To what extent is social media exposure correlated with financial performance for early stage digital consumer-facing startups?

By

Solene Genre

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Submitted to the MIT Sloan School of Management on
May 9, 2014 in partial fulfillment of the requirements for
the degree of Master of Science in Management Studies

ABSTRACT

It is very hard to identify and evaluate very early stage investment opportunities in disruptive digital consumer-facing startups as they usually don't have any meaningful revenue data yet.

However, these growing startups have "momentums". In classical mechanics, momentum is the product between mass and velocity. When it comes to startups, we can see revenue and web traffic as the mass and unique page views, social presence and sentiment, page rank, inbound links... as velocity (cf. Danielle Morrill start ups momentum index). Analyzing all these data is usually the most relevant way for investors to evaluate investment opportunities. It is however very unclear to what extent startups momentum is an indicator of financial performance. I would like to focus on social media exposure as an indicator of velocity for startups, and investigate further the correlations between social media exposure and revenue data.

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Thank you also to Science Inc, Mike Jones, Tom Dare, Peter Sellis and all the other people at Science Inc who helped me throughout my research. Their contribution was incredible and I couldn't have conducted my research without them

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Chapter 1 – Introduction

1.1 Preliminary Historical Considerations

Business has always been a matter of community. In the Greek empire, business transactions used to take place when socializing in the forum. Transactions were agreed on with a firm handshake. All through the course of history, making money and being well established in one's community have always come together. Take the Arab merchants making connections all over the Middle East and North Africa to sell their camels or 18^{th} century France when the only way to be successful was to be part of Louis XIV court. Looking back at all these examples, I can't quite be sure what came first though, financial success or social recognition…

The social sphere has shifted from a geographical one to a web one and one's community now consists of its digital connections. **In a few words, the digital sphere has replaced the Agora.** The correlation between money and social recognition remains though, and takes an even bigger role as the social sphere evolved. Indeed, the web 3.0 made the social sphere way bigger and way more complicated, and its frontiers way blurrier. It also empowered it with the ability to grow exponentially. As the social sphere evolved, the money associated evolved with it. **But the question remains: What is the correlation between one's presence on the social sphere and the money it can generate?** This question is even more *important* in the venture capital world, with big amounts of money from investors at stake and an always-increasing number of digital start ups.

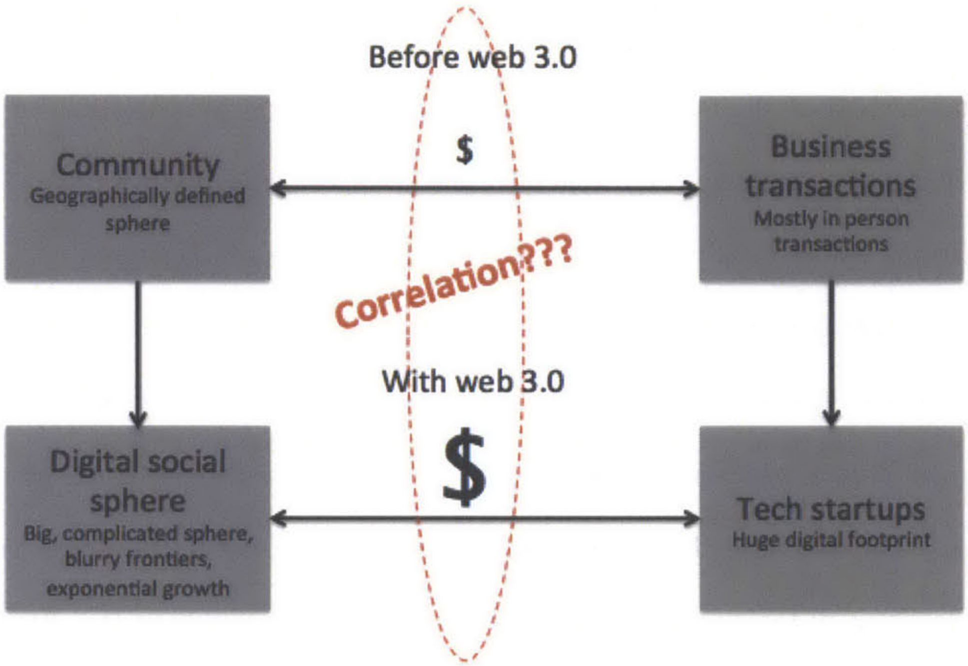


Figure 1: Before and After Web 3.0

1.2 Motivation

I am passionate about early stage digital consumer-facing startups and how to evaluate them. It is very hard to identify and evaluate very early stage investment opportunities in disruptive digital consumer-facing startups as they usually don't have any meaningful revenue data yet.

However, these growing startups have "momentums". In classical mechanics, momentum is the product between mass and velocity. When it comes to startups, we can see revenue and web traffic as the mass and unique page views, social presence and sentiment, page rank, inbound links… as velocity (cf. Danielle Morrill Startups Momentum Index [1]). Analyzing all these data is usually the most relevant way for investors to evaluate investment opportunities. It is however very unclear to what extent startups momentum is an indicator of financial performance. I would like to focus on social media exposure as an indicator of velocity for startups, and investigate further the correlation between social media exposure and revenue data.

Research Question:

➔ From early stage social media exposure to financial performance: To what extent has social media become a core driver of growth, performance and valuation for digital startups?

[1] link: http://www.daniellemorrill.com/2013/05/april-2013-startup-index-1183-companies-71-are-growing/).

Chapter 2 – Secondary Research

2.1 Literature Review

2.1.1 Methodology

The Literature Review was conducted to find out the current take on social media exposure, from both the operator's and the investor's perspective. I was able to find several publications on the qualitative return from social media influence for companies, from articles to books and blog publications. On the other hand, I found that very little has been done when it comes to quantifying the return on influence.

2.1.2 The concept of Return on Influence

Mark Schaefer's book, Return on Influence, was the first book to explore how companies are leveraging social media influence to create awareness. This book was especially enriching in the context of my research as it helped me gain a deeper understanding of how social media influence can be used by companies to improve their performance. Mark Schaefer explains that the crush of data that people are bombarded with is *"creating automatic, mindless compliance in people, a willingness to say yes without thinking first"*. Dr. Rober Cialdini, a doctor and researcher, explains: *"In any situation where information is so dense and overwhelming, the* *irony is that there is so much information that it becomes irrelevant to the choice"*. As Rory O'Connor explains in Friends, followers and the future, the challenge is to *"separate signal from noise in the crowded and chaotic news-and-information environment"*. This is why companies need to monitor and understand the online conversation and sentiments and to separate the signals from the noise. Mark Schaefer's book also helped me a lot with understanding what digital influence is made of. There are two components to a person's digital influence: a quantitative and a qualitative one. The quantitative component (ie. number of Facebook Likes or Twitter Followers) acts as a social proof. On the qualitative side, the criteria to achieve digital influence are much more diverse: Authority, Consistency and Commitment, Likability, Scarcity, Reciprocity and Content all play a part in a person's digital influence.

Klout is the market leader when it comes to quantifying individuals' online influence. Klout tracks over 100 signals from a dozen online platforms and assigns to its customers a score from 1 to 100 – a *"personalized assessment of influence"*. This kind of tools can be very powerful when helping companies figure out who their real advocates are and reach out to them.

The next step is to **connect online behavior to offline results, which Schaefer describes as "dicey".** Schaefer uses the example of Quora to show how social media influence can determine a company's success. Quora grew dramatically in 2010. This whole spike in the company's growth can be explained by just one person's influence: Robert Scoble. As Schaefer puts it, ***"Robert doesn't just move his 200,000 Twitter followers, 5,000 Youtube subscribers, and 5,000 Facebook fans to actions, he moves markets".*** Scoble digital popularity began when he joined Microsoft's MSDN video team and kept growing thereafter. But he most certainly reached the top of his influence between December 26, 2010 and January 30, 2011. On December 26, 2010, Scoble wrote a blog post called "Is Quora the biggest blogging innovation in 10 years?". Within one week, the traffic on Quora had increased by over 400%. A month later, Scoble changed his mind and published "Why I was wrong about Quora as a blogging service..." Traffic on Quora decreased dramatically, pretty much going back to its pre-buzz level. This is a great example of how one person's digital influence can shape a company's performance.

2.1.3 From Return on Influence to Return on Investment

Bjoern Lasse Hermann, co-founder of Compass, a benchmarking tool for startups born out of the Startup Genome project, published his research on November 2013 on the importance of social media as a growth engine for businesses in an article called "Should you bank on Twitter? Yes, if you product is free, Compass benchmark analysis has found". They conducted their research based on their active user base of 30,000 businesses and found that about 30% of the technology companies with less than 100 employees and over a million dollars in annual revenue, *"primarily rely on social media to acquire customers with a growing trend"*. They defined effectiveness as user growth. They found that social media is a primary acquisition channel for free products with indirect monetization, but that traditional marketing is 10% more effective for paid products.

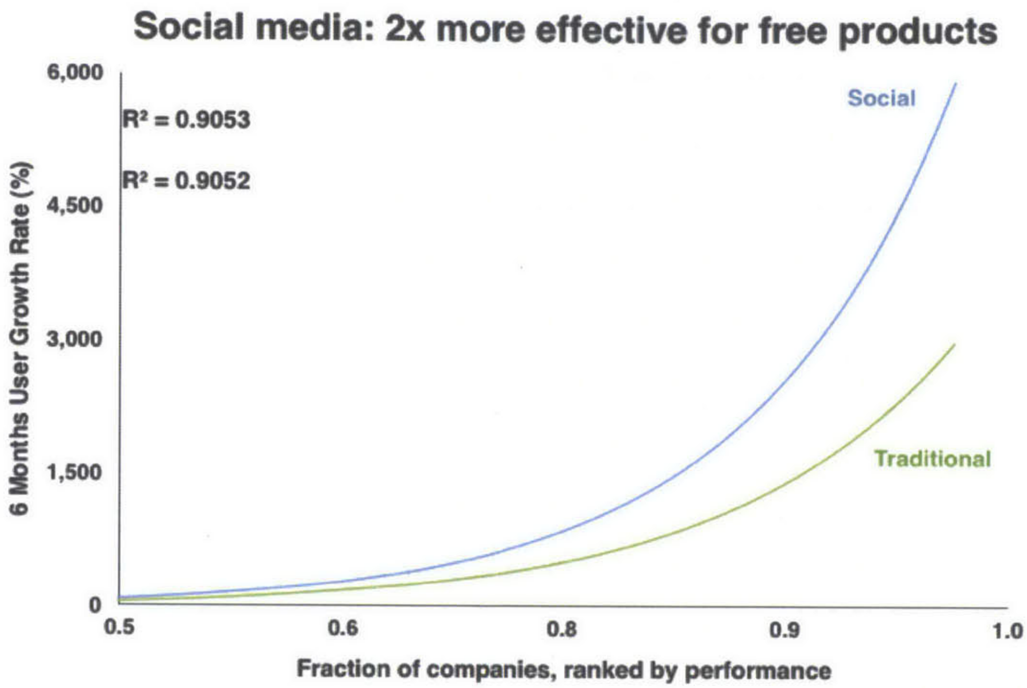


Figure 2: Social Media Effectiveness, Compass Benchmark Analysis

According to a survey from over 2,500 marketers from Exacttarget, a well-known digital marketing platform, called *"2014 State of Marketing"*, **34% of Marketers generate a return from their social media effort and 52% think that they will eventually produce ROI thanks to their social media efforts.** It is interesting to note that the majority of marketers do not see any return on their social media efforts for now, but still believe that they will see ROI on social media someday.

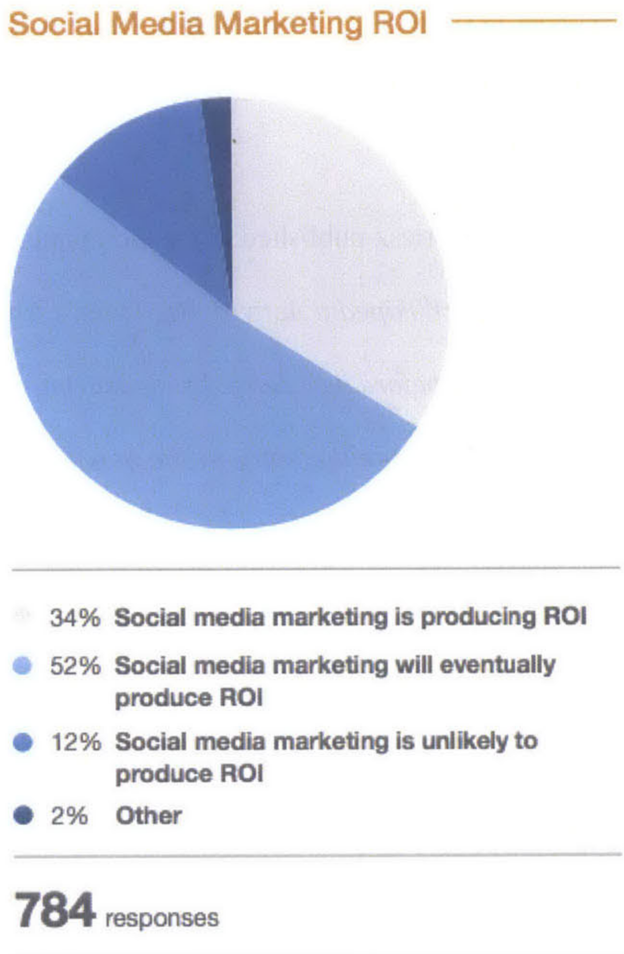


Figure 3: Social Media Marketing ROI, Exacttarget 2014 Survey

2.1.4 From Tracking Online Behavior to Predicting Performance

In December 2009, Lynn Wu and Erik Bryjolfsson published a research paper on *"The Future of Prediction: How Google Searches Foreshadow Housing Prices and Sales"*. They demonstrated how Google queries can predict housing market trends. They underlined in their paper the revolutionary power of search engines' and related information technologies' data to predict supply and demand and therefore change the way business decisions are made. They concluded the paper by saying that *"as these data and methods become more widely used, we can only conclude that the future of prediction is far brighter than it was only a few years ago."*

In August 2013, Marton Mestyan, Taha Yasseri and Janos Kertesz published a research paper on the *"Early Prediction of Movie Box Office Success Based on Wikipedia Activity Big Data"*. They found that *"the popularity of a movie can be predicted much before its release by measuring and analyzing the activity level of editors and viewers of the corresponding entry to the movie in the Wikipedia..."*

This research is a great example of using digital exposure to assess or predict financial performance.

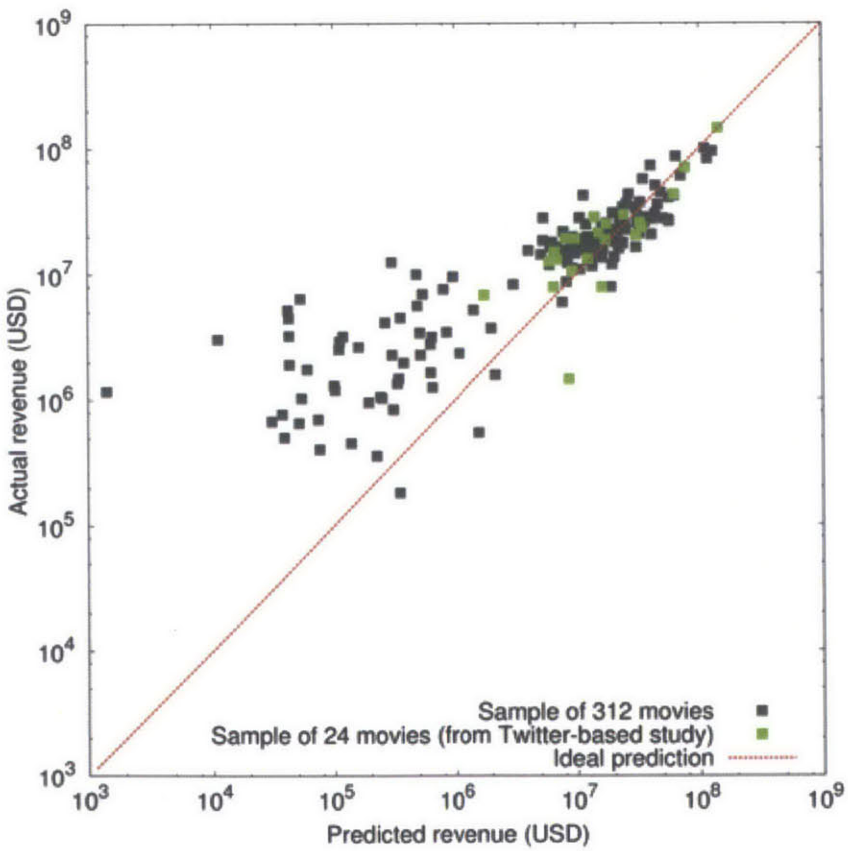


Figure 4: Actual vs. Predicted revenue, "Early Prediction of Movie Box Office Success Based on Wikipedia Activity Big Data" paper

2.1.5 Venture Capital Considerations

I have found in my researches many articles on the growing importance of social media for Venture Capitalists. In September 2013, the Wall Street Journal published an article called *"If you look good on Twitter, VCs may take notice"* on how an increasing number of Venture Capitalists check out a startup social media exposure before investing. According to Ten Leonsis, partner at the Venture Capital firm Revolution LLC, *"Ten years from now, social media will be the starting point of any investment"*. Mr Leonsis calls this social media due diligence a "**digital footprint audit**". I investigated this statement further through my Investors' Interviews (part 4.2.2 On taking social media into account in your due diligence).

2.2 Software Review

2.2.1 Methodology

The software review was conducted to analyze what has already been done to monitor and understand startups' digital exposure and performance metrics. I found that, although many softwares already offer to help startups gathering data on their social media exposure, very little has been done so far when it comes to giving meaning to these data in terms of impact on performance.

2.2.2 Mattermark: Ranking startups based on their social media exposure

In classical mechanics, momentum is the product between mass and velocity. Mattermark's founder Danielle Morrill applies the concept of Momentum to startups, *"where mass is the company's share of web traffic (as measured by Alexa rank) and velocity is the growth trajectory of different signals (social, inbound links, page rank, etc)."* Mattermark aims at ranking startups by tracking their digital signals and granting them the "Mattermark Score". The "Mattermark Score" is a 90 days moving average of the company's digital signals' weekly growth. The idea is to identify startups whose social exposure is consistently growing week over week. Below is the April 2013 list of startups that gained/lost the most "Momentum" according to the Mattermark Score. Although Mattermark obviously doesn't take into account financial performance or number of customers in its ranking, the underlying idea is that these startups ability to grow their digital signal is a good indicator for their current and future financial performance. I investigated this idea further through my Operators and Investors Interviews (parts 4.2.3 and 4.2.6 On ranking startups based on their social media exposure)

"In a town of gamblers, Mattermark is counting cards" – Venturebeat

20 Startup Who *Gained* the Most Momentum

1. BuzzFeed
2. News Blur
3. Coinbase
4. Dropbox
5. Codecademy
6. Disqus
7. Rap Genius
8. Weebly
9. ROBLOX
10. Priceonomics
11. Strikingly
12. Teespring
13. Creative Market
14. Aereo
15. Virool
16. BuildZoom
17. Thalmic Labs
18. Bitnami
19. Perfect Audience
20. Tapas Media

20 Startup Who *Lost* the Most Momentum

1. ChirpMe
2. Causes
3. Payvment
4. Udemy
5. StumbleUpon
6. Lockitron
7. Svbtle
8. Crowdbooster
9. Grubwithus
10. Kaleidoscope
11. Oh Life
12. SplashUp
13. Tumult
14. LaunchRock
15. Ecomom
16. FamilyLeaf
17. Imgfave
18. LeanMarket
19. OpenX
20. Iconfinder

Table 1: Danielle Morrill - April 2013 Startup Index

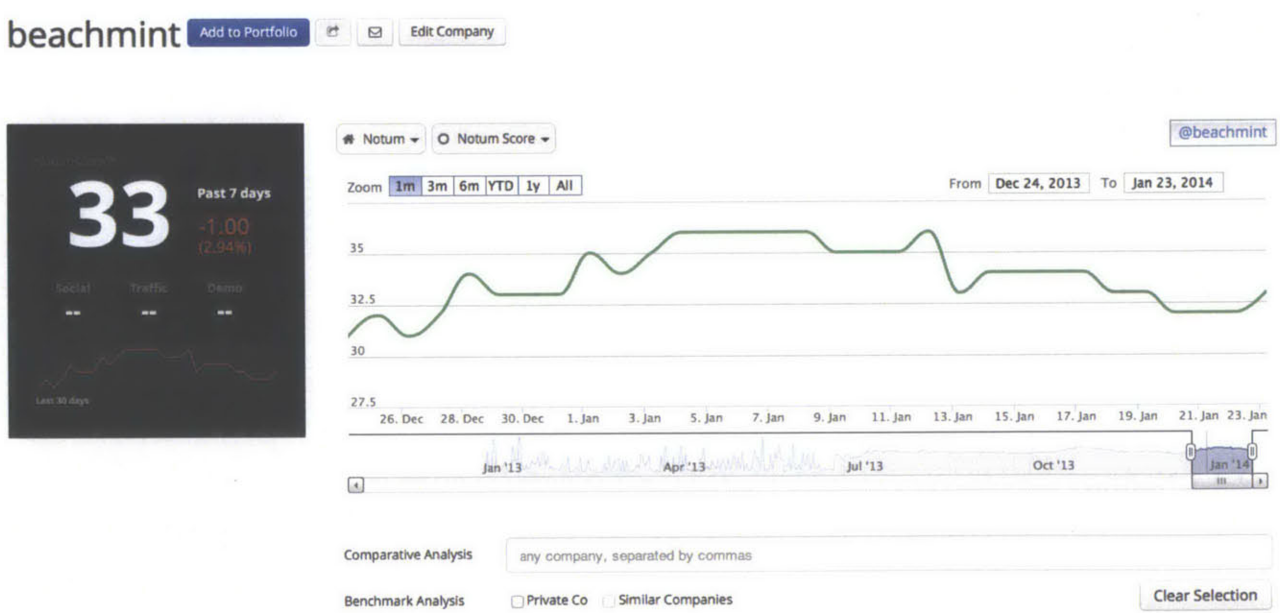
2.2.3 Notum

Notum is a proprietary software developed by Science Inc, a technology studio based in Santa Monica. Notum's is a data intelligence tool that applies big data to social listening and trend analytics for brands, companies, startups and movies all over the web. The use cases are diverse:

- As a portfolio/startup manager, I want to access real time data in an intelligent way. I also need to understand how my social media exposure drives my performance.
- As a Hedge Fund/Venture Capitalist, I want to have access to various companies social, traffic and sentiment indicators and to predict trends.

The Notum Score is calculated using all the social metrics that Notum tracks, scaling them to a similar size and getting a score from 1 to 100 out of them. It is meant to help keep track of a company's social exposure evolution.

Below is an example of Beachmint's Notum page, a famous LA based e-commerce startup. The idea is to have an all one-place dashboard with both performance and social media exposure data.



Social Trends

Facebook	Total	Change	Change %	30 Day
Likes	511.0	↑1.0	0.2%	
Talking	3.0	↓1.0	-25%	

Twitter	Total	Change	Change %	30 Day
Followers	1.4K	0.0	0%	
Tweets	73.0	↑1.0	1.4%	

Pinterest	Total	Change	Change %	30 Day
Likes	0.0	0.0	0%	
Followers	6.0	0.0	0%	

Figure 5: Notum's Company Page for Beachmint

2.3 Conclusion on the Secondary Research

The Secondary Research helped me gain a better understanding of the components of digital influence. I also analyzed the few papers or publications I found on a more quantitative analysis on digital influence. Finally, the Secondary Research left me with several questions that I wanted to investigate further, which was extremely helpful when designing the Investors and Operators Interviews.

Chapter 3 - Correlation Analysis

3.1 Introduction

My goal is to study the correlation between social media exposure and performance for early stage digital startups. It is worth noting that correlation doesn't mean causation and that a statistical dependence doesn't necessarily imply a causal relationship. The most common correlation coefficient, measuring the degree of correlation between two variables, is the Pearson correlation coefficient, which is only sensitive to linear relationships, ie. one variable is a linear function of the other. [2]

The correlation coefficient is symmetric and can't exceed 1 in absolute value. It is only defined if both standard deviations are finite and different from zero. +1 means a perfect increasing linear relationship: -1 means a perfect decreasing linear relationship. The closer the coefficient is to zero, the lighter the relationship between the two variables. If the variables are independent, then the coefficient is zero. However, if the coefficient is null, this doesn't necessarily means total independence between the variables. A correlation matrix is a n * n matrix with Xi,j = corr (Xi,Xj). Instead of showing the rough numbers, a correlation heat map represents colors. Below is the color code that I used in my analysis.

2

The population correlation coefficient $\rho_{X,Y}$ between two random variables X and Y with expected values μ_X and μ_Y and standard deviations σ_X and σ_Y is defined as:

$$\rho_{X,Y} = \mathrm{corr}(X,Y) = \frac{\mathrm{cov}(X,Y)}{\sigma_X \sigma_Y} = \frac{E[(X-\mu_X)(Y-\mu_Y)]}{\sigma_X \sigma_Y},$$

where E is the expected value operator, *cov* means covariance, and, *corr* a widely used alternative notation for the correlation coefficient.

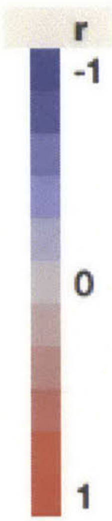


Figure 7: Correlation Heat map color code

3.2 Methodology and Considered Metrics

3.2.1 Social Metrics

Facebook	**Likes**
	Talking About
	Were here – number of people that have checked in a particular location
Twitter	**Followers/Followings**
	Tweets/Re-tweets
Pinterest	**Followers/Followings**
	Likes/Pins
Youtube	**Subscribers**
	Video Views
Instagram	**Followers/Followings**
	Posts

3.2.2 Performance Metrics

- **Daily Revenue:** the money that the startup earned on a daily basis in US dollars.
- Traffic:
  - Number of Pageviews: number of requests to load a single web page of a website.
  - Number of Unique Visitors: number of people who visited the website once or more in a given amount of time, measured using their unique IP addresses.
- Conversion Rate: percentage of Unique Visitors who converted into purchases, calculated by dividing total number of orders for a given period by total number of unique visitors for this given period.

3.2.3 Methodology

I analyzed the above listed metrics for 6 different startups:

- 5 e-commerce startups
- 1 services marketplace

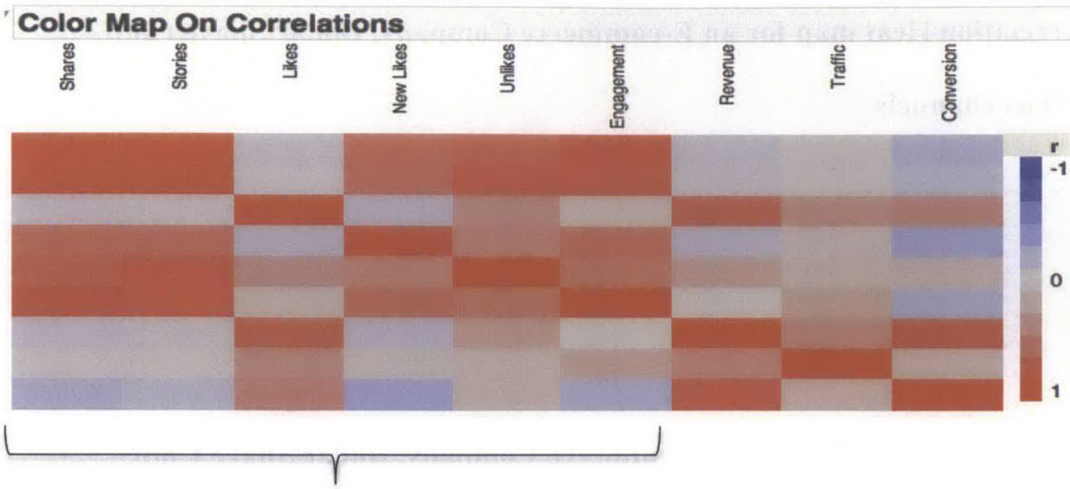
Among the 5 e-commerce startups, 3 of them were 100% digital and especially targeting tech savvy consumers (including startups A and B, whom data are analyzed below), and the 2 other startups were targeting more "traditional consumers" and acted more as online "displays" that were complementing physical brick and mortars.

I used JMP, a statistical analysis software, to analyze the data. As explained below, I started with discovering the statistical relationships via correlation matrixes and heat maps. This enabled me to spot the social metrics that had a relevant influence on revenue, and rule out the ones that were irrelevant. Then, I was able to build regressions with one or multiple predictors. I focused in the analysis below on 3 of the e-commerce startups. In the 3.4 Conclusion on correlations part, I take a step back and extract the meaning of the correlation analysis I have run for the 6 startups.

3.3 Analysis

3.3.1 Discovering the relationship

To discover the relationships between the variables and spot interesting correlations, I built correlation heat maps (see above for explanation). The correlation heat maps enabled me to spot the correlations very quickly. Below are two correlation heat maps: the first one is for an e-commerce company that mostly uses Facebook as a marketing channel (Prize Candle), the second one is for an e-commerce company that uses several different social media channels (Dollar Shave Club).



Facebook

Figure 8: Correlation Heat map for an E-commerce Company, Prize Candle – Focus on Facebook

Correlations

	Shares	Stories	Likes	New Likes	Unlikes	Engagement	Revenue	Traffic	Conversion
Shares	1.0000	0.9797	-0.0607	0.6532	0.7157	0.8154	-0.1049	0.0260	-0.2153
Stories	0.9797	1.0000	-0.0356	0.6263	0.7695	0.7762	-0.0668	0.0206	-0.1507
Likes	-0.0607	-0.0356	1.0000	-0.1435	0.4024	0.1010	0.7219	0.4174	0.4978
New Likes	0.6532	0.6263	-0.1435	1.0000	0.4694	0.6256	-0.1527	0.0803	-0.2957
Unlikes	0.7157	0.7695	0.4024	0.4694	1.0000	0.5610	0.3050	0.1277	0.1625
Engagement	0.8154	0.7762	0.1010	0.6256	0.5610	1.0000	0.0027	0.2866	-0.2319
Revenue	-0.1049	-0.0668	0.7219	-0.1527	0.3050	0.0027	1.0000	0.4505	0.7525
Traffic	0.0260	0.0206	0.4174	0.0803	0.1277	0.2866	0.4505	1.0000	0.1653
Conversion	-0.2153	-0.1507	0.4978	-0.2957	0.1625	-0.2319	0.7525	0.1653	1.0000

Figure 9: Correlations Matrix for an E-commerce Company, Prize Candle – Focus on Facebook

Figure 10: Correlation Heat map for an E-commerce Company, Dollar Shave Club – Exploring various channels

	Revenue	Fb _ Like this	Fb_Talking about	Instagram Posts	Instagran followers	Instagram following	Twitter_Tweets	Twitter_Following	Twitter Followers	Twitter_Listed	Youtube_Suscribers	Youtube_Videoviews
Revenue	1.0000	0.6742	0.5157	0.6783	0.6632	0.1708	0.6654	0.6412	0.6684	0.6605	0.6569	0.6700
Fb _ Like this	0.6742	1.0000	0.7282	0.9849	0.9596	0.2408	0.9683	0.9367	0.9703	0.9663	0.9563	0.9764
Fb_Talking about	0.5157	0.7282	1.0000	0.6725	0.6653	0.0986	0.7949	0.8387	0.7736	0.7766	0.7550	0.7662
Instagram Posts	0.6783	0.9849	0.6725	1.0000	0.9767	0.2979	0.9591	0.9222	0.9637	0.9560	0.9540	0.9682
Instagran followers	0.6632	0.9596	0.6653	0.9767	1.0000	0.4024	0.9712	0.9490	0.9743	0.9735	0.9801	0.9793
Instagram following	0.1708	0.2408	0.0986	0.2979	0.4024	1.0000	0.2995	0.3258	0.2828	0.3384	0.3374	0.3001
Twitter_Tweets	0.6654	0.9683	0.7949	0.9591	0.9712	0.2995	1.0000	0.9896	0.9981	0.9892	0.9887	0.9947
Twitter_Following	0.6412	0.9367	0.8387	0.9222	0.9490	0.3258	0.9896	1.0000	0.9833	0.9856	0.9818	0.9820
Twitter Followers	0.6684	0.9703	0.7736	0.9637	0.9743	0.2828	0.9981	0.9833	1.0000	0.9873	0.9888	0.9953
Twitter_Listed	0.6605	0.9663	0.7766	0.9560	0.9735	0.3384	0.9892	0.9856	0.9873	1.0000	0.9924	0.9940
Youtube_Suscribers	0.6569	0.9563	0.7550	0.9540	0.9801	0.3374	0.9887	0.9818	0.9888	0.9924	1.0000	0.9952
Youtube_Videoviews	0.6700	0.9764	0.7662	0.9682	0.9793	0.3001	0.9947	0.9820	0.9953	0.9940	0.9952	1.0000

Figure 11: Correlations Matrix for an E-commerce Company, Dollar Shave Club – Exploring various channels

Correlations

	Revenue F
Revenue	1.0000
Fb _ Like this	0.6742
Fb_Talking about	0.5157
Instagram Posts	0.6783
Instagran followers	0.6632
Instagram following	0.1708
Twitter_Tweets	0.6654
Twitter_Following	0.6412
Twitter Followers	0.6684
Twitter_Listed	0.6605
Youtube_Suscribers	0.6569
Youtube_Videoviews	0.6700

Figure 12: Correlations Matrix for an E-commerce Company, Dollar Shave Club – Zoom on the correlations between revenue and various social media channels

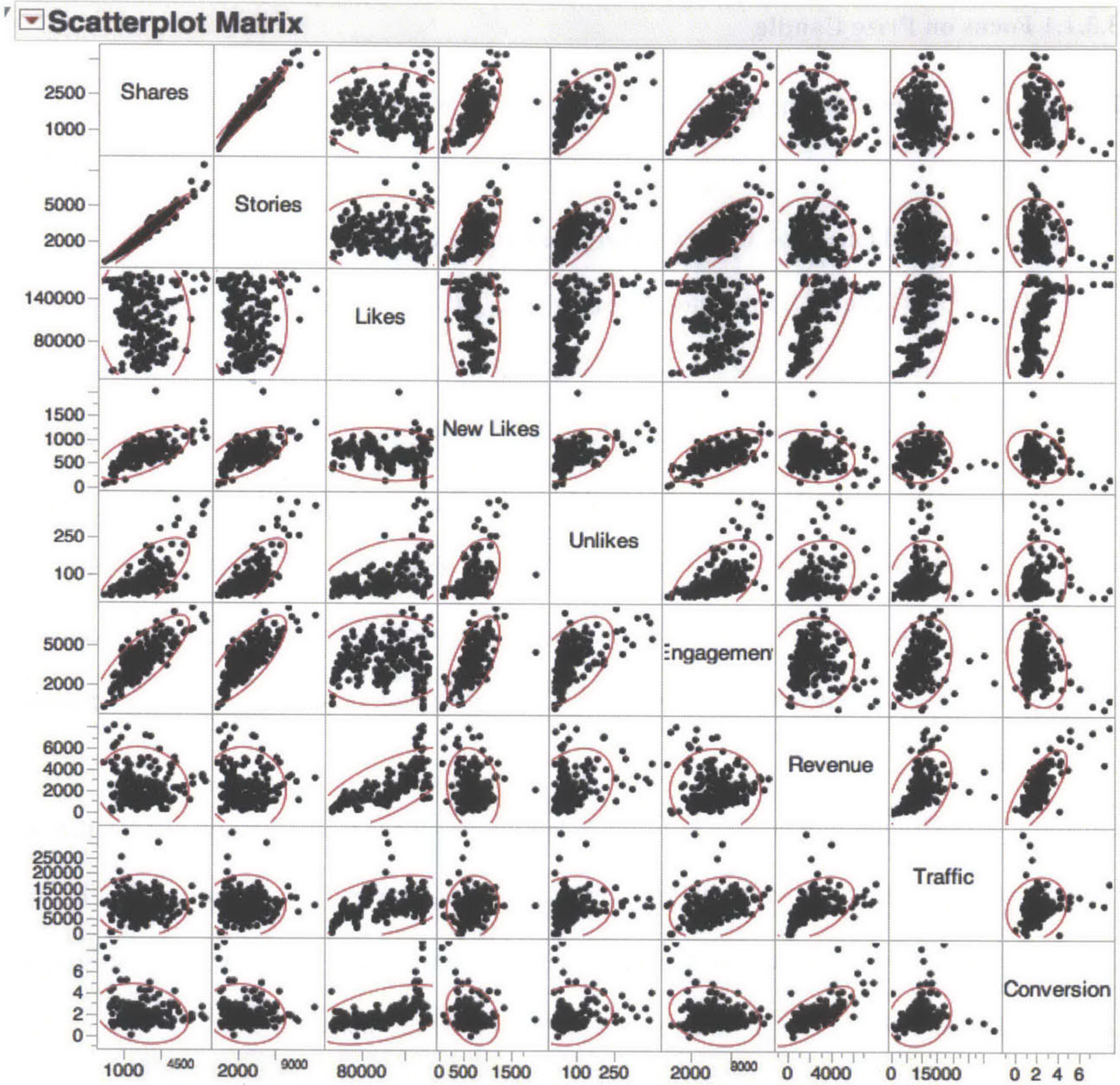


Figure 13: Scatterplot Matrix for an E-commerce Company, Prize Candle

Both the correlation heat map and the scatterplot matrix allow me to explore the correlations between the social variables and the performance variables.

3.3.1.1 Focus on Prize Candle

I can see on the correlation heat map in Figure 8 that the highest social-performance correlations are:

- Revenue and Facebook Likes are correlated with a 0.7219 correlation coefficient
- Traffic and Facebook Likes are correlated with a 0.4174 correlation coefficient
- Conversion and Facebook Likes are correlated with a 0.4978 correlation coefficient

To take into account the fact that there might be a time lag between Facebook exposure and revenue, I created multiple "lagged" variables (see Figure 16 for illustration of a lagged variable). I then ran the same multivariate analysis as above (Figure 14) and focused on the relationship between Facebook Likes and the multiple lagged Revenue variables (see Scatterplot Matrix, Figure 15). I found that the correlation remains quite similar whether the Revenue is lagged or not.

I also wanted to try out bigger lags. I created a "minus 30 days lagged revenue" and ran the same multivariate analysis as before, using this "lagged revenue". I found that the correlation between this "lagged revenue" and the social metrics (here Facebook Likes) is lower. The difference is tiny though, and makes it hard to draw any conclusion from the analysis.

Correlations

	Shares	Stories	Likes	New Likes	Unlikes	Engagement	Revenue	Traffic	Conversion	Lag Revenue 1	Lag Revenue 2	Lag Revenue 3	Lag Revenue 4	Lag Revenue 5	Lag Revenue 6	Lag Revenue 7
Shares	1.0000	0.9797	-0.0607	0.6532	0.7157	0.8154	-0.1049	0.0260	-0.2153	-0.1325	-0.0924	-0.0881	-0.1281	-0.0717	-0.0884	-0.0025
Stories	0.9797	1.0000	-0.0356	0.6263	0.7695	0.7762	-0.0668	0.0206	-0.1507	-0.1024	-0.0596	-0.0586	-0.0875	-0.0339	-0.0534	0.0318
Likes	-0.0607	-0.0356	1.0000	-0.1435	0.4024	0.1010	0.7219	0.4174	0.4978	0.7250	0.7336	0.7332	0.7329	0.7345	0.7309	0.7302
New Likes	0.6532	0.6263	-0.1435	1.0000	0.4694	0.6256	-0.1527	0.0803	-0.2957	-0.1664	-0.1097	-0.1097	-0.1355	-0.1332	-0.1569	-0.1186
Unlikes	0.7157	0.7695	0.4024	0.4694	1.0000	0.5610	0.3050	0.1277	0.1625	0.2900	0.3235	0.3499	0.3161	0.3866	0.3593	0.4710
Engagement	0.8154	0.7762	0.1010	0.6256	0.5610	1.0000	0.0027	0.2866	-0.2319	-0.0484	-0.0101	0.0068	-0.0569	-0.0268	-0.0554	-0.0166
Revenue	-0.1049	-0.0668	0.7219	-0.1527	0.3050	0.0027	1.0000	0.4505	0.7525	0.7900	0.7165	0.6963	0.6693	0.6734	0.6753	0.6727
Traffic	0.0260	0.0206	0.4174	0.0803	0.1277	0.2866	0.4505	1.0000	0.1653	0.2703	0.2279	0.2477	0.2532	0.2480	0.2518	0.2109
Conversion	-0.2153	-0.1507	0.4978	-0.2957	0.1625	-0.2319	0.7525	0.1653	1.0000	0.6496	0.5658	0.5205	0.5443	0.5512	0.5655	0.5771
Lag Revenue 1	-0.1325	-0.1024	0.7250	-0.1664	0.2900	-0.0484	0.7900	0.2703	0.6496	1.0000	0.7908	0.7171	0.6969	0.6693	0.6769	0.6760
Lag Revenue 2	-0.0924	-0.0596	0.7336	-0.1097	0.3235	-0.0101	0.7165	0.2279	0.5658	0.7908	1.0000	0.7943	0.7204	0.6985	0.6783	0.6805
Lag Revenue 3	-0.0881	-0.0586	0.7332	-0.1097	0.3499	0.0068	0.6963	0.2477	0.5205	0.7171	0.7943	1.0000	0.7937	0.7202	0.6980	0.6773
Lag Revenue 4	-0.1281	-0.0875	0.7329	-0.1355	0.3161	-0.0569	0.6693	0.2532	0.5443	0.6969	0.7204	0.7937	1.0000	0.7936	0.7199	0.6971
Lag Revenue 5	-0.0717	-0.0339	0.7345	-0.1332	0.3866	-0.0268	0.6734	0.2480	0.5512	0.6693	0.6985	0.7202	0.7936	1.0000	0.7960	0.7198
Lag Revenue 6	-0.0884	-0.0534	0.7309	-0.1569	0.3593	-0.0554	0.6753	0.2518	0.5655	0.6769	0.6783	0.6980	0.7199	0.7960	1.0000	0.7960
Lag Revenue 7	-0.0025	0.0318	0.7302	-0.1186	0.4710	-0.0166	0.6727	0.2109	0.5771	0.6760	0.6805	0.6773	0.6971	0.7198	0.7960	1.0000

There are 7 missing values. The correlations are estimated by Pairwise method.

Figure 14: Correlations Matrix with multiple lagged variables for Revenue for an E-commerce Company, Prize Candle

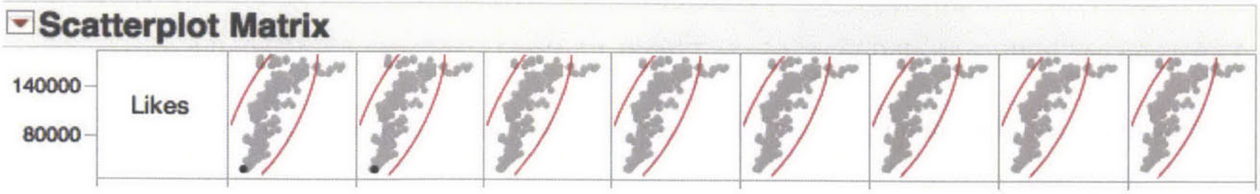


Figure 15: Scatterplot Matrix of Likes and Multiple Lagged Revenue Variables (from 0 to 7 days lags)

Correlations

	Shares	Stories	Likes	New Likes	Unlikes	Engagement	30 days lagged revenue
Shares	1.0000	0.9752	-0.1226	0.6103	0.6634	0.7793	-0.1193
Stories	0.9752	1.0000	-0.0828	0.5871	0.7539	0.7352	-0.1286
Likes	-0.1226	-0.0828	1.0000	-0.1894	0.3298	0.1822	0.6684
New Likes	0.6103	0.5871	-0.1894	1.0000	0.4393	0.5653	-0.1627
Unlikes	0.6634	0.7539	0.3298	0.4393	1.0000	0.5532	0.0970
Engagement	0.7793	0.7352	0.1822	0.5653	0.5532	1.0000	0.1270
30 days lagged revenue	-0.1193	-0.1286	0.6684	-0.1627	0.0970	0.1270	1.0000

Figure 16: Correlations Matrix with a "minus 30 days lagged revenue" for an E-commerce Company, Prize Candle

3.3.1.2 Focus on Dollar Shave Club

I found from the correlation heat map in Figure 10 that revenue was quite highly correlated with all the considered social media metrics - with a correlation coefficient above 0.6 for all the metrics but Facebook "Talking about" and Instagram following. I decided therefore to exclude Facebook "Talking about" and Instagram following from my multiple predictors' regression model for Dollar Shave Club.

3.3.1.3 Focus on Urban Remedy

As we can see in the correlation matrix in Figure 17, there is no correlation at all between revenue and social media metrics for Urban Remedy, with all the correlation coefficients being between -0.1 and +0.1.

	Revenue Pa
Revenue	1.0000
Pageviews	0.6082
Unique Visitors	0.4522
Conversion rate	0.3011
Fb _ Like this	0.0935
Fb_Talking about	-0.0955
Fb_Talking ratio	-0.0972
Instagram Posts	0.1024
Instagran followers	0.0925
Instagram following	-0.0405
Instagram_Boards	0.0752
Pinterest_Pins	0.0791
Pinterest_Likes	-0.0817
Pinterest_Following	-0.0876
Pinterest_Followers	0.1459
Twitter_Tweets	0.1429
Twitter_Following	0.0379
Twitter Followers	0.1458
Twitter_Listed	0.1055

Figure 17: Correlation Matrix for Urban Remedy

3.3.2 Building the Regressions Model

3.3.2.1 Using Regression with one Predictor

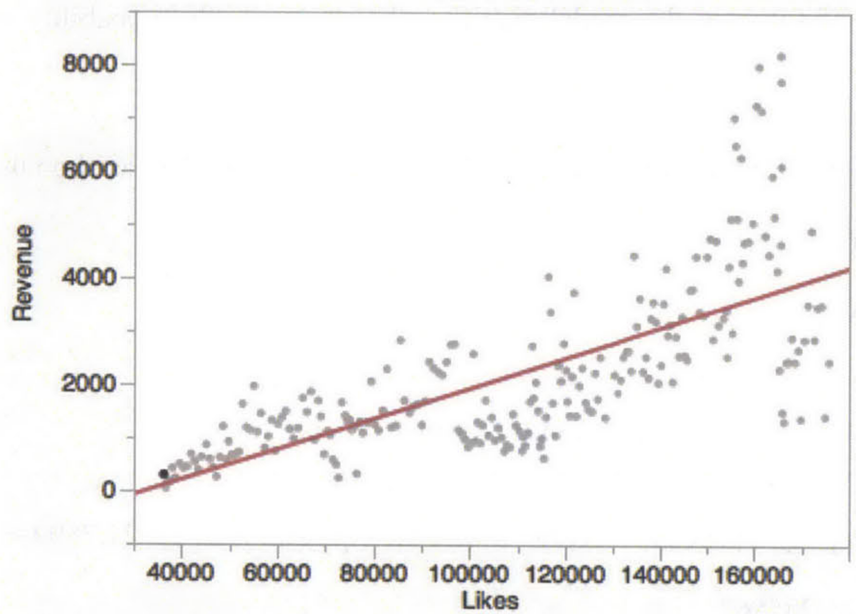
Given that the highest social media-revenue correlation I found for Prize Candle was between Revenue and Likes, I decided to build a linear regression between these two variables. Within the report, note the following results:

- p-value < 0.0001. The p-value is less than the significance level of 0.05. Therefore including the number of Likes in the model significantly improves the probability to predict revenue.
- The R-Square value of 0.521105 is quite large, which confirms that a model based on the number of Likes can predict Revenue.
- The Prediction Equation is:

Daily Revenue = -933.8891 + 0.0285567 * Total Number of Likes

For example, if the company's page has 100,000 Likes, the equation is as $1921.7809 = -933.8891 + 100,000 * 0.0285567

Bivariate Fit of Revenue By Likes



Linear Fit

Linear Fit

Revenue = -933.8891 + 0.0285567*Likes

Summary of Fit

RSquare	0.521105
RSquare Adj	0.518928
Root Mean Square Error	1110.433
Mean of Response	2209.797
Observations (or Sum Wgts)	222

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	295183486	295183486	239.3908
Error	220	271273474	1233061.2	Prob > F
C. Total	221	566456960		<.0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	-933.8891	216.4193	-4.32	<.0001*
Likes	0.0285567	0.001846	15.47	<.0001*

Figure 18: Linear Regression of Revenue by Likes for E-commerce Startup A

3.3.2.2 Using Regression with Multiple Predictors

Given the relatively high, positive correlation coefficients that I found between daily revenue and Facebook "Like this", Instagram Posts, Instgram Followers, Twitter Tweets, Twitter Followings, Twitter Followers, Twitter Listed, Youtube Suscribers and Youtube Videoviews, I decided to build a multiple predictors regression model to predict revenue using the above mentioned metrics.

The Actual by Predicted Plot shows the actual revenue vs. the predicted revenue. The RSquare value measures the percentage of variability in revenue, as explained by the model (1 means that the model is predicting perfectly). In this example, we have a RSquare of 0.47, which means the prediction is quite imprecise. Although each social variable had a pretty high correlation with revenue, the multiple regression model is not statistically significant.

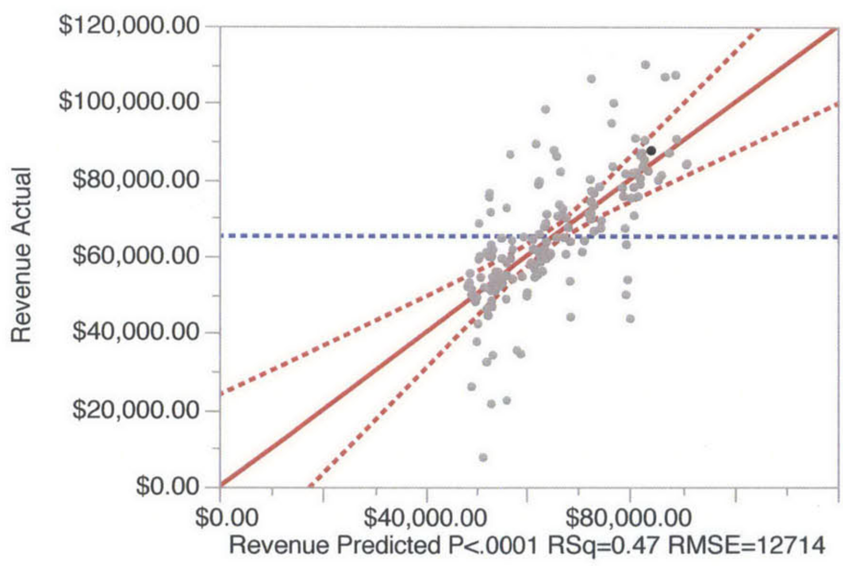


Figure 19: Actual by Predicted Plot for Dollar Shave Club

Summary of Fit

RSquare	0.472668
RSquare Adj	0.440382
Root Mean Square Error	12714.09
Mean of Response	65194.82
Observations (or Sum Wgts)	157

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	9	2.1299e+10	2.3666e+9	14.6402
Error	147	2.3762e+10	161648198	Prob > F
C. Total	156	4.5061e+10		<.0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	-425423.4	250487.4	-1.70	0.0916
Fb _ Like this	-0.345695	0.286005	-1.21	0.2287
Instagram Posts	1463.6209	1290.106	1.13	0.2584
Instagran followers	-10.28128	29.47687	-0.35	0.7277
Twitter_Tweets	180.92507	289.4701	0.63	0.5329
Twitter_Following	-78.30651	83.95357	-0.93	0.3525
Twitter Followers	-4.169101	9.306381	-0.45	0.6548
Twitter_Listed	403.20018	696.8344	0.58	0.5637
Youtube_Suscribers	-24.5101	19.05744	-1.29	0.2004
Youtube_Videoviews	0.0490891	0.036809	1.33	0.1844

Figure 20: Parameters Estimate Report for Dollar Shave Club

3.4 Conclusion on the Correlation Analysis

As explained in the methodology part, I analyzed the social and performance metrics for 6 startups, with 3 of them addressing a tech savvy audience, and 3 of them addressing a more "regular" audience. I found a very strong difference in terms of correlations according to the type of audience that was targeted. Indeed, the 3 "tech savvy" startups – including startups A and B – had pretty strong correlations between revenue and some of their social metrics, like number of Facebook Likes. On the other hand, I did not find any interesting correlations for the "non tech savvy" startups. In Chapter 4, I focus on investigating deeper the differences between two startups from the two different "types" I found in this Correlation Analysis.

Focusing on these "tech-savvy" startups, I was able to build some regression models and, for example, to attribute a dollar value to a Facebook Like. However, I believe that there is a big limit to attributing a general dollar value to a social activity: indeed, the value of a person's Like (for example) depends on the person's digital influence and authority, as explained by Mark Schaefer in Return on Influence (see part 2.1.2).

Chapter 4 – Comparative Analysis

4.1 Introduction

I decided to focus on two companies from the two different "types" I identified in Chapter 3 – Correlation Analysis to get a deeper understanding of how their audiences, their stories, their products and their strategies differentiate and how this explains that social media can be correlated with revenue for one and not for the other.

Below is a comparative analysis of Dollar Shave Club and Urban Remedy, which data I analyzed in Chapter 3.

4.2 Comparative Analysis

	URBAN REMEDY	DOLLARSHAVECLUB.COM SHAVE TIME. SHAVE MONEY.
CEO and Founder	**Neka Pasquale, *"licensed acupuncturist, herbalist and certified Chinese nutritionist"***	**Michael Dublin, *"marketing and media expert"***
Starting point	*"Her passion for cooking led her to create 3-5 day juice…*	*"I saw a market that was ripe for disruption, so I went for*

	then, the word spread"	*it"*
Founded	Beginning 2012	March 2012
Product	Organic food and juices	Razor blades
Business Model	**Sell online and in physical stores across California**	**Subscription e-commerce, 100% online**
Price point	Around $60 for a 3 days cleanse	$1/$6/$9 a month
Philosophy	***"Food is medicine"***	***"Shave time Shave money", "DSC is all about being smart", "data driven company"***
Goal	**Educate and sell**	**Sell and grow as fast as possible**
Target customers	Wealthy, health conscious women in their 40s	Busy young men, executives in their 20s and 30s
Focus on social media marketing (ie. has a social media team)	Yes	Yes
Social media exposure – revenue correlations	**Very low, between -0.1 and +0.1 for all channels**	**Quite high, over +0.6 for all channels**
Number of Twitter followers	2,070	39,825
Number of days on Twitter	1,137	1,094
Retweets	**20.0%**	**52.8%**

Number of followers with over 1,00 followers	645	3,415
% of followers that have been on Twitter for over 4 years	35.9%	48.1%
Social Authority Score based on Twitter (source: followerwonk)	24	55
Number of Facebook Likes	67,497	385,279
Average Facebook talking about score	**Around 1,000**	**Around 15,000**

Table 2: Comparative Analysis of Dollar Shave Club and Urban Remedy – source for the analysis of the Twitter followers: followerwonk.com

Overall, we can see that Dollar Shave Club has a much higher social media exposure than Urban Remedy, and that within the two audiences, DSC's social media audience is much more engaged and active that UR one.

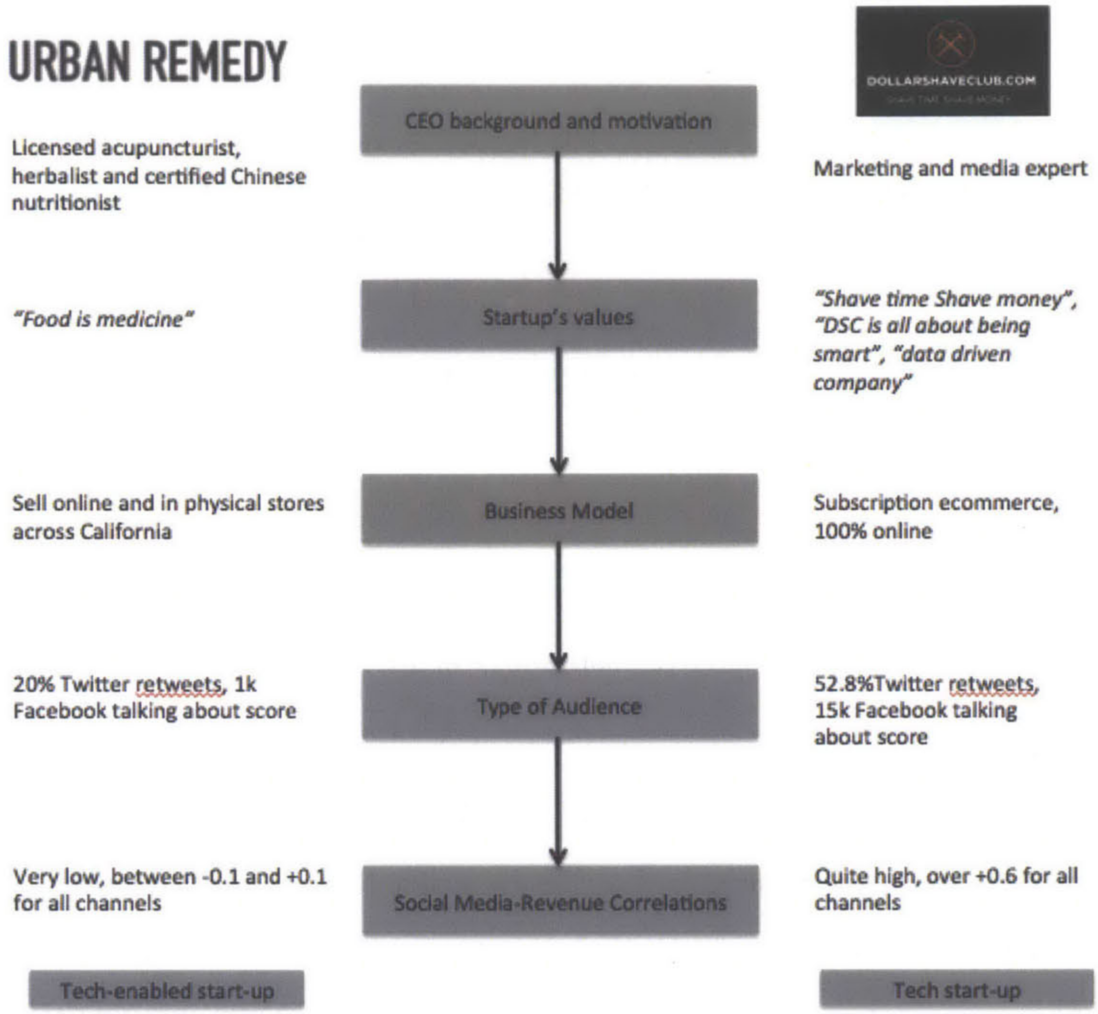


Figure 21: Urban Remedy vs. Dollar Shave Club

4.3 Conclusion on the Comparative Analysis

Both the Chapter 3 - Correlation Analysis and Chapter 4 – Comparative Analysis helped me state that:

- Social media exposure is highly correlated with revenue for some startups, and not correlated at all with revenue for others.
- To what extent social media exposure drives revenue depends on the startup's story, **philosophy**, target customers and overall, to how tech savvy the audience is. The very stories, backgrounds and respective motivations of the two CEOs can explain the different types of audience.
- Being present online doesn't mean being a "tech startup" – and doesn't mean that your audience is tech savvy. We need to make the **distinction between "tech startups" and "tech enabled startups".**
- In a nutshell, social media can play a totally different role for two companies if their markets, and thus their audiences, are different. Even though Urban Remedy and Dollar Shave Club seem similar - both being digital e-commerce startups – their different philosophies led them to have different types of customers, with different relationships to social media and different levels of engagement on them.

Chapter 5 – Interviews

5.1 An insider look at Venture Capital evaluation

5.1.1 Introduction

The previous parts explored the correlation between social media exposure and revenue for different consumer-facing startups, and the characteristics behind these correlations for two of these startups. To better understand how these considerations already are or could be taken into account by Venture Capitalists in their due diligence, Interviews were conducted with three Venture Capitalists from Science Inc: Mike Jones, Science Inc CEO, former CEO of Myspace and serial Internet Entrepreneur, Tom Dare, Science Inc CFO and former VP of Business Intelligence of Myspace, and James Hicks, Venture Capital Associate with Science Inc. The goal of these interviews was to extract the role of social media in both spotting investment opportunities and evaluating them, and whether they should be used as a qualitative or quantitative tool (or both).

5.1.2 On taking social media exposure into account in the due diligence

James H. usually looks at companies at so early a stage – pre-seed or seed investments – that there is not much social media exposure to take into account yet. The social media exposure usually occurs later, after the Series A stage. But overall what he looks for is not the number of Facebook Likes – companies can buy them - but customers' stories and insights on the product or service - *"Investors look at social media to find customers' stories. In the end, the number of Likes doesn't matter as much as the few compelling stories that were shared"*. For example, a few months ago, as one of his portfolio companies was looking for a new investment round, negative comments started to come up on Facebook about the time of the delivery, the quality of the product, etc. The potential new investors saw it and it almost killed the deal.

For Tom Dare, social media as an indicator for investors is part of a feedback loop. Many years ago, his company at the time was trying to raise money from Credit Suisse and bought the billboard right in front of Credit Suisse office to put in Credit Suisse employees' mind that his company was the next big thing. Social Media is not that different – companies put their footprint all over the web so that it becomes part of their audience's world. However, as an investor, one needs to get out of that bubble to find the next big thing.

For Mike Jones, social media show a company's brand quality and strength. A few highly enthusiastic comments from passionate customers mean more than a million Facebook Likes to him. What investors look for when exploring a startup's social footprint is really this ability to get customers engaged and passionate about their products - *"What I look for when exploring a startup's social media exposure is the brand reach, not mass adoption."* .

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5.1.3 On social media as a direct vs. indirect performance driver

I asked the interviewees to choose between the following statements:

- Social Media indirectly impacts your business performance (1st Statement)
- Social Media is a critical enabler of business/services your business provides (2nd Statement)
- Your business' primary revenue source is directly linked to social marketing (3rd Statement)

James H chose the first statement: For him, no one has cracked the code of social media sales yet.

For Tom Dare, social media as a direct vs. indirect performance driver fully depends on the company's audience. Nest is a great example of how social media can drive performance for tech-oriented products. After gaining the trust of the tech-community, Nest was able to win over the mainstream audience. Digital strategies are efficient for tech-savvy customers. Therefore, he could not choose between the three Statements.

Mike Jones agrees with Tom Dare on the importance of being aligned with one's audience. He takes the example of a recent promotion run by the shopping site Fab.com. Both Ashton Kutcher (7.3million Twitter followers) and Kevin Rose (1.3million Twitter followers) posted the promotion on their Twitter. Kutcher's link resulted in 5,888 sign-ups vs. 4,356 for Rose's link. But Rose's links resulted in more revenue. Rose's followers, who are mostly tech-savvy as he is, passed the link along much more than Kutcher's followers. In the end, Kutcher's post resulted in $2,183 in revenue vs. $7,121 for Rose's. **This is a great example of how the quality of the audience is a way better performance driver than the quantity. *"Broad reach doesn't mean mass adoption"* (Mike Jones).**

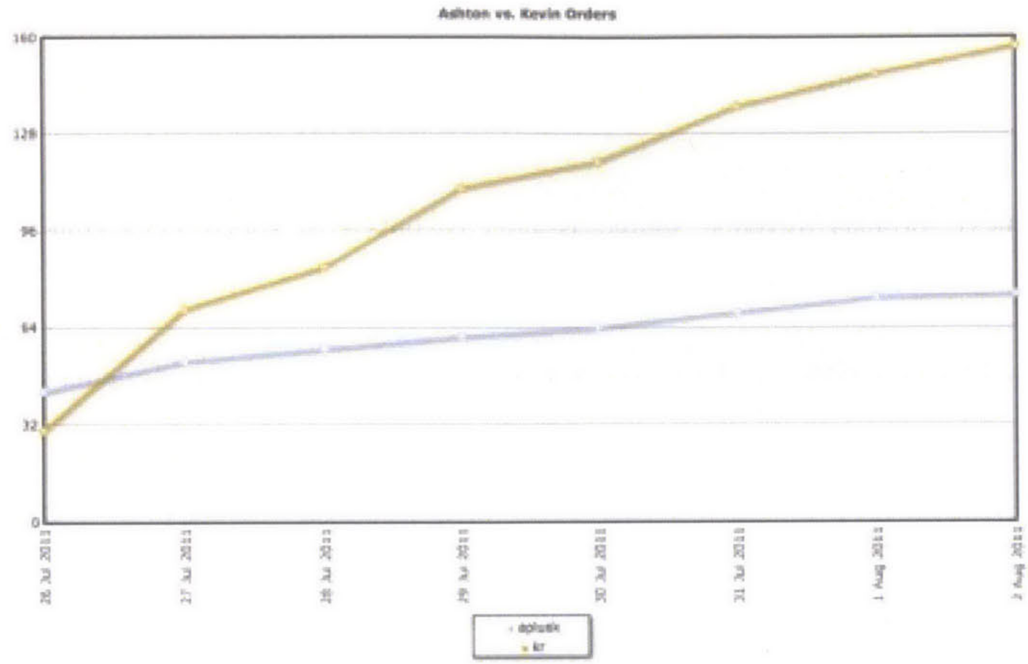

Figure 22: Ashton (blue line) vs Kevin (yellow line) orders, Techcrunch

5.1.4 On ranking startups based on their social media exposure

For James H., what comes first between the social media exposure and the revenue is a "chicken and the egg" issue. Usually, momentum occurs after a funding event that gave the team the opportunity to focus on their social media exposure. Moreover, a company usually needs to have been around for a while to get their customers engaged on social media. This is thefore unfair to invest according to startups' social media exposure.

Tom Dare likes closed information better, that comes from a tighter community of well-qualified people. For him, *"the challenge is to separate the signals from the noise"*. One tweet from someone he trusts is much more powerful than thousands of tweets from random people. He believes in the power of networks that enable users to evolve within constructive groups of people they trust. This is the only way for social media to truly influence offline behaviors.

For Mike Jones, the goal as an investor is to spot apps and websites that are growing fast before the others do.

5.2 An insider look at Startups take on Social Media

5.2.1 Introduction

After having explored the investors' perspective on the subject, the next step was to explore the operators' perspective. Operators are the people within the companies who work with social media exposure on a day-to-day basis and have to deal with the issue of quantifying their return on social media marketing investments. I therefore interviewed Alex Osborne, a Performance Marketer for Consumer Goods Companies (Cult, Prize Candle...), Kate Shaw, Social Media Marketer for Urban Remedy, and Jason Hayward, SEO Director with Science Inc.

5.2.2 On social media marketing vs. traditional marketing

For Alex Osborne, the main difference between social media and traditional marketing is that social media marketing implies a permanent conversation with the customers. All the companies that he works with have websites that are built around a social type of audience and play with the fact that users want a very engaging experience.

For Kate, social media exposure is like having a website in 2000: it is the face of a business and it provides the company with social validation. Startups just have to do it because everybody else does.

For Jason, social media marketing is definitely more effective than traditional marketing as it allows a deeper level of engagement from the customers and a two-way communication.

5.2.3 On measuring social media marketing effectiveness

Alex Osborne currently uses traditional Customer Lifetime Value calculations but will shortly implement a by channel tracking system for his companies. For him, measuring social media marketing effectiveness is an everyday challenge: *"As Performance Marketers, we need to constantly track everything, to attribute every dollar. However, we can't track the Lifetime value of a Facebook Like..."*

For Kate, the metrics to measure effectiveness depends on the company's goals: if its goal is brand awareness, then Shares and Comments are the most useful. If the goal is to generate sales, you have to look at the bigger picture and look at the campaigns' impact on revenue over a longer period.

For Jason, social activity (Likes, retweets...) is the best way to measure brand awareness as it is the most widespread interaction between the customers and the brand.

5.2.4 On paid vs. earned social media Marketing

For Alex Osborne, the problem with earned media is that you can not measure them. For example, there is no way you can calculate the Lifetime Value of a Facebook Like. This lack of visibility is a big issue for an early stage startup that needs to see return from every dollar it spends. He, however, reckons that it depends whether the startup is focusing on brand awareness or financial performance. As for the most effective channel, for Alex Osborne, there is no debate here: the most effective channel is Facebook.

For Kate, they work closely together. She used the metaphor of a house party: the paid media are the invitations you send out and the earned media are the food and the atmosphere. That being said, buying Likes is necessary to her to reach the X number of Likes threshold and become a "legitimate" company. When it comes to choosing the most efficient channel, for Kate, Pinterest is THE channel by excellence to drive sales. Facebook and Twitter are necessary for engagement and customer service but can not really become revenue sources to her because of their messiness and lack of focus.

For Jason, this is the same debate as eight years ago between SEO and SEM: both are critical for different reasons. As much as paid media gets you the ROI, earned media are critical for reach and credibility.

5.2.6 On ranking startups based on their social media exposure

For Alex Osborne, although he does not expect the number of Facebook Likes for example to be negatively correlated with revenue, he has no idea to what extent social exposure is linked to performance.

For Kate, except for a few viral exceptions like Dollar Shave Club, you need time and money first to become influential. You need to get the customers first before turning them into engaged social media fans or followers. So it is almost unfair to rank companies based on their social media exposure and invest accordingly when the very early stage ones needs the money to get the product out there and get paying customers before they can afford to focus on their social media effort.

For Jason, ranking startups based on their social media exposure will make the venture capital market more transparent and therefore more efficient, which sounds both great and scary.

5.3 Conclusion on the Interviews

The main take away I got from both the Investors and the Operators Interviews is that social media exposure has to be assessed in a qualitative way for early stage digital start ups. When the social legitimacy threshold is reached – in terms of number of Facebook Likes or Twitter followers – the mission is to create brand awareness and reach, to create a community of true advocates for the brand. When doing their due diligence and scrolling social media, investors should not look for mass adoption but for true, passionate customers' stories.

Chapter 6 – Conclusion and the future of quantifying social media exposure for startups

I investigated throughout my research how social media exposure is correlated with business metrics for early stage digital startups. I found that it mostly depends on the target customers: it seems that the correlations between social and revenue metrics are quite significant for startups with a "tech savvy" audience, whereas social media exposure does not seem to be correlated with performance for "non tech savvy" startups. The same way Kevin Rose was able to drive more revenue than Ashton Kutcher from his "Fab.com" tweet even though he has less followers, the ability for a consumer-oriented startup to drive revenue through social media depends on its philosophy: different philosophies lead to different types of customers, with different relationships to social media and different levels of engagement on them. **In a few words, to assess the impact of social media exposure on financial performance for an early stage digital consumer-facing startup, one should ask whether this startups is a tech startup or a tech-enabled startup.**

Going forward, **we need to overcome the issue of noise on the social web and assign a value to each and every individual customer.** Indeed, having a million Facebook Fans or Twitter followers means a totally different things whether they include influencers or not, true advocates for your company or not, whether they are passive or active. So even when a startup addresses a generally tech savvy audience, we need to quantify the digital influence and authority of each and every one of its advocates.

This is why I think that the next step will be to combine tools that separate the signals from the noise – like Klout - with a quantified analysis of social media exposure's impact on key business metrics - like revenue and traffic. As Tom Webster, Vice President at Edison Research, said, ***"Measures like Klout are going to take off when they can show the link to other key business metrics".***

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Appendix 1 – Interview Questions

The Operators

1. **What do you find more effective, traditional marketing or social media marketing?**

2. **How do you define and measure effectiveness?**

Rank Metrics:

- Conversion rate
- ROI (Revenue generated)
- LTV
- Social Activity (likes, shares, retweets)
- Others

3. **Do you find social media to be a direct or indirect performance driver? Choose one of the following statements**

- Social Media indirectly impacts your business performance
- Social Media is a critical enabler of business/services your business provides
- Your business primary revenue source is directly linked to social media marketing

4. **What is your take on paid vs. earned social media marketing?**

5. What channels do you find the most effective?

Rank Channels:

- Facebook	-
- Twitter	-
- Linkedin	-
- Blogs	-
- Youtube	-
- Instagram	-
- Pinterest	-
- Google +	-
- SlideShare	-
- Others	-

6. What do you think of websites like Mattermark that aim at ranking startups based on their social media "momentum"?

The Investors

1. **How do you take social media into account in your due diligence?**

2. **What channels do you take into account the most?**

3. Do you find social media to be a direct or indirect performance driver? Chose one of the following statements

- Social Media indirectly impacts most businesses' performance
- Social Media is a critical enabler of most businesses/services
- Most businesses' primary revenue source is directly linked to social marketing

4. **Ten Leonsis, partner at the Venture Capital firm Revolution LLC, said *"Ten years from now, social media will be the starting point of any investment":* Do you agree?**

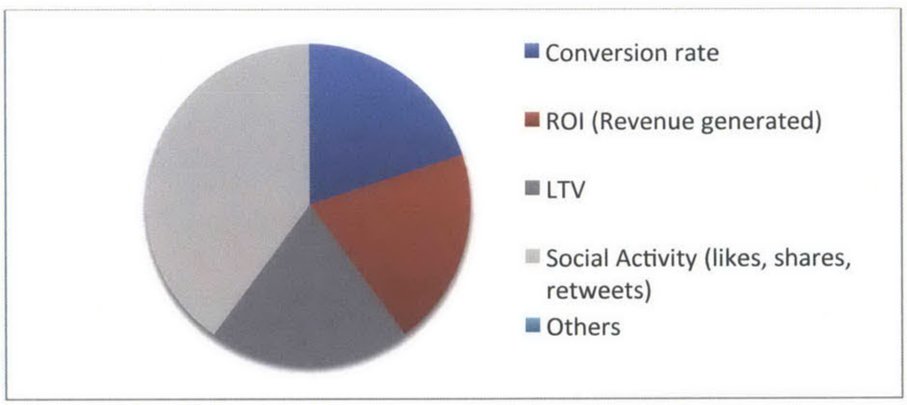
5. **What do you think of websites like Mattermark that aim at ranking startups based on their social media "momentum"?**

6. **Do you think social media exposure is really a predictor for success?**

Appendix 2 – My Questionnaire and Results

Rank Metrics:

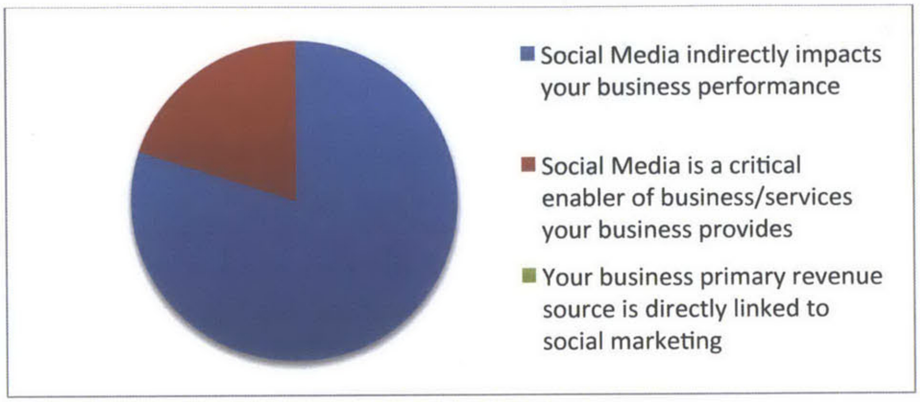
Conversion rate	**20%**
ROI (Revenue generated)	**20%**
LTV	**20%**
Social Activity (likes, shares, retweets)	**40%**
Others	**0%**



Do you find social media to be a direct or indirect performance driver? Chose one of the following statements

Social Media indirectly impacts your business performance	**80%**
Social Media is a critical enabler of business/services your business provides	**20%**

Your business primary revenue source is directly linked to social marketing	**0%**



What channels do you find the most effective?

Rank Channels:

Facebook	1
Twitter	5
Linkedin	7
Blogs	4
Youtube	6
Instagram	2
Pinterest	3
Google +	Useless

SlideShare	Only for BtoB
Others	

Appendix 3 – Addshoppers Results

Addshoppers is a social marketing apps agency for merchants. Addshoppers analyzed the data they collected in 2013 from their 10k + merchants (who generated over 1.2bn page views) to figure out what a social share is worth to retailers on various social networks. Below are the main findings from Addshoppers 2013 Social Commerce Breakdown report.

What are Shares worth?

Email	$12.10
Google +	$5.08
Facebook Share	$3.58
Facebook Like	$1.41
Pinterest	$0.87
Twitter	$0.85
Other	$0.63

Who drives revenue?

Pinterest	24.30%
Facebook	24.19%
Twitter	20.86%
Email	19.22%
Google +	6.58%
Others	4.85%

How do Shares Convert?

	Conversion rate
Email	7.02%
Google +	3.14%
Facebook Share	3.09%
Facebook Like	1.32%
Twitter	0.69%
Pinterest	0.51%
Other	0.33%

Who drives traffic?

	Clicks per share
Twitter	0.96
Tumblr	0.9
Pinterest	0.78
Faacebook	0.71
Email	0.35
Google +	0.19