ABSTRACT

ENTERPRISE VALUE/MONTHLY ACTIVE USERS: A VALID SECTOR SPECIFIC MULTIPLE FOR THE VALUATION OF SOCIAL MEDIA FIRMS?

by Christopher Michael Haught

Investment professionals have been using traditional multiples such as EV/Revenue, EV/EBITDA, and Price/Earnings to determine the value of firms. However, as technology firms have become more prominent, EV/MAUs is a new multiple utilized when valuing user based technology firms. In the following paper, I explore whether MAUs explains movements within traditional multiples in order to motivate using EV/MAUs as a valid multiple. After showing it significantly explains movements in this multiple, I run an empirical analysis showing that EV/MAUs is a better estimator than all traditional multiples except EV/Revenue and should be used in applications of multiple analysis within the technology space going forward.

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Part 1: Introduction

As the internet has grown over the past decade, so too have the methods to value user based technology companies. One of the emerging methods of valuing these technology companies is the sector specific multiple enterprise value to monthly active users (EV/MAUs). This paper sets out to compare EV/MAUs to traditional multiples such as Price/Earnings, EV/Revenue, and EV/EBITDA.

User based technology firms, internet based firms whose core function is gaining users to increase profitability, have experienced significant growth in their number of users over the last decade. From 2005-2010, user based technology firms increased in number and importance. In 2004, Mark Zuckerberg founded Facebook, and in 2007, Netflix pioneered their online video streaming service. Over the past five years, these firms grew in numbers as internet traffic increased on a widespread basis, undergoing compounded annual growth of 20.2% over the past five years.[1]

As user based technology firms have grown, so has their need for capital. After undergoing a few rounds of private equity funding, firms often turn to the public market as a source of capital. Facebook was one of the first to IPO in 2012, and Snap Inc. was the latest to IPO in March of 2017 with many companies undergoing initial public offerings between them. When these firms underwent their IPOs, many analysts characterized them as start-up firms. Some of the key characteristics of start-up firms are their limited history, minimal revenues, negative earnings, and reliance on private equity investment (Damodaran, 2009). When the major user based tech companies went public, they embodied the characteristics of these startup companies as shown in Table 1.

[Insert Table 1]

With the need for capital to sustain growth, Wall Street employs both traditional techniques such as a discounted cash flow analysis, a precedent transactions analysis, and a comparable companies analysis as well as start-up specific methodologies like the venture capital method, the first Chicago method, the Damodaran approach, and the real options method to value companies

[1] IBISWorld Reports via Cisco Systems, Inc. Report that internet traffic volume has increased from 41.3 exabytes per month in 2012 to 103.56 exabytes per month in 2017. This change is equivalent to a compounded annual growth rate in internet traffic volume of 20.2% annually.

(Gobel, 2016). All of these methods apply relative valuation multiples in one way or another to determine firm value. For many of these methods, the large determinant of value is the firm's terminal value that utilizes the multiples method. Thus, employing an accurate multiple in conducting a valuation analysis is important. As touched on earlier, EV/MAUs has been discussed as a multiple for these young technology companies, but little is known about how it compares with traditional multiples.

As illustrated in Figure 1, monthly active users seem to move concurrently with changes in firm enterprise value, suggesting that monthly active users is a large driver of firm value.

[Insert Figure 1]

When looking at other historical drivers of value within the firm (revenue and EBITDA), these metrics do not appear to have as high of a correlation to firm value (enterprise value), suggesting a lower firm value explanatory power.

[Insert Figure 2]

Additionally, the R-squared fit of a linear model between the dependent variable (enterprise value or market capitalization) and each independent variable (MAUs, revenue, EBITDA, or net income) is strongest for MAUs when predicting firm value.

[Insert Table 2]

MAUs trends closer to enterprise value than other historical valuation measures, and thus, MAUs may better explain fluctuations in firm value. Thus, throughout this paper, I explore the question of whether EV/MAUs is a better valuation multiple than traditional multiples for a user based technology firm.

At first, I discuss the widespread use of valuation multiples within many different types of valuation analysis, showing the importance of having an accurate market multiple. Furthermore, within this section, I point out the limitations of the traditional valuation multiples in comparison to the EV/MAUs multiple. Secondly, I utilize Fama Macbeth regression analysis to show that a firm's monthly active users metric has a high explanatory power on traditional multiples (EV/Revenue, EV/EBITDA, and Price/Earnings). Finally, in the last part of this paper, I find evidence, in many situations, EV/MAUs is as accurate as or more accurate than traditional multiples.

Part 2: Market Multiples in Tech Valuation

Market multiples are widespread way of valuing companies used by many different types of investment professionals. Utilizing market multiples in order to value a company really gained traction during the late nineteenth century as many firms utilized earnings multiples (i.e. Price/Earnings) in determining value (Simkovic, 2016). As the amount of capital within the public markets increased, the number of methods for valuing companies have also increased. However, these methodologies do not vary far from their foundation as all of these methods utilize market multiples for a large part of their valuation. Below, I give an overview of the market multiples method and the market multiples method's applicability to other traditional and emerging valuation techniques.

2.1 - Overview of Market Multiples Method

Two types of traditional valuation methods utilize market multiples to determine valuation: the public comparables method and the precedent transaction method. Both of these valuation methods utilize the same general principle to value a company: extrapolate a value utilizing financial ratios of companies with publically available information on market value and financial performance. Generally, three different groups of multiples exist for a company (Verninmen, 2014):

- <u>Equity Value Multiples</u>: Equity value multiples utilize market capitalization and operating performance to calculate firm value. These multiples provide an easy way to compare stock prices between companies without the difficult calculation of enterprise value. One of the most common price multiples is the Price to Earnings multiple.
- <u>Enterprise Value Multiples</u>: Enterprise value multiples are a ratio of the whole value of a firm to key operating statistics. These multiples include both the equity value of the firm as well as the value of the firm when including net debt, non-controlling interests, and preferred stock. The most common multiples used in valuation are the Enterprise Value/Sales and Enterprise Value/EBITDA ratios.
- <u>Sector Specific Multiples</u> – Sector specific multiples are a ratio of total firm value (i.e. enterprise value) to sector specific company information. For example, in the oil industry, enterprise value to production as well as enterprise value to proven & provable resources are sector specific multiples utilized to value companies within that industry. Similarly,

within the user based technology industry, analysts utilize an enterprise value to monthly active users multiple to value firms.

2.1.1 - Public Comparables Analysis

For the public comparables method of valuing a company, analysts utilize similar publically traded companies to the company being valued to extrapolate a valuation. In order to determine the best companies to use as comparables, analysts typically filter companies first on their business profile and then on key financial metrics (Pearl, 2009). Qualitatively, companies are first filtered by their sector, products and services, customers, distribution channels, and geography. When filtering by financial profile, analysts first look at size, profitability, growth profile, return on investment, and credit profile to determine which companies to be in their public comparables set. After determining the publically traded companies with most similar characteristics to the valuation target, analysts then calculate the average and median price multiples, enterprise value multiples, and sector specific multiples for the comparable companies. Then, utilizing the key financial metrics of the firm being valued (i.e. Revenue, EBITDA, and Net Income), the firm's value is calculated.

2.1.2 - Precedent Transaction Analysis

Conducting a precedent transaction analysis is very similar to conducting a public comparables analysis. In a precedent transaction analysis, analysts utilize price and enterprise value multiples from firms that have recently been bought or sold in order to extrapolate a valuation for the firm being valued. In the first step of a precedent transaction analysis, analysts sift through firms recently been bought or sold within the industry based on their business profile and financial metrics. Similar to the public comparables analysis, analysts use the same five business profile criteria as well as the same five financial metrics in order to assess the relevance of the precedent transaction. After determining the most comparable transactions, analysts calculate market multiples for firms recently bought that disclose this information (oftentimes acquisitions of publically traded companies). Then, utilizing these multiples and financial metrics from the firm being valued, firm value is calculated.

The key difference when comparing these two market multiple methods is the premium pricing that is present in the precedent transaction method. In the public comparables method, analysts utilize enterprise value and market capitalization on a stand-alone basis. When buyers purchase a company, buyers typically pay a premium for the control of the company; thus, the precedent transaction analysis generally leads to a higher firm valuation.

2.2 – Utilization of the Market Multiples Method in Other Valuation Methods

Not only do the public comparables and precedent transactions methods utilize market multiples, but the discounted cash flow method, venture capital method, first Chicago method, and Damodaran method also utilize multiples within their terminal value calculation. Below, I give a brief overview of how analysts utilize the market multiples method in each methodology.

2.2.1 - Discounted Cash Flow Analysis

The discounted cash flow method determines the current value of the firm by discounting the firm's future free cash flows by the firm's cost of capital. The first step in a discounted cash flow analysis is to project the future free cash flows until the firm reaches a steady state. Typically, when valuing mature companies, this projection period is from 3-5 years; though, when valuing young, high growth technology firms, this projection period is typically 5-10 years. Then, analysts discount these annual free cash flows as well as the terminal value of the firm by the firm's weighted average cost of capital (WACC).

$$Enterprise\ Value = \sum_{t=0}^{n} \frac{FCFF_n}{(1+WACC)^n}$$

Analysts calculate the firm's terminal value in one of two ways: the perpetuity growth rate method or the exit multiple method.

<u>The Perpetuity Growth Rate</u>

The perpetuity growth rate method assumes that a firm's free cash flows will grow at a constant rate in the future. Typically, this rate is somewhere between the rate of inflation (the lower bound) and the U.S. economic growth rate (the upper bound). Using this selected growth rate, the firm's steady state free cash flow, and the weighted average cost of capital, analysts calculate a firm’s terminal value using the following formula, which is the standard formula for calculating the present value of a growing perpetuity.

$$Terminal\ Value_t = \frac{FCFF_t * (1+g)}{(WACC_t - g)}$$

Exit Multiple Method (EMM)

The second method to calculate a firm’s terminal value is the exit multiple method. In the exit multiple method, analysts utilize the current market multiple from the public comparables and precedent transaction analyses to calculate the terminal value of the firm.

$$Terminal\ Value = Terminal\ Multiple\ x\ Firm's\ Multiple\ Value\ Driver$$

When utilizing the exit multiple method in calculation of the firm’s terminal value, analysts make the key assumption that market multiples paid today reflect future market multiples in a firm’s steady state.

2.2.2 - The Venture Capital Method

The venture capital method builds off the principles of the discounted cash flow analysis, but adds a couple nuances. Concisely, the venture capital method is the discounted cash flow method, but takes into account that an investor has an exit timeline for their investment. For example, when venture capital and private equity firms invest in companies, they typically plan to exit their investment within 2-5 years (Gobel, 2016). Since firms within the technology industry are growing and should continue to grow far into the future, the venture capital method is applicable to valuing emerging technology firms.

In the venture capital method, analysts first project the firm’s future free cash flow until an investor plans on a liquidity event. After projecting out free cash flows, an investor calculates the terminal value of the firm by applying the market multiples to the firm’s final year metrics. When calculating the terminal value, analysts use the multiples from public comparables and precedent transaction analyses. When applying these multiples, many firms have negative earnings and EBITDA due to their high growth nature. Thus, analysts employ revenue multiples. After calculating the terminal value, analysts discount the firm’s cash flows and terminal value at a higher rate than the typical weighted average cost of capital for a similar publically traded firm due to the risky nature of firms with negative cash flows.

The key difference between the venture capital method and the discounted cash flow method is the projection period. In the discounted cash flow method, analysts project the firm's cash flows until the firm reaches their steady state. In the venture capital method, analysts project the firm's cash flows until the investor expects to sell their equity stake. In this latter case, the firm typically has high growth prospects; thus, only the exit multiple method is applicable since the firm is not in steady state.

2.2.3 – Other Methods

The first Chicago method as well as the Damodaran method utilize the multiples method in determining firm value. In both of these methods, investment professionals utilize forward multiples to calculate the terminal value and then discount this value back at the appropriate discount rate.

2.3 – Limitations of Traditional Market Multiples

For many mature companies within developed industries, the traditional multiples of EV/Revenue, EV/EBITDA, and Price/Earnings are accurate and applicable for valuing companies. In the emerging internet technology sector, traditional multiples are limited due to their inability to gain a meaningful comparison metric between companies, the limited availability of data in transactions, and unequal accounting principles.

- <u>Inability to Gain Applicable Multiples:</u> The most common multiples that are utilized in valuation are the EV/Revenue, EV/EBITDA, and Price/Earnings multiples. Since many technology firms are aggressively growing, oftentimes these firms have negative net income, EBIT, and EBITDA. Thus, these multiples are negative which yield a non-meaningful value. Furthermore, young technology firms typically are investing quite substantially in their companies and thus, burning through large amount of cash due to their high growth nature which results in minimal free cash flow. Additionally, many user based technology firms have struggled monetizing their user base leading to minimal revenue. Thus, revenue and free cash flow multiples are highly inflated and thus inapplicable for comparison.

- Limited Availability of Transaction Data: One of the big differences when comparing the precedent transaction method to the public comparables method is the disclosure of information about the comparable company. Since many transactions occur between two private companies, these transactions may disclose the purchase price paid for the company, but they rarely disclose pertinent financial metrics to calculate multiples based on EBITDA, EBIT, and net income. However, analysts find size-based metrics such as revenue and MAUs much easier. Thus, traditional multiples such as Price/Earnings and EV/EBITDA are limited due to unavailable information.
- Unequal Accounting Principles: Even when high growth firms disclose financial information, many technology start-up firms have different accounting principles. Thus, analysts calculate certain financial metrics differently from company to company. This disparity could lead to a large discrepancy in the accuracy of multiples in the valuation analysis, ultimately leading to an inaccurate valuation.

Due to these limitations of traditional multiples within the user based technology industry, a sector specific multiple like EV/MAUs provides a viable alternative. In the following sections, I first describe the dataset used in the analysis. I then demonstrate how monthly active users explains traditional valuation multiples, showing the applicability of monthly active users as a valuation multiple. Finally, I report the results of a comparable companies exercise that demonstrates the accuracy of EV/MAUs relative to traditional valuation multiples.

Part 3: Creating the Dataset

3.1 – Determining the Companies in the Dataset

In order to create a dataset for my empirical analysis, I use the entire population of publically traded companies that disclose their number of monthly active users. In order to filter through companies, I use Bloomberg to identify comparable companies to commonly known user based technology firms (Facebook, Twitter, LinkedIn, etc.). After compiling a list of companies, I filter through published quarterly reports (10-Q, 10-Ks, and 20-Fs) to determine which companies disclose their number of monthly active users. From this process, I find 10 companies that disclose their number of monthly active users. In order to expand the number of observations, I then search for firms whose first two digits of their SIC code align with the first two digits of any of the ten companies I found from Bloomberg. For example, Facebook's SIC code is 7370. Thus, I look through lists of companies classified as 7300-7399. Through this search process, I find 10 more user-based technology companies. Through this process, I identify the entire population of publically traded companies that disclose their monthly active users on audited financial statements. I report these companies in Table 3.

[Insert Table 3]

Many of these companies also disclose other measures of users like daily active users, page views, and mobile monthly active users. However, these companies disclose monthly active users most frequently. Thus, I utilize monthly active users as the primary variable of interest in the analysis that follows.

3.2 - Control Variables

After determining the sample companies, I gather financial statement and historical stock price information on a quarterly basis from Bloomberg. Specifically, I retrieve total assets, EBITDA, net income, sales, dividends, total debt, total equity, IPO date, and company location. Using these financial metrics, I create seven control variables: total assets, EBITDA margin, profit margin, return on invested capital (ROIC), a continuous variable that measures the time elapsed (in quarters) since the company's IPO, and a dummy variable for whether a firm is international. In Table 4, I report descriptive statistics for control variables.

[Insert Table 4]

As mentioned previously, many of the firms have characteristics similar to start-up firms: negative earnings (shown by the negative profit margin and EBITDA margin) and short firm histories (average time publically traded less than 6 years). Furthermore, many control variables have a large variation in values. Most notably, total assets ranges from $90 million to $13 billion. In figure 3, I demonstrate the significant number of outliers for total assets.

[Insert Figure 3]

In order to reduce this skewness, I take the natural log of the total assets. In Figure 4, I report the distribution of the natural log of total assets. Notice the reduced skewness after the transformation.

[Insert Figure 4]

In the following analysis, I report regressions with both the nominal value of total assets and the log of total assets.

3.3 - Key Regressor

In Table 5, I detail key statistics on the MAUs variable.

[Insert Table 5]

Most companies do not have a user base like Facebook and We-chat, with a sample average of 296.6 million users. Furthermore, the kurtosis of 7.31 and skewness at 2.34 shows that the sample is largely right tailed.

3.4 - Dependent Variables

For dependent variables, I create three traditional multiples (EV/Revenue, EV/EBITDA, and Price/Earnings). I retrieve information on historical market value and last twelve months financial information from Bloomberg. I report the ranges of these multiples in Table 6.

[Insert Table 6]

As reported in Table 6, a large proportion of Price/Earnings and EV/EBITDA multiples are negative. If I use a negative multiple to calculate company value, the calculation yields a negative enterprise value. This implies that a company pays an investor to buy their stock, which is not realistic. Thus, I follow industry practice and set negative values to missing. After discarding negative multiples, my sample size reduces from 323 observations to 183 observations for Price/Earnings multiples and from 323 observations to 232 observations for EV/EBITDA multiples.

Additionally, Table 6 demonstrates that there are a few outliers at the top end of the multiples distributions. In order to minimize the impact of these outliers, I employ a winsorizing process. After looking at the top ten highest multiples for each of these traditional multiples, I winsorize each at the percentage where the largest jump in multiples takes place. For the EV/Revenue and EV/EBITDA multiples, I winsorize at the 1% level, and for the P/E multiple, I winsorize at the 2% level. Table 7 below shows the new descriptive statistics after eliminating negative multiples and winsorizing these multiples.

[Insert Table 7]

Part 4: Does MAUs explain Traditional Valuation Multiples?

Below, I use a Fama-Macbeth regression to determine whether MAUs explains the traditional valuation multiples of EV/Revenue, EV/EBITDA, and Price/Earnings.

4.1. – Setting up the Regression Model

4.1.1 – Determining Appropriate Control Variables

Since the population of publically traded firms disclosing MAUs is limited to approximately 320 observations, I include a parsimonious set of control variables that have previously been shown to have an impact on firm value. Specifically, I utilize control variables that serve as proxies for firm size[2], profitability[3], age[4], location[5], and management's investment efficiency[6].

4.1.2 – Generalized Regression Model

In the equation below, traditional multiples are regressed upon the key regressor, MAUs, as well as a vector of control variables.

$$Traditional\ Multiple = \beta_0 + \beta_1 * MAUs + \ \beta_2 * [Control\ Variables] + \ e$$

Where Control Variables include total assets, profit margin/EBITDA margin, international dummy variable, Quarters since IPO, and ROIC

[2] In a study in 2016, Ramadan shows that firm size as represented by the total assets of a firm is a significant determinant of firm value at the 90% level (Ramadan, 2016). As firm size increases, firm value also increases.
[3] In a study in 2006, Mancinelli & Aydin conclude that a firm's profitability and leverage effect the value of a firm (Mancinelli, 2006). Mancinelli & Aydin shows that increases in profitability increase the firm value. Thus, profit margin is used as a control variable for EV/EBITDA and EV/Revenue multiples, and EBITDA margin is used as a control variable for P/E multiple.
[4] In a study in 2016, Ramadan shows that the age of a firm a significant impact on firm value at the 90% significant level (Ramadan, 2016). The age of a firm has a positive relationship with the firm value. Thus, I calculate the age of the firm since IPO on a quarterly basis as a control variable.
[5] Rosembaum and Pearl utilize geography as a determinant for comparable companies, inherently implying that location has an effect on firm value.
[6] In a study in 2007, Michaely and Roberts conclude that any changes to profits as well as the dividend payout ratio of a firm affect a firm's value (Michaely, 2007). Thus, I utilize Return on Invested Capital as a control variable.

I perform two separate regressions for each multiple, one regression utilizing total assets in raw form and one regression utilizing the log of total assets as a control variable for the size of a firm.

Referring to Figure 1 and 2, firm value and MAUs of all four firms are both trending upwards through time. Thus, spurious correlation is a concern because both MAUs and company valuations have been increasing over time with no relation to one another. In order to fix this issue, I utilize a Fama-Macbeth regression (Fama, 1973).

4.1.3 – Fama-Macbeth Regression

As popularized in asset pricing models, I use a Fama-Macbeth regression model to account for spurious correlation. Below, in Table 10, I include the Fama-Macbeth regression results when utilizing the nominal value of total assets within the regression.

[Insert Table 9]

In Table 9, I show that MAUs explains a large amount of the variation in EV/EBITDA and EV/Revenue multiples at the 99% and 95% significance levels respectively. Though, MAUs is not significant in the Price/Earnings regression. Through these regressions above, I show that MAUs explains a significant amount of the variation in traditional multiples. Thus, due to limitations in other multiples, I can use the EV/MAUs multiple that captures part of the variation in traditional multiples.

Additionally, in Table 10, I include the Fama-Macbeth regression results when utilizing the log of total assets.

[Insert Table 10]

Similar to the previous regression, MAUs explains a large amount of the variation in these traditional multiples.[7][8] This finding demonstrates that EV/MAUs captures a large amount of the variation in traditional multiples without many of the limitations of these multiples.

[7] As a robustness check, I also run a Fama-Macbeth quantile regression. From this regression, the coefficient of MAUs explains the variation in EV/Revenue and EV/EBITDA regressions at the 99% and 95% confidence level.

[8] Additionally, as a robustness check, I run a regression and then calculate the Newey West standard errors. At the 99% level, MAUs is significant in predicting the EV/Revenue and Price/Earnings multiples. However, MAUs does explain variation in the EV/EBITDA multiple when using Newey West standard errors.

4.1.4 - Takeaways

In the two regression tables above, MAUs is significant for both the EV/Revenue and EV/EBITDA regression, but is not significant for the Price/Earnings multiple. In the EV/EBITDA and EV/Revenue regressions, I include 71.8% and 100% of the total observations respectively. Though, in the Price/Earnings regression, I include only 57% of total observations. With a significant decrease in observations, variation within the sample also decreases which could lead to this discrepancy in results.

Furthermore, as touched on earlier, utilizing traditional multiples when performing a public comparables or precedent transaction analysis on a user based technology firm often yields inaccurate valuations due to minimal revenues, negative earnings, limited availability of transaction data, and unequal accounting principles. In the regressions above, MAUs explains a significant amount of the variation in EV/Revenue and EV/EBITDA multiples without many of the problems inherent in traditional multiples. Thus, EV/MAUs is an appropriate proxy to traditional multiples within the internet technology sector.

Part 5: An Empirical Example of the Accuracy of EV/MAUs

In the following section, I utilize the current population of companies disclosing MAUs to determine whether EV/MAUs is a more accurate than traditional multiples for valuing a user-based technology company.

5.1 - Creating an Unbiased Public Comparables Set

As mentioned previously, the public comparables analysis utilizes multiples from similar publically traded companies in order to calculate the enterprise value of the valuation target. Below, I conduct a public comparables analysis using traditional multiples and the EV/MAUs multiple. Since a public comparables analysis considers both business and financial factors to determine comparable firms, I use both of these factors in selecting comparable firms. In the equation below, I show my calculation of the comparison score I create for each comparable company relative to the company being valued. Both financial and business characteristics are included in this calculation.

$$
\begin{aligned}
&Comparison\ Score \\
&\quad = \frac{(Profit\ Margin_{VF} - Profit\ Margin_{CC})^2}{\max((Profit\ Margin_{VF} - Profit\ Margin_{CC})^2)} * .2 \\
&\quad + \frac{(Sales_{VF} - Sales_{CC})^2}{\max((Sales_{VF} - Sales_{CC})^2)} * .2 + International * .2 + Marketplace * .2 \\
&\quad + Subscribers * .2
\end{aligned}
$$

Where:

VF – Firm being valued

CC – Comparable Company

International – International Dummy Variable

Marketplace – Marketplace Dummy Variable

Subscribers – Subscriber Dummy Variable

5.2 - Calculