficiency score for each industry is calculated by categorizing the efficiency scores with the associated industries then taking the mean for each industry. In Figure 4, each industry is plotted with their mean efficiency score to show the distribution and industry information. The industry size distribution, descriptive statistics, top 10 efficient industries, and top 10 least efficient industries are all found in Appendix 3. The distribution of the industries' mean efficiency scores ranges between 0.29 and 0.41 and has a low standard deviation. The industry size distribution ranges greatly in the sample given that some industries are very broad such as software and others are very specific.[2] The results of these figures imply that the top industries allow startups in them to proceed through funding rounds faster because of their demand and/or product type. The worst performing industries tend to have longer product timelines and more competition which makes them

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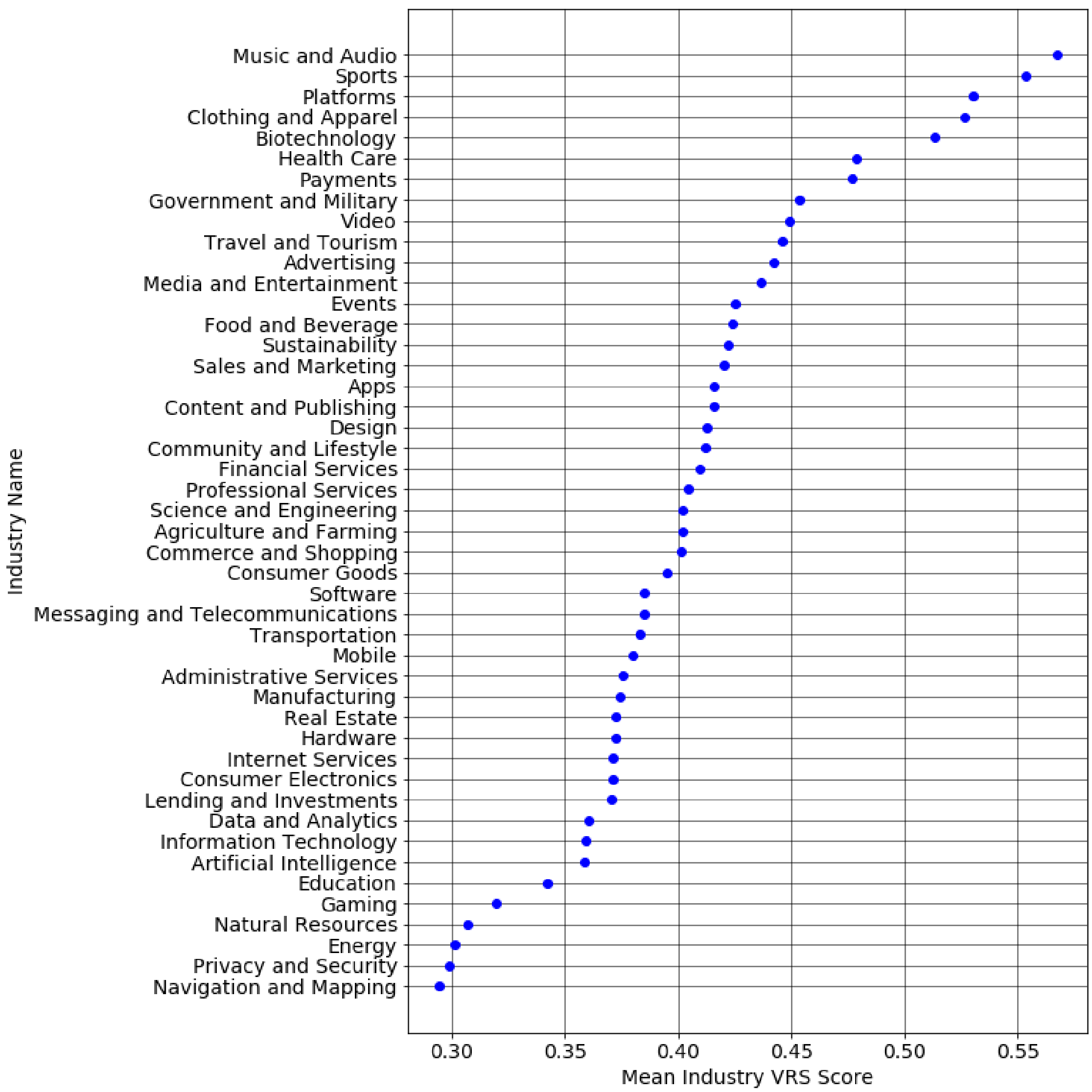
[1] Note: The acquisition score input variable does not have statistical significance affecting efficiency score. However, including it in the model adds to the overall understanding of the characteristics of the startups.
[2] Note: Rank-Order Correlation Analysis was done to compare the industry mean efficiency scores and the industry size. The result showed that the there is a -0.26 correlation between them but was this was not statistically significant at the 5% level.

progress slower than their efficient peers. Entrepreneurs who are looking for a new business or Venture Capital Funds that are looking to invest can gain a better understanding of the industries by looking at their efficiency scores. Overall, the industry score distributions show that a startup's success could already be biased by the field they are in.

