Funding a Start-up

Evaluating the Business Impact of Funding Types, Sources, Amounts and Timing

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1. Abstract

This study reviews several questions of interest for entrepreneurs as well as investors about Start-up organizations. We performed our analysis using the Kaggle dataset from Crunchbase's 2014 snapshot, which includes approximately 50,000 companies. We found that the average amount of money raised, and the average number of funding rounds, both vary by industry. We concluded that the average amount of seed money invested is increasing 13.5% annually. We also found, controversially, that companies that did not have seed rounds are 4 times more likely to have a venture round. Our results should be received with caution, as our dataset included strong survivorship, regional, and market bias.

2. Introduction

Developing a new business takes time, money, and expertise. Accelerating its growth takes even more of the same. It can take years to achieve profitability so many new businesses look to investors to bridge the financial gaps.

This study will examine relationships between various features of the fundraising process (such as amount and type of money raised), how financing differs between industries, and whether seed funding is a good predictor of venture funding.

We will be attempting to answer the following questions using statistical analysis:

1. Is the average amount of money raised correlated with the industry the company is in?
2. Can a company expect to have more financing rounds if they're in a particular industry?
3. Does the amount of money raised in the seed round correlate with the year it was raised?
4. Does the proportion of companies that get seed funding also get venture funding?

3. Dataset Description

Our original source of data is **Crunchbase.** Although we haven't directly used any Crunchbase APIs to obtain this data, we obtained it via a secondary source on kaggle. Crunchbase is a platform for finding business information about private and public companies. Crunchbase information includes investments and funding information, founding members and individuals in leadership positions, mergers and acquisitions, news, and industry trends. Originally built to track startups, the Crunchbase website contains information on public and private companies on a global scale.

Crunchbase sources its data in four ways: the venture program, machine learning, an in-house data team, and the Crunchbase community. Members of the public can submit information to the Crunchbase database. These submissions are subject to registration, social validation, and are often reviewed by a moderator before being accepted for publication.

This dataset was found on Kaggle consisting of funding, investments and other details about startup companies collected via Crunchbase. This dataset contains 49,437 data points where each point represents a startup company. There are 40 different attributes associated with the data. There's basic location information such as country, state and city. Important dates associated with each startup such as when they received their first and last funding or when they were founded, are included. We also have important links to the websites of these companies, the type of industry they operate in and the markets they cater to. The rest of the information is mainly based on funding amounts and types of funding received. Then we have an attribute called status that shows whether a startup is operating, acquired or closed.

The data is largely composed of different types of funding amounts (in USD) and is mostly quantitative in nature. There are other fields that describe important dates and years. The survivorship of startups described by the status is nominal in nature. Apart from this we have other fields that provide more qualitative information about each of the companies like their market areas, categories, and location.

3.1 Issues and Biases

Upon an initial quick exploratory data analysis (EDA) of the dataset, we ran into some barriers regarding the data. The total data contains about 5% closed startups, 11% null and above 70% operating startups. This can be contrasted with a 90% failure rate of startups. (Bryant, 2020) Therefore any analysis performed on this database regarding survivorship might be intrinsically biased because data doesn't include a lot of failed startups. This eliminates the possibility of using the “status” attribute for any statistical analysis on the entirety of the dataset forcing us to filter in on particular aspects of the data for study. If we can choose certain parameters to look at and eliminate the confounding variables to some degree then we can have better statistical significance in our analysis results.

It appears that 46.3% of the total data comes from the USA. This means that almost half of the data is mostly from America and in that data almost 36% is only from California. We realized that the amount, type and means of funding from region to region can vary greatly depending on socio-economic factors at play in that region. After deciding we would be looking only at the USA data, another concern was with the distribution of data across different markets which led us to find that almost 30% of the companies didn't have a clear distinction of which market they were from (filled in with “other”). Among the remaining that did have clear market information, around 15% operated in only the Software and Biotechnology markets.

We found a couple of other discrepancies, biases and interesting findings in the data. The year at which a company was founded dated back further than 1950 which seemed concerning as there could have been an issue in recording the data. However, most companies were found to be between 1980 to 2014. The average total funding came to be around 15 million USD across the different companies. We found that the highest total funding received was about 30 billion USD by Verizon Communications. This was an interesting finding that encouraged us to go back and see what range of data we were looking at with such outliers. Regarding funding types, it was also found that only 28% of companies got funding in the “seed” stage. Such information about the different funding sources allowed us to shape our questions about the data for analysis.

These issues and discrepancies were explored more as we designed our approach and narrowed down our scope which will be explained in further detail in the following sections. Keeping in mind all of this information, we proceeded to frame our questions accordingly and ensured quality in our analysis.