Figure 4: Mean Industry Efficiency Scores

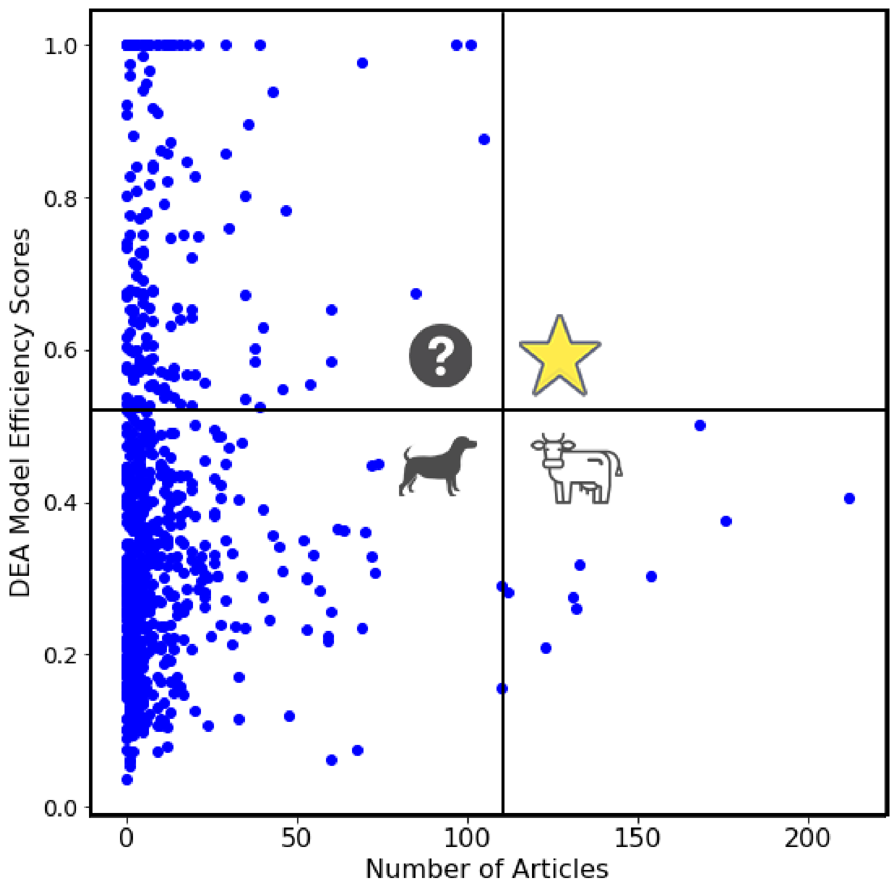


There are several takeaways from the DEA results. First, the startups in the sample are relatively inefficient. The efficient startups in the sample have an overall higher output and number of employees compared to their average or least efficient peers. The most efficient startups also progress through a higher number of funding rounds in a similar time span which gives them more investment opportunities. Second, these efficient startups grew their organization faster by increasing their number of employees while still maintain a high level of efficiency. This implies a company has a strong organizational capital given that they can expand their employees while still being efficient. Finally, the industry that a startup is in may have an impact on the startup's product demand and competition. The mean efficiency score of an industry can be seen as an proxy for an industry's speed. Overall Model A and Model B were found to be statistically correlated and thus only one model needs to be analyzed. This thesis will continue to use the efficiency scores from Model B in the following Boston Consulting Group Analysis and in the Case Studies.

4.3 Boston Consulting Group Matrix Analysis

In addition to Data Envelopment Analysis, modified Boston Consulting Group Matrices are created to further analyze social variables alongside startups' efficiency scores. Modifying a BCG Matrix provides insight on social factors and how they relate to efficiency scores. The original BCG Matrix as previously discussed in section 3.2 compares relative market share against the market growth rate. In this thesis, social capital variables such as the number of press articles and the number of events attended will be used as a replacement for relative market share. These variables show how much attention a startup receives online and at conferences. The number of articles refers to the number of online articles that startup has received from other sources. The number of articles can refer to positive or negative articles that reference a startup, however the overall number is a proxy for exposure. The number of events refers to the number of startup conferences or conventions a startup has attended. Startups register and pay for booths to promote their company to customers and investors at these events. A graph where the X axis is the tested social capital variable and the Y axis is efficiency score can be considered a modified Boston Consulting Group Matrix by having the top right region by Stars, the bottom right to be Question Marks, the bottom left to be Dogs, and the top right to be Cash Cows. Figure 5 and 6 show the plotted modified BCG matrices for the number of articles and the number of events. First the BCG Matrix for the number of articles will be analyzed, then the BCG Matrix for events will be analyzed.

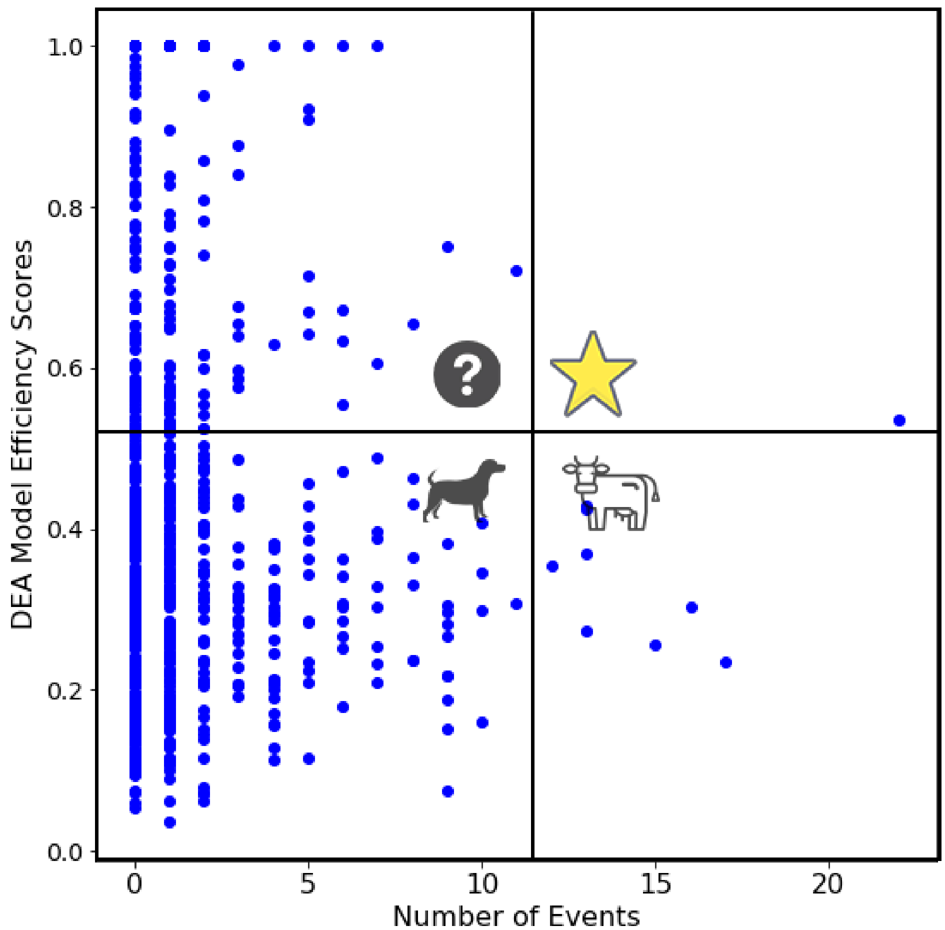
Figure 5: Modified BCG Matrix – Number of Press Articles



The Modified BCG Matrix shows the density of startups in each region. The density order ranking is Dogs, Question Marks, Cash Cow, and Stars. The densest region is the dog category which has low exposure and low efficiency. These startups should look to become more operationally efficient, look to be acquired, or shut down soon to minimize sunk costs. The next largest density of startups in the sample is in the question mark category which has relatively low exposure but high efficiency scores. One explanation is that these companies are focusing internally on becoming well managed rather than look for media exposure. Given that there are no stars in this sample, this implies that it is nearly impossible for startups to sustain peak efficiency while gaining maximum exposure. The cash cows in the sample can be seen as startups that receive great amounts of attention in the online media however have low efficiency scores. Depending on the age of the startup, cash cows should look to be acquired or become more efficient with their exposure level to become a star. Startups should asses their current categorization in the BCG Matrix and look to move upward by becoming more efficient with their structural (organizational) capital.

Most of the startups have less than 100 articles written about them. Startups with more than 100 articles can be considered outliers, so a smaller sub-set BCG matrix analysis was performed with startups with 100 or less articles and can be found in Appendix 1-C. The difference between the BCG matrices allow more startups to be spread out and in all categories. Both BCG Matrices have the same region density order: Dogs, Question Marks, Cash Cows, and Stars. However, the smaller sub-set allows for some startups to be considered stars for a limit of 100 articles. Overall, most startups should focus internally on the effectiveness of their employees rather than the number of articles to move upward into the question mark category or into the stars.

Figure 6: Modified BCG Matrix – Number of Events Attended



The next variable analyzed is the number of events that a startup has attended. One observation of the data is that most startups do not attend a conference or event and it is not required to be success. However, for most startups it can be beneficial to gain more exposure at these events. This is seen in the BCG Matrix by largest density of startups being in the 0 position. The density rank ordering is Dogs, Question Marks, Cash Cows, and Stars. Figure 6 shows that attending less than 10 events is where most of the startups reside, and that possibly more than 10 events can be considered an outlier. Another BCG Matrix with a limit of 10 events can be found in Appendix 1-D which allows the average startups to be more diversified in the different groups. The results show that more startups shift to the stars and cash cow category as expected. Since more startups are considered Cash Cows, this suggests that for an average startup they should not be worried about attending as many events as possible. Both models follow a similar pattern of a decrease in performance after 7 events which implies that attending too many of these events can hinder a startup's progress. Startups should spend their efforts on increasing their organization and progress faster through funding rounds.

The modified Boston Consulting Group matrix analysis shows the relationship between the number of articles and events and a startups efficiency score is not necessarily positive. First, most startups are in the Dog region which suggests that these startups do not have a large social network and they are not efficient yet. This aligns with previous literature of Xiao and Zhao (2012) who mentioned that social capital is often a bottleneck for startups. For the number of events, most of the startups in the sample had the highest density around 0. This implies that it is not a requirement of efficient startups to need more exposure at events. Startups should focus on becoming internally efficient with their resources regardless of their current exposure level. In both analyses there were little to no startups in the Star region because it is difficult for a startup to stay efficient while gaining mass attention in the press and at events. These modified BCG analyses provided a different light on social capital variables that were not included in the DEA models.

4.4 Case Studies

Case Studies of select startups provide further insight into qualitative factors that could affect their efficiency score. Two startups have been hand-selected to drill down into the details of the company history, the founders, the culture, and other factors. The first case study will be about "The Athletic", a startup in the sample that is efficient and in one of the highest performing industries as well. The Athletic is a sports media publishing startup that provides in-depth sports coverage in 15+ markets in the United States and Canada. The second case study will be about "AceBot.ai" one of the least efficient startups in the sample. AceBot.ai provides humanized survey experiences through an online chat bot on Facebook Messenger and other chats. The purpose of the rest of this section is to go more in-depth in The Athletic and AceBot.ai to learn more about the company history, founder background and skills, and other characteristics not covered in the DEA and BCG Analysis.

According to CrunchBase.com, The Athletic was created on Nov 6, 2015 with two founders, Alex Mather and Adam Hansmann. Alex Mather, the main founder, had a previous entrepreneurial history founding success companies before founding The Athletic. Adam Hansmann, the co-founder, had previous business experience working with venture capital firms as an analyst and in business operations. Together these two founders mixed entrepreneurial qualities with organizational qualities to form a great team. Within the last four years, The Athletic has expanded to 100+ employees, gone through 4 funding rounds, and achieved a total funding amount of 67.7 million dollars with 17 investors. This rapid growth and success can be attributed to the backgrounds and combination of the founders along with the industry market and timing. In the BCG Analysis with articles, The Athletic is on the border of becoming a star and is in the question mark category. The Athletic gains a lot of press articles by giving key sports journalism information to major news corporations. These news corporations discuss information The Athletic gave to them and in return give The Athletic more exposure. Since The Athletic is in the journalism industry, the number of articles can be naturally higher than other industries. However, The Athletic generates revenue off its subscription-based model and not press relationships. This implies that this information exchange to news corporations is more of a marketing strategy to gain more exposure. In comparison to the BCG Analysis of the number of events, The Athletic has only attended one event suggesting that attending events is not necessarily important. The Athletic also has an acquisition score 10 implying that they acquired two other startups within the last 4 years. The Athletic’s advantages compared to other journalists is that they are one of the most credible, have locker room access, focused on small markets, and started with a team with an entrepreneurial and organizational skill set.

In 2015, AceBot.ai was founded by Ralph Vaz, Ravindra Krishnappa, and Sameera Vanekar. In the Information Services and Mobile Apps industry, AceBot.ai has had one investor, been in one accelerator, and has only received 650,000 in total funding. The AceBot.ai team consists of a technical person, marketing person, and businessperson. Compared to The Athletic team, AceBot.ai does not have as much previous industry experience and expertise. CrunchBase.com states that AceBot.ai has between 11-50 employees, however, only the three co-founders still seem to be active with the startup. AceBot.ai's office is located in San Jose, California and the company has one office in India as well. After researching the founders online, two of the founders work in the San Jose office while the other founder works in the India office. It is hard for a startup to build a culture and company while people work remotely and have a work time zone difference. Recently, Acebot.ai is gaining a lot of monthly hits from India as they are trying to shift their customer base while its United States market declines. This implies that the company is trying to focus on their India segment and possibly shift markets given their low efficiency in the San Francisco Bay Area. AceBot.ai has become one of the least efficient startups in the sample by starting in one of the least efficient industries, spreading their offices too early, not building a team, and shifting its market focus.

Comparing The Athletic and AceBot.ai shows where these startups are different and gives lessons for current startups and future entrepreneurs. Both startups were founded within the same year and had a similar founding team. However, The Athletic founding team had more industry experience and better distribution of work. This allowed the Athletic to hire more people while still being efficient compared to AceBot.ai. Another area of difference between the startups is the markets they focused in. The Athletic started by focusing on a small market then slowly expanding to more while AceBot.ai split its offices and its markets. The industry that these startups were in could also be a factor for their efficiency scores. The Athletic is in one of the most efficient industries while AceBot.ai is in one of the least performing industries.

Chapter 5

Conclusion and Future Research Opportunities

After conducting Data Envelopment Analysis, Boston Consulting Group Matrix Analysis, and performing Case Studies on select startups there a few observations that investors, entrepreneurs, and readers can learn from this research. First, is that the startups in the sample are relatively inefficient which aligns with previous research and media on the difficulties of becoming a successful startup. However, a few select startups have managed to hire faster, gain more exposure, and be more efficient. These companies seem to focus on hiring more people at a faster rate, growing their internet traffic, and not focus on social capital greatly. The average startup in the sample was founded with a team of two people, but what really mattered is what happened after the founding. Speed is an important factor to be efficient. Certain industries might be tougher since the research and development process and customer demand may take longer. After looking at the results of the BCG Analysis, most of the startups are also in the dog category because they have low efficiency scores and low exposure as well. Startups should look to become more efficient with their resources to stay competitive within the market or look to leave the market to limit the wasted resources. One way to stay competitive in the market is to focus on the structural (organizational) capital of the startup to be able to expand without losing much efficiency. The most efficient startups in the sample managed to outperform their peers by the number of employees and the monthly hits as well. If a startup cannot achieve a high level of efficiency or growth they should look to be acquired, merged, or leave the market to limit wasted resources.

For entrepreneurs looking to start a new venture, the industry which a startup is in can affect the relative efficiency score. As previously discussed in the startup industry analysis in section 4.2, The mean efficiency score varies across industries, thus, to achieve faster growth entrepreneurs should look to start ventures in smaller industries with higher mean efficiency scores. Music and Audio, Sports, Clothing and Apparel, and Biotechnology are some industries that entrepreneurs can look into given their average efficiency and size. Entrepreneurs might want to stay away from Navigation and Mapping, Privacy and Security, and Energy industries given their underperforming efficiency scores. The results of the mean efficiency scores from the industry analysis imply that some industries can have longer production timelines, less customer demand, or are just generally less efficient than others. For new startups entering the market, entrepreneurs should look for a less competitive industry with room to grow fast to have a better chance of being more efficient. The sample also aligns with previous research suggesting that the founders usually start with a team given that the average number of founders was 2.

Current startups in the sample should look into increasing their structural (organizational) capital to expand their number of employees while still maintaining efficiency. Hiring more people alone does not guarantee higher output, however growing a startup's organization and maintaining the company values as it grows allows it to be highly efficient. Startups have a disadvantage against larger corporations in terms of size, so by operating more efficiently, it can leverage them to succeed. As discussed in the BCG Analysis, current startups should not focus too heavily on gaining exposure through press articles or attending events. Startups have a small area of focus and therefore should focus on their product, funding, and organization structure rather than media exposure and conferences.

Venture Capital Investment Funds looking to add startups to their portfolio can also gain from this thesis' analysis. These Venture Capital Funds can look into the most efficient startups in the sample to see if they meet their investment needs. The most efficient startups have some of the lowest risk given that they are the most relatively efficient with their human capital and organizational capital. These startups are usually later stage (3-4) and should be expected to IPO or be acquired in the future. Another area that investors can look for startups is the Question Marks categories from the BCG Analysis section. These company have relatively little exposure from the media however, their efficiency scores speak from themselves. These startups have some of the highest efficiency scores in the sample and have room gain more exposure. By looking at the characteristics of efficient startups and underperforming startups, investors can also takeaway what to look for in a startup as well.

After concluding this thesis, there are some areas for future research. First, this thesis was limited to San Francisco Bay Area startups. An expanded version of this thesis' model can be used to measure the efficiency scores of the entire United States and compare differences between a small sample area and the entire US population of startups. Based on this thesis, it would be expected for startups to have a lower average efficiency score given the distribution in the San Francisco Bay Area alone. Another possibility for future research is to continue studying this sample in the next 5 years to see how the efficiency scores change and which startups get acquired, merged, or possibly IPO.

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Appendix 1: Model B Figures

Figure A: Startups in the efficient frontier for Model B

Organization Name	Number of Founders	Number of Employees	Acquisition Score	Number of Investments	Monthly Website Hits (in thousands)	Estimated Revenue (in millions $)	Average Funding Per Investor (in millions $)
Singular	3	176	1.0	6	12276.32	5.00	8.33
The Athletic	2	176	10.0	17	11359.73	1.00	3.98
Netlify	2	31	1.0	8	8122.72	3.00	5.51
Tubi	1	176	1.0	13	7620.77	2.00	2.00
OneSignal	1	31	1.0	11	2479.59	4.50	0.82
Journal	3	6	1.0	1	2111.53	1.00	1.50
StackShare	1	6	1.0	9	1267.33	2.00	0.78
Samsara	2	751	1.0	2	741.84	5.00	115.00
Rothy's	2	376	5.5	5	712.01	140.00	8.40
Checkr	2	176	1.0	24	710.43	60.00	6.21
Triplebyte	3	31	1.0	35	666.82	3.00	1.37
Truebill	2	6	1.0	19	325.31	1.00	0.36
Flutterwave	1	31	1.0	23	119.97	1.00	0.88
Symphony Communication Services	1	376	1.0	29	104.96	7.00	10.21
Vlocity	5	751	1.0	8	60.43	110.00	19.10
Habit Food Personalized	1	176	1.0	1	58.09	3.40	32.00
PayJoy	4	75.5	1.0	39	56.67	1.48	1.31
Zoox	2	376	1.0	11	45.58	20.00	71.82
Lightform	3	6	1.0	9	44.39	12.00	0.86
Ample Foods	1	6	1.0	15	44.05	2.00	0.27
Second Measure	2	75.5	1.0	29	24.90	12.50	0.88
Unchained Labs	1	75.5	1.0	4	12.97	55.00	20.00
Lendeavor	3	31	1.0	1	8.13	1.17	124.03
Castle	2	31	1.0	29	7.67	3.65	0.40
Dispatch	3	6	1.0	4	5.79	13.50	0.50
NextGen Jane	1	6	1.0	5	2.17	7.80	2.26
NFWare	1	31	1.0	8	1.82	25.00	0.31
Forty Seven	2	6	1.0	5	1.79	2.00	30.00
Cricket Health	4	6	1.0	16	1.73	4.00	1.73
Terns Pharmaceuticals	1	6	1.0	4	0.98	2.00	27.50
Worklife	3	6	1.0	19	0.96	1.20	0.14
Tenaya Therapeutics	6	6	1.0	1	0.72	2.00	50.00
Cloudwirx, Inc.	2	31	1.0	1	0.13	49.00	5.10

Figure B: List of Top 10 Worst Startups in Model B

Organization Name	Number of Founders	Number of Employees	Acquisition Score	Number of Investments	Monthly Website Hits (in thousands)	Estimated Revenue (in millions $)	Average Funding Per Investor (in millions $)	VRS Score
Xberts	2	31	1.0	1	25.23	0.08	0.12	0.04
Boutir	2	31	1.0	1	89.66	0.71	0.05	0.05
Pocketlab	1	31	1.0	1	11.67	0.39	0.14	0.05
Shypmate	4	6	1.0	1	0.13	0.18	0.12	0.06
Clarity Movement	5	31	5.5	1	5.62	1.00	2.11	0.06
DecorMatters	3	31	1.0	1	5.12	1.25	1.50	0.06
SenseiHub	2	31	1.0	2	0.13	0.11	0.08	0.07
Foxpass	1	31	1.0	1	4.88	1.10	0.12	0.07
AppAnalytics	1	31	5.5	1	0.71	1.20	0.30	0.07
Mailburn	3	6	1.0	1	0.54	0.49	0.05	0.07

Figure C: Modified BCG Analysis for the number of articles in Model B (limit: 100)

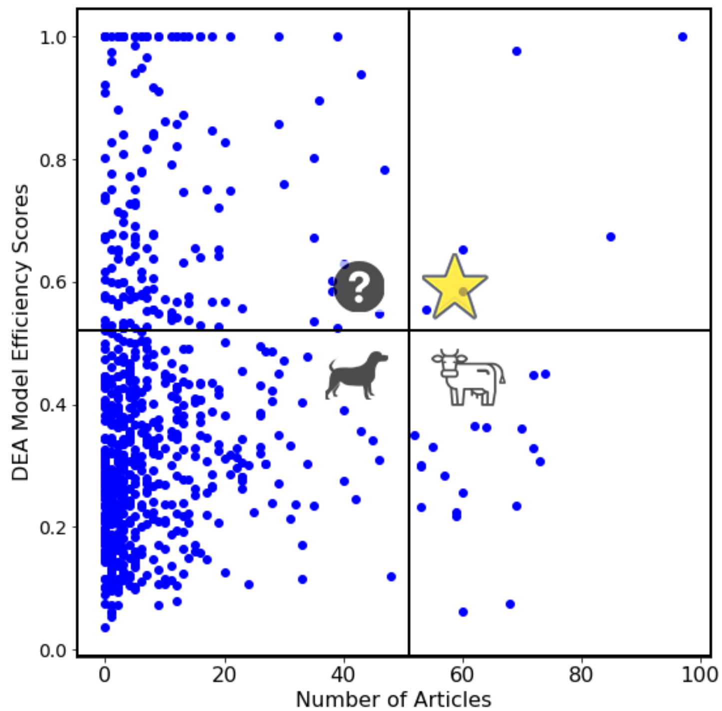


Figure D: Modified BCG Analysis for the number of events in Model B (limit: 10)

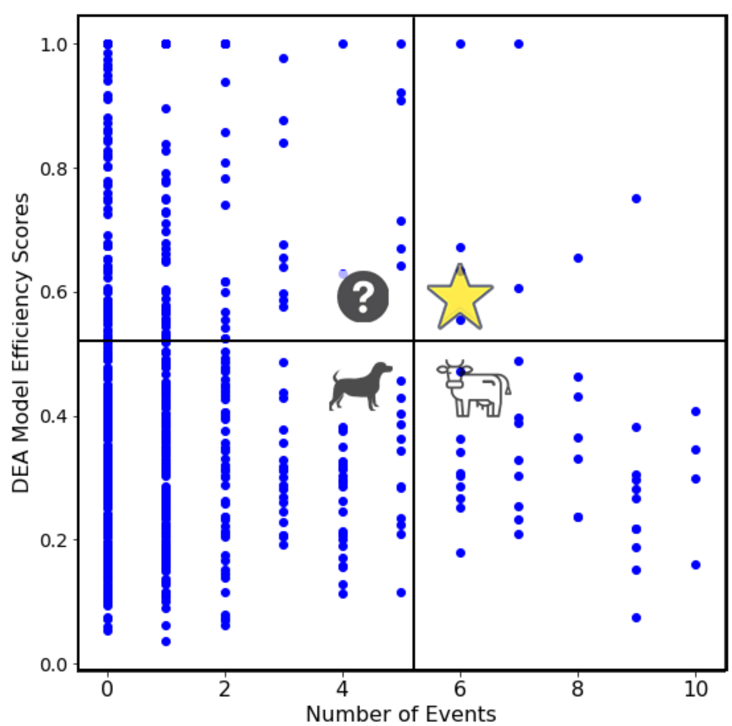


Figure E: Rank Order Correlation Model A vs Model B

Correlation	0.6377
P-Value	1.1449 E-87

Figure F: Rank Order Correlation Model B Acquisition Score vs No Acquisition Score

Correlation	0.9999
P-Value	0.0

Appendix 2: Model A Figures

Figure A: List of Startups in Efficient Frontier Model A

Organization Name	Number of Founders	Number of Employees	Acquisition Score	Monthly Website Hits (in thousands)	Total Amount of Funding (in millions $)	Estimated Revenue (in millions $)
Dispatch	3	6	1.0	5.79	2	13.50
OneSignal	1	31	1.0	2,479.59	9	4.50
Forty Seven	2	6	1.0	1.79	226.7	2.00
Tubi	1	176	1.0	7,620.77	26	2.00
NextGen Jane	1	6	1.0	2.17	11.32	7.80
Terns Pharmaceuticals	1	6	1.0	0.98	226.7	2.00
Journal	3	6	1.0	2,111.53	1.5	1.00
Cloudwirx, Inc.	2	31	1.0	0.13	5.1	49.00
Denali Therapeutics	3	75.5	1.0	13.85	347	6.59
Rothy's	2	376	5.5	712.01	42	140.00
The Athletic	2	176	10.0	11,359.73	67.7	1.00
StackShare	1	6	1.0	1,267.33	7	2.00
Unchained Labs	1	75.5	1.0	12.97	80	55.00
Zoox	2	376	1.0	45.58	790	20.00
Netlify	2	31	1.0	8,122.72	44.1	3.00
Singular	3	176	1.0	12,276.32	50	5.00
Livongo	1	376	1.0	147.48	235	30.00
Symphony Communication Services	1	376	1.0	104.96	296	7.00
Vlocity	5	751	1.0	60.43	152.8	110.00
Checkr	2	176	1.0	710.43	149	60.00
NFWare	1	31	1.0	1.82	2.5	25.00

Figure B: Descriptive Statistics for Efficient Startups in Model A

N=10	Number of Founders	Number of Employees	Acquisition Score	Monthly Website Hits (in thousands)	Estimated Revenue (in millions $)	Total Funding (in millions $)
mean	2.21	122.92	1.41	1484.80	17.07	131.97
std	1.24	196.34	1.73	3285.49	32.06	185.49
min	1	6	1	0.13	1.00	1.50
max	6	751	10	12276.32	140.00	790.00

Figure C: List of Top 10 Worst Startups in Model A

Organization Name	Number of Founders	Number of Employees	Acquisition Score	Monthly Website Hits (in thousands)	Total Amount of Funding (in millions)	Estimated Revenue (in millions)	VRS Score
SenseiHub	2	31	1.0	0.13	0.16	0.11	0.00
Xberts	2	31	1.0	25.23	0.12	0.08	0.01
Hideez Group Inc	3	31	1.0	2.98	0.83	0.26	0.01
Terbine	1	31	1.0	0.42	0.55	0.29	0.01
Shypmate	4	6	1.0	0.13	0.12	0.18	0.01
Chefling Inc	1	31	1.0	2.37	1.2	0.31	0.01
MightySignal	2	31	1.0	16	2.82	0.22	0.02
AwesomeBox	2	6	1.0	1.04	0.34	0.16	0.02
Radius	2	31	1.0	12.79	2.5	0.31	0.02
Kakaxi, Inc.	3	6	1.0	0.84	1.85	0.13	0.02

Figure D: Descriptive Statistics for Top 10 Worst Startups in Model A

N=10	Number of Founders	Number of Employees	Acquisition Score	Monthly Website Hits (in thousands)	Estimated Revenue (in millions $)	Total Funding (in millions $)	VRS Score
mean	2.20	23.5	1	6.19	0.21	1.05	0.01
std	0.92	12.1	0	2.77	0.09	1.01	0.00
min	1.00	6.0	1	0.13	0.08	0.12	0.00
max	4.00	31.0	1	25.23	0.31	2.82	0.02

Figure E: Model A Efficiency Score vs Articles

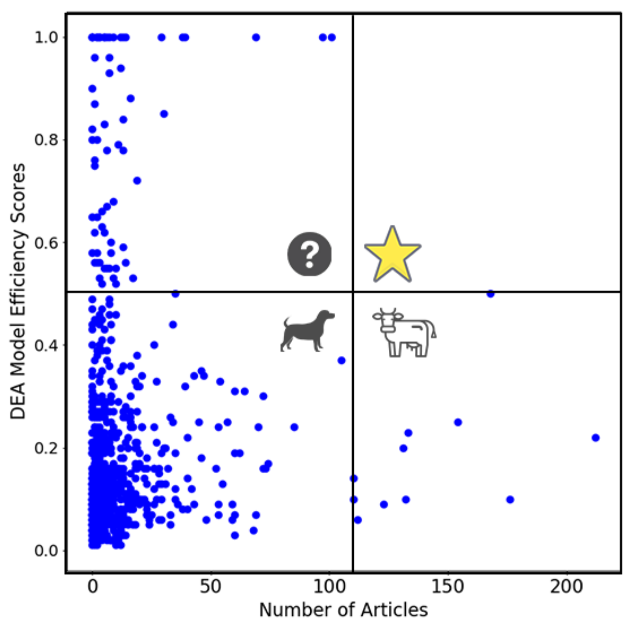


Figure F: Model A Efficiency Score vs Articles (Limit 100)

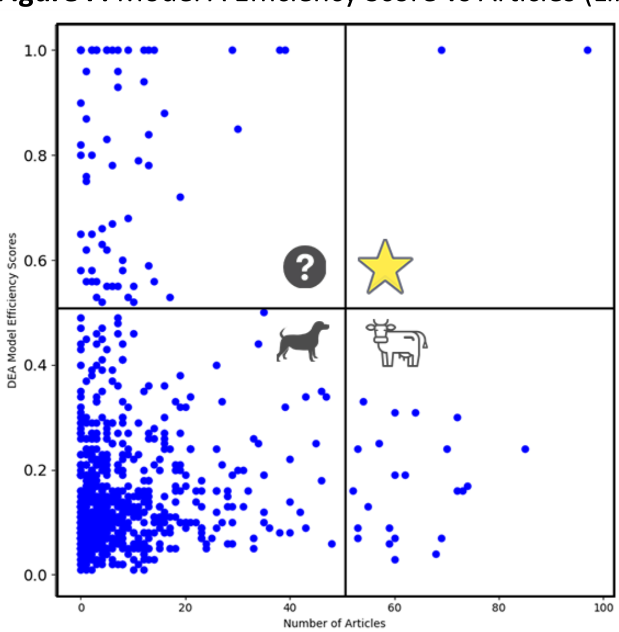


Figure G: Model A Efficiency Score vs Events

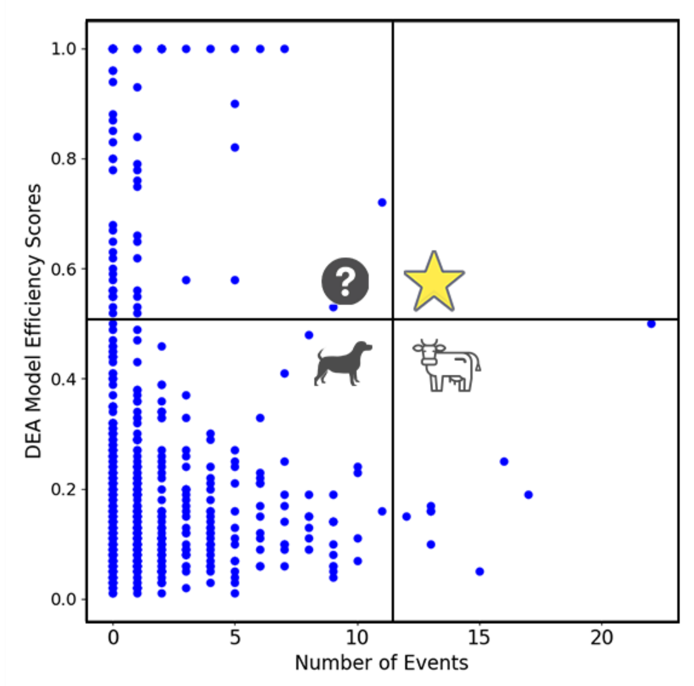
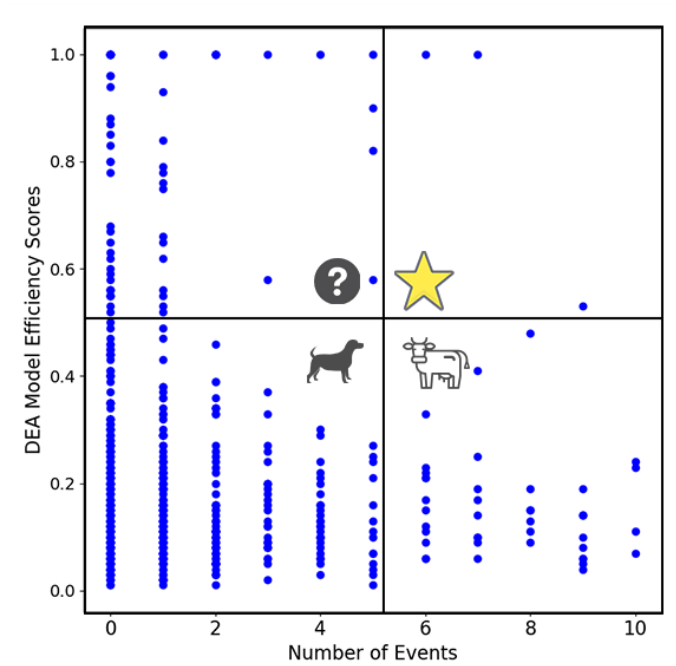


Figure H: Model A Efficiency Score vs Events (Limit 10)



Appendix 3: Industry Figures

Figure A: Descriptive Statistics for All Startup Industries

N=46	Industry Mean VRS Score
Average	0.41
Standard Deviation	0.06
Minimum	0.29
Maximum	0.57

Figure B: Top 10 Most Efficient Industries

Industry Name	Industry VRS Score
Music and Audio	48%
Biotechnology	41%
Sports	35%
Clothing and Apparel	32%
Health Care	32%
Advertising	30%
Messaging and Telecommunications	30%
Design	26%
Sales and Marketing	26%
Media and Entertainment	25%

Figure C: Top 10 Least Efficient Industries

Industry Name	Industry VRS Score
Gaming	12%
Energy	12%
Administrative Services	17%
Privacy and Security	17%
Navigation and Mapping	17%
Payments	17%
Lending and Investments	18%
Real Estate	18%
Professional Services	18%
Mobile	18%