4. Approach

4.1 Exploratory Analysis

Our approach to tackling these questions is to first perform exploratory analysis on the data and run some descriptive statistics on the features of the dataset. The immediate action we took was to identify inaccurate and missing data and determine how to handle these cases.

Out of the 49,439 organizations, 438 did not have a current operating status, and 490 did not include a designated market. We decided to remove these organizations from our dataset, since we need these fields for our analysis. We decided to filter the dataset to only include start-ups founded in the USA since 46.3% of the organizations are from the USA, and there is not a large distribution of organizations from other countries. We also filtered the data to be those organizations that were founded between 1980 - 2014, since this composed approximately 99% of the data.

The relative value of the dollar has changed considerably over the time frame of this analysis. To account for this change, we used the consumer price index (CPI) to adjust the seed funding dollar values to 1980 levels (U.S. Bureau of Labor Statistics, n.d.). This was only possible for the seed funding values because that was the only funding event that had a date provided in our data set.

4.2 Project Assumptions

In reviewing this dataset of start-up companies, there are several general assumptions that we have to make in order to continue our analysis and report on our findings. We make assumptions about the representativeness, accuracy, and minimization of survivorship bias through the use of accelerators. We assume that our cleaned and refined dataset gives an accurate representation of all USA start-ups that were founded between 1980 - 2014.

Based on our exploratory analysis, we found that a majority of the organizations were found in the USA between the years of 1980 - 2014. Thus we have refined the data set to only include the organizations that fall within these categories and make the assumption that our refined dataset is a representative sample of all startups within the previously stated criteria, and that we can generalize our findings to these populations. We also removed organization from our data set with missing key fields and extreme outliers. Our assumption is that removing these incomplete values and extreme outliers will not give us inaccurate results.

In an attempt to minimize survivorship bias, we chose to work with Crunchbase data, which is gathered from a number of accelerators. Our assumption is that accelerators would have more accurate information on start-ups that failed than more generalized startup sources. We also assume that companies that go through an accelerator will have a higher survivorship rate than those that go it alone, but have no way to measure the amount of organizations that fail due to the fact that failing organizations may not communicate that they're failing, so it would be difficult or impossible to collect that data.

4.3 Fundraising by Industry

The first question we pose is whether the average amount of money raised is different between the following industries:

- Travel
- Transportation
- Games
- Music
- Video
- Finance
- Cloud Computing
- Health Care
- Hospitality
- Education

These industries are of interest to us because we wanted to compare all of the groups that our class cohort were studying to compare them and see if there would be any difference in the amount of funding each group is likely to raise. This study is interesting because it may help new founders better understand how much capital they can expect to raise based on what market their company is in. To answer this question, we will be using an ANOVA test to compare the difference in the total amount raised by each company within and across industries. ANOVA was chosen because we did not suspect that the total funding amount would have a linear relationship, so ANOVA would be an effective way to test differences in population means. The null hypothesis of our ANOVA test is that the average amount of money raised by a Start-up does not vary by industry.

Checking Assumptions of ANOVA

To verify that our dataset is valid for an ANOVA test, we will assess that our data fits the assumptions that ANOVA requires, that the data is normally distributed, the samples are independent, and that there are equal variances across all groups.

Data is normally distributed

To ensure we are satisfying this assumption, we calculate the sample size from each of our ten industries and found that each industry had at least 30 companies represented. By the Central Limit Theorem, we are safe to assume that the data is normal enough for our analysis.

Independent samples

There doesn't seem to be any reason to believe that one observation (company) would have any impact on another. There is no way to test for this with the data we currently have, so all we can do is assume independence.

Equal variances across groups

Across the 10 industries, the variances vary drastically. We found that this is due to some companies having many, increasingly larger, funding rounds that contribute to their total amount raised while others may be just starting out. Another contributing factor to this variance is also the time variance of this analysis, since our data set ranges over a period of 34 years. To remedy this issue, we decided to perform a log transform of the total funding amounts in our data set because the amount of total funding some companies receive can be different by many orders of magnitude. The result of this was that the variance between markets was much more reasonable and only varied slightly between groups.

Methodology

1. Create a subset of our original dataset to only include the industries of interest.
2. Perform a log transformation on the total funding to account for unequal variances.
3. Perform an ANOVA F-Test to determine if there is a difference of total average funding between industries.
4. If a difference exists between groups, explore the difference visually and report on statistics of our sample.

Another way to measure which industries get more funding than others is to look at the average number of funding rounds across each market. In the next section, we will explore how to approach the question of, does the number of funding rounds vary by industry, and if so, how does that compare to our analysis of the comparison of total average funding by industry.

4.4 Investment Rounds by Industry

Another question of interest, is can a company expect to have more financing rounds if they're in a particular industry?

This is interesting to us so that we can see how financing varies for the various markets, and if the amount of rounds is correlated to a particular industry. We will be performing this analysis through a variety of visualizations and compare the most extreme results using a two sample t-test. Our null hypothesis is that the average number of financing rounds per industry will be the same.

In order to use the two sample t-test, we will first verify that our data set meets the necessary requirements. That the dataset is large enough that the Central Limit Theorem applies, and that there is independence between the industry groups.

Checking Assumptions of ANOVA

To verify that our dataset is valid for an ANOVA test, we will assess that our data fits the assumptions that ANOVA requires, that the data is normally distributed, the samples are independent, and that there are equal variances across all groups.

Data is normally distributed

To ensure we are satisfying this assumption, we calculate the sample size from each of our ten industries and found that each industry had at least 30 companies represented. By the Central Limit Theorem, we are safe to assume that the data is normal enough for our analysis.

Independent samples

There is no theoretical reason to suspect that firms in the same industry are not still independently sampled, and because these are startups there is a small chance of a significant number of firms belonging to the same parent company, founders, etc.

Equal variances across groups

The variances of individual industries are nearly uniformly distributed with a range of 0.61 to 5.25, which well exceeds the range of means (1.4 to 2.9). Because of this, we will not assume that variances are equal between industries and will not perform an ANOVA test.

Methodology

1. Visualize different aggregated market metrics using bar charts (sum of amount raised, count of companies.
2. Compare a fitted exponential curve to see if a certain amount of rounds is more likely than the fit suggests.
3. Scatterplot of funding type.
4. Compare top 5 and bottom 5 industries by funding round to the total population using a 2-sample t-test, to see if the group means are different from the general population.
5. Within top and bottom 5 groups, pairwise t-test comparison with Bonferroni correction to determine if they are significantly different.
6. Welch T.test comparison of venture funding within any identified significant groups to see if the additional rounds impact funding raised.

4.5 Seed Funding Over Time

The next question we will explore is if the amount of seed funding correlates with the year of the first funding received.

We examined the trend in investing behavior over time by comparing the inflation-adjusted seed funding raised in the years 1980 to 2014.

This was interesting to us to see if we could detect an overall trend in investing behavior from year to year. The data is largely continuous and we initially expected to see a linear relationship, so we attempted to use a linear regression, with the null hypothesis that seed funding amounts were not related to the year they were raised in.

However, upon further examination, linear analysis was not suitable for this study. The data showed distinct heteroskedasticity, with residuals growing much larger in later years. The interpretation was also nonsensical, with negative fundraising values being predicted for a significant portion of the years studied. Grouping data by year before performing the regression did not solve these problems. Instead, a number of preparation steps were taken, and then a Poisson regression was performed.

Removal of Zeros

The zero values should be interpreted differently from positive ones. While all positive values indicate some amount of seed funding, a zero indicates that no seed was sought or received, and is less of a scale difference than a positive value and more of a classification difference.

To confirm this, we calculated the proportion of companies that received non-zero amounts of funding each year. A linear regression on this annual data had well behaved residuals, and did not provide enough evidence to reject the null hypothesis that the chance of receiving a non-zero amount of funding has not changed over time. With this assumption, we removed zero values in our further analysis.

Checking Assumptions for Poisson Regression

We performed a Poisson regression on the remaining non-zero data, after validating the below assumptions.

Sufficient Sample Size

There were 5,996 remaining samples. This should be sufficient for a Poisson regression, and simulation studies support this assumption.

Independent samples

There doesn't seem to be any reason to believe that one observation (company) would have any impact on another. There is no way to test for this with the data we currently have, so all we can do is assume independence.

Variance of errors is proportional to Mean

The hard assumption of variance equal to mean was not met. However, by dividing the deviance by the degrees of freedom of the residuals, an estimated dispersion parameter of approximately 1.1 million was used, and significance of results was evaluated using this estimated dispersion.

Methodology

1. Calculated proportion of samples in each year that were zero. Confirmed by linear regression that there is no evidence of an association between year and proportion of seed funding. Remove 0's from further analysis.
2. Conducted linear regression on the log of seed funding. Found evidence that Simpson's Paradox could be suppressing coefficients.
3. Calculated percentiles for funding in each year. Confirmed using linear regressions that 90th and 75th percentile show significant growth per year, while 25th has no evidence of change.
4. Verified assumptions needed for Poisson Regression.
5. Conducted Poisson Regression on all non-zero data.
6. Grouped data by year and performed Poisson Regression on grouped data.

4.6 Seed and Venture Funding

Finally, we want to explore whether the proportion of companies that get seed funding also get venture funding?

This question would help potential investors understand the risk of investing in a seed round at a startup. An investor in a seed round is most interested in the company getting to further funding rounds, so this would be a great indicator for the success of an early stage startup.

Checking Assumptions for Conditional Probability

To answer this question, we chose to use conditional probability under the following assumptions:

Causal relationship between events

To use conditional probability, there must be a causal relationship between the two events. In this case, we need to establish a causal relationship between a company receiving seed funding and a company receiving venture funding. From our domain knowledge, we know that to get venture funding, you must have first been through a seed funding round. Therefore, it is safe to assume that there must be a causal relationship between the two events. To further prove this, we performed a chi square test for independence between the seed and venture variables and found that the two variables are dependent.

Sample proportion is equal to the probability

Because our sample size is sufficiently large, we are safe to assume that the sample proportion is roughly equal to the probability of that event occurring.

We will first calculate the proportion of companies that received seed funding, received venture funding, and received both seed and venture funding. We will then use these proportions, along with the proportion of companies that did not receive either funding sources, to determine the probability of receiving venture funding with and without the presence of seed funding.

5. Results

5.1 Fundraising by Industry

Performing the ANOVA F-Test, we found evidence that the average amount of money raised varies by industry ($p < 0.05$). Next, we decided to plot the average amount of money raised by industry, to view how much the average amount of money varies and which industries raise the most (and the least) amount of funding on average.

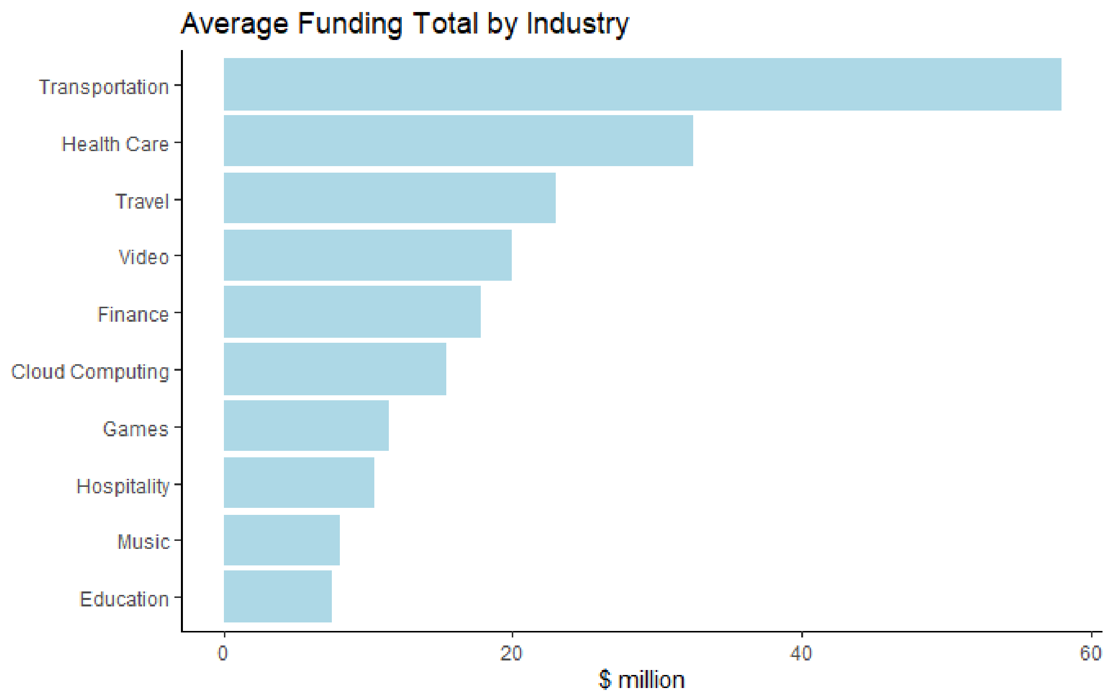

Figure 5.1: Average Funding Total by Industry

In the above barchart (Figure 5.1), we can see that the Transportation industry is the most likely to raise the most amount of money. We would expect that Start-ups in the Transportation industry would raise an average of $58 million, which is $38 million, or 184%, more than the average startup in the industries selected for analysis.

5.2 Investment Rounds by Industry

Performing the ANOVA F-Test, we found evidence that the average number of funding rounds varies by industry ($p < 0.05$). Next, we decided to plot the average number of funding rounds by industry, to view how the average number of rounds varies and which industries are likely to have the most (and the least) number of rounds on average.

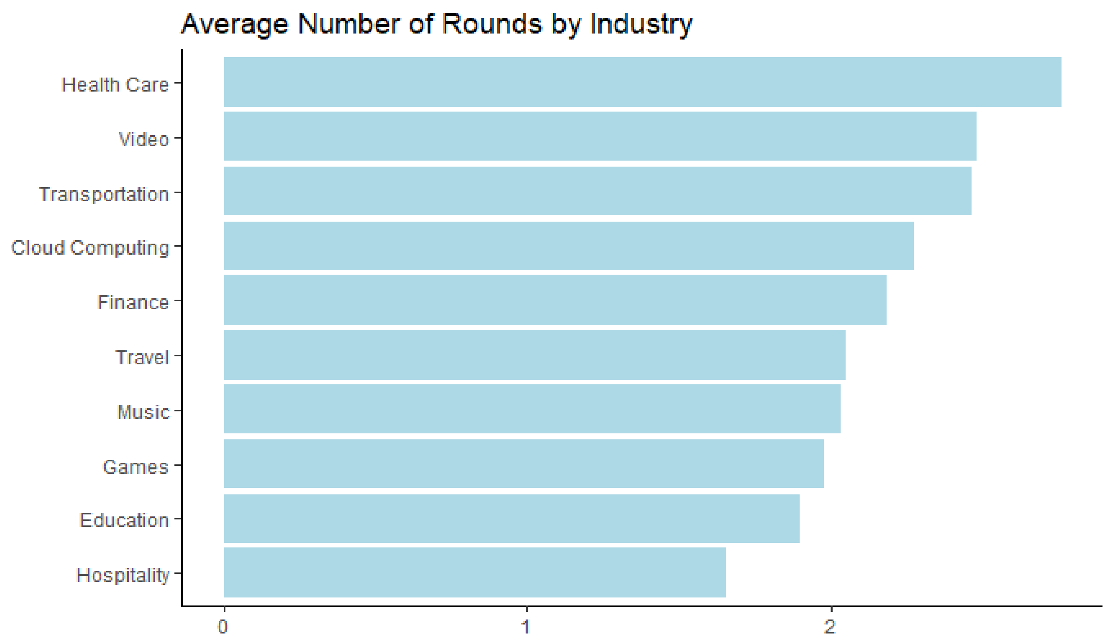

Figure 5.2: Average Number of Rounds by Industry

In the above barchart (Figure 5.2), we can see that the Healthcare industry is the most likely to have the most number of funding rounds. We would expect that start-ups in the Healthcare industry would have 2.8 rounds on average, 0.6 (27%) more than the average number of funding rounds in these industries.

5.3 Seed Funding Over Time

Annualized Poisson Regression Results

A Poisson Regression conducted on the average amount of seed funding per year was found to be significant, with p-value close to zero. On average, seed funding was found to increase by 13.5% annually.

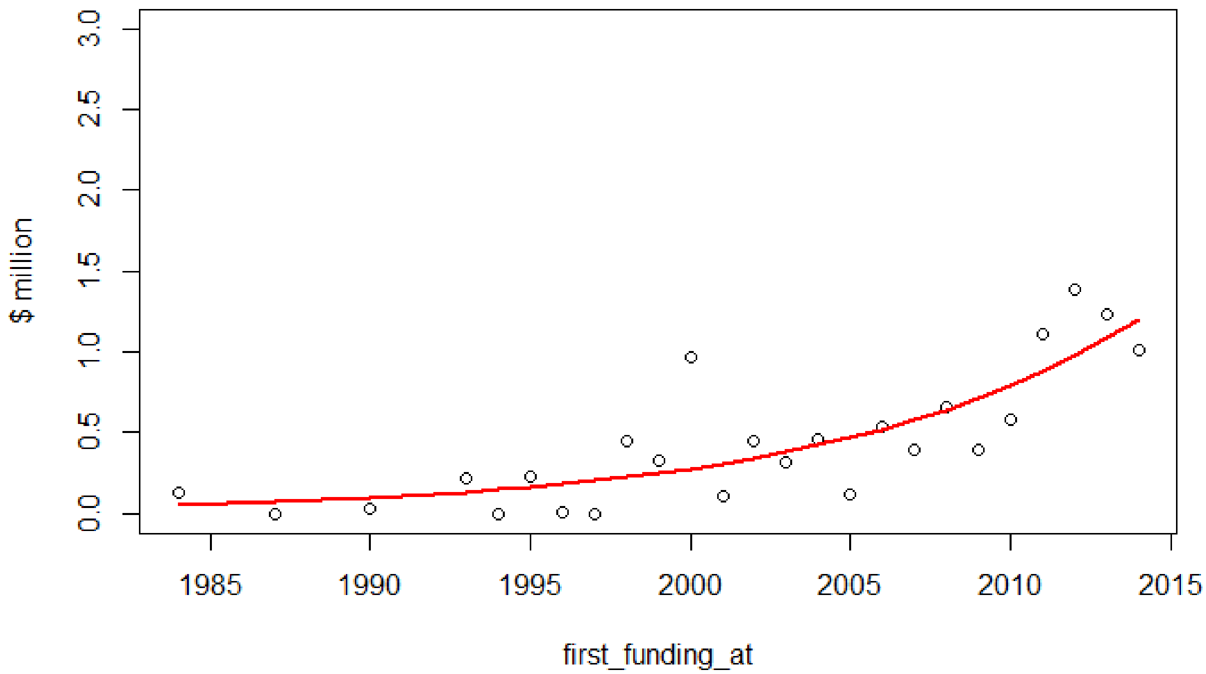

Figure 5.3: Seed vs Year Poisson Regression Model

Skewness Analysis

When analyzing seed funding at different percentiles per year, no relation was found between the 25th or 50th percentiles and year. Basically, the bottom 50% of seed funding has not changed significantly since 1980.

However, the 75th percentile showed a significant relationship, with an estimated 5.2% annual growth, and the 90th percentile showed even faster and significant growth at an estimated 5.7% annual rate.

This suggests that all of the growth in seed funding found in the Poisson Regression is coming from growth of the highest amounts. The middle and bottom of the pack seed funding rounds have not changed, but the amount of money that the top raisers are getting has grown exponentially.

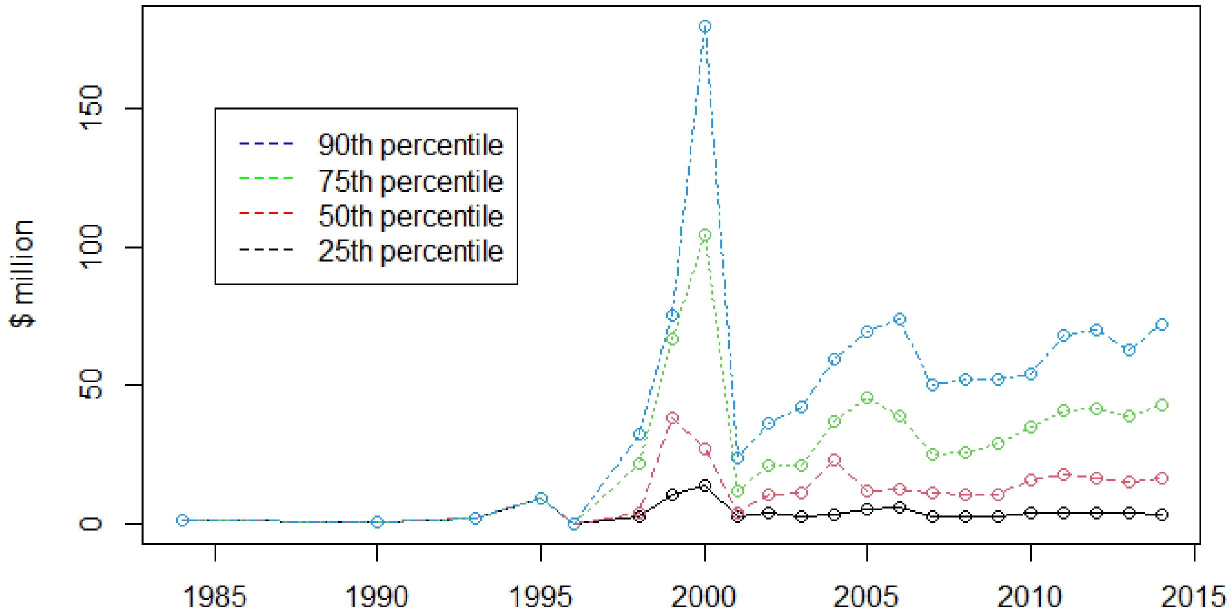

Figure 5.4: Seed Funding Amount as Percentile Divisions (1980-2014)

5.4 Seed and Venture Funding

The results of our analysis on the proportions of seed and venture funding in our data set showed that venture funding was much more prevalent in our data set than seed funding was. Seed funding was reported in 34% of companies while venture funding was reported in 64% of companies. Using these proportions as well the proportion of their intersection, we are able to calculate the conditional probability of a company receiving venture funding with and without the presence of seed funding.

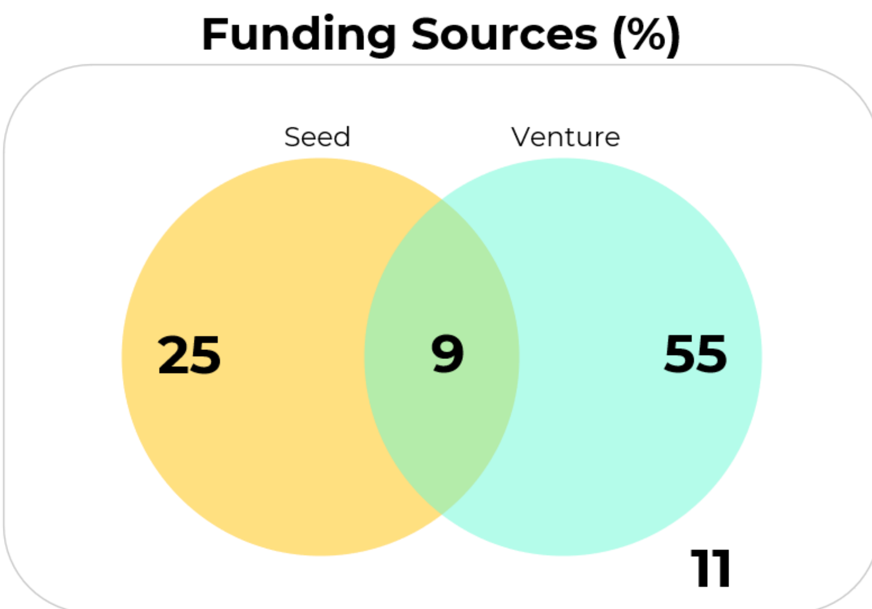

Figure 5.5: Funding Sources Venn Diagram

$P(Venture \mid Seed) = P(Venture \cap Seed) / P(Seed) = 0.09 / 0.34 = 0.26$

$P(Venture \mid !Seed) = P(Venture \cap !Seed) / P(!Seed) = 0.55 / .66 = 0.83$

Thus the probability of a company receiving venture funding without having a seed round is 3.19 times larger than if that company did not have a seed round.

6. Discussion

6.1 Fundraising by Industry

We found strong evidence that the amount of total fundraising is related to industry. This is unsurprising after looking at the data visualized in the barplot in section 5.1 The transportation industry has a much higher average, $57.9 million, compared to the next highest healthcare at $32.5 million and the mean of $20.4 million. This industry is dominated by rideshare and adjacent technologies, with Uber at $1.5 billion and Lyft at $332 million. Since these companies are largely responsible for the high average, and have already saturated the rideshare market, we do not believe this result is predictive, and future transportation startups likely will not raise as much as the ones in this set.

Although we found evidence to conclude that the average amount of funding varies by the industries, we must take these results with some caution, given that we are not guaranteed that the data was collected independently, and that this was a observational study as compared to the more preferential random sampling method. In addition, as previously mentioned, there is a strong survivorship bias in our dataset, which means that our conclusions are heavily biased towards successful companies.

6.2 Investment Rounds by Industry

We also found strong evidence that the number of fundraising rounds is related to industry. There is a less dramatic difference than seen in total funding, but it is still noteworthy that Health Care averaged 2.76 rounds, while the next highest was Video at 2.48. This gap of 0.28 rounds is the highest seen in the examined data. This is not a surprising result, because the healthcare companies with the most number of rounds are generally pharmaceuticals or biotech, both fields that rely heavily on demonstrating results and that can face multiple stages of capital raising, from proof-of-concept to expanded testing to production and commercialization challenges. This trend is likely predictive: healthcare startups in the future will probably still face more rounds of funding than the average startup, especially those in pharmaceuticals or biotechnology.

6.3 Comparison of Total Fundraising and Investment Rounds

When we compare the results of total fundraising and investment rounds side-by-side, we see that they tell similar stories, but not the same. Transportation is a huge frontrunner in fundraising, but only third highest in number of rounds. Hospitality faces the least number of funding rounds, but has higher fundraising than Music and Education. But despite these minor differences, the overall ordering is very similar: No industry's rank is different by more than two spots between fundraising and rounds.

The greater difference in the two studies comes in scale. Fundraising experiences a wide range of possibilities, with the Transportation receiving over six times the amount of Education on average. The range in funding rounds data is much narrower, limited to a ⅔ difference between the smallest and largest value. Even considering the different scales of the studies, this suggests there is more differentiation in total fundraising than there is in rounds. In fact, when we rank industries by the average fundraising per round, the order we get exactly matches the total fundraising amounts, showing that these amounts are generally more influential than the number of rounds.

6.4 Seed Funding Over Time

The ultimate result was expected: seed funding has been increasing over time. However, the manner and rate of growth is of some interest. First, the results strongly support an exponential rate of growth, with an estimated 13.5% increase each year. This is significant because this is growth *in inflation-adjusted dollars*. This indicates that it's not simply the presence of more money in the economy that drives this growth, but that seed investing is significantly outpacing the growth of the money supply and becoming a larger piece of the nation's investment pool.

The other result of interest was the nature of the observed growth. Growth was driven almost exclusively by an increasing skewness of the funding amounts. The bottom half of amounts raised have not increased since 1980 when adjusted for inflation, but the upper percentiles show massive growth. The typical entrepreneur gets no more money than they did in 1980, but the few who top the leaderboards are getting massive payouts. Getting seed funding is becoming less of an investment with a steady range of payouts and more of a lottery, with a small number of people winning extremely large.

6.5 Seed and Venture Funding

Perhaps the most surprising finding was the negative correlation between seed and venture funding. Venture capital (VC) investors are professional investors who will be looking for a company to hit specific milestones before they are willing to consider investing. These milestones typically include customer and sales growth. Implicit in these milestones is the need to have an existing product or service to sell, and a channel to sell it through - both of which require time, effort, and money to develop. Where does this money come from if not from a VC? Typically, the answer would be a seed/angel round.

The dataset partitions seed and angel funding into separate categories, along with some other categories that could also be considered “early stage” financing. We didn’t include this combination in our primary analysis to avoid introducing our own biases. Out of curiosity, we did still explore the impacts of combining particular rounds into early stage financing. Even though this gave stronger weight to early stage financing, it was still negatively correlated with venture funding.

This leads us to conclude that either the data is biased towards companies that received venture funding or that our own perceptions of when a VC would invest are incorrect. One possible explanation would be that the companies in this dataset had more visibility among VCs and may have garnered more early attention. This may have led a “seed” round to be led by a VC and potentially miscatagorized as a Venture and not a seed round. Since we can’t tell if the bias lies with the data or with us, we would urge the reader to interpret the results with caution.

7. Conclusion

In the analysis of the crunchbase dataset, we discovered a number of statistically significant features. We found that within this data group:

- The average amount of funding a company raises is associated with the industry the company is in.
- The average number of fundraising rounds are associated with the industry the company is in.
- The amount of seed money being invested is increasing over time (13.5% annualized growth).
- Companies that don’t do a seed round tend to do venture rounds more frequently.

It can’t be overstated that given the previously mentioned biases in the data, these findings should be viewed with skepticism. It is not realistic to assume that 55% of all startup companies are going to receive venture capital funding, especially when industry norms are closer to 0.05% (Wood, 2020). With this result in doubt, we have to consider that our other results could also be strongly biased, putting the statistical significance of all our findings into question. While we would recommend using our methodology for further study in this area, we can't recommend extrapolating the results to real world predictions.

8. Future Works

Grouping Markets

A difficulty that arose while assessing markets and how different types or funding amounts varied between them was that there were about 754 different categories of markets that start-ups operated in. We chose to scope down our project by selectively handpicking a few markets that were of interest to us. We found that many categories of markets were largely similar and could be grouped into larger umbrellas of categories. The groups could be centered around software, healthcare/medicine, multimedia and so on. There was also the possibility of creating two categories of Technology and Not Technology that was considered. A study further developing the idea of grouping these markets and testing hypotheses based on funding types for these larger groups would be interesting to pursue. This would give us a better understanding of more successful markets or market-types in terms of funding.

Bubbles and Lower-Percentile Seed Funding

One discovery of interest was that the 25th and 50th percentiles of seed funding only showed growth during the early 2000's dotcom boom, and dropped back to a constant rate after the crash. Further exploration is warranted in determining if this type of behavior could be useful in predicting future bubbles before they crash.

Impact of Industry on Seed Funding Over Time

The dotcom bubble had a dramatic impact on the average seed funding levels, even though it should have primarily impacted software companies. A further analysis into seed funding trends by industry may reveal how deeply our findings are the result of just software or specific industries experiencing heavy growth.

Validate Seed and Venture Funding Findings

With the many issues and biases that we came across in this dataset, we realized that we could never have a high confidence in generalizing our results. We decided that in order to validate our findings, the only path forward would be to find similar datasets which are less biased and conduct the same tests. In this way we could validate our findings regarding seed and venture funding and develop more generalized results useful for further study into start-up funding type dynamics.

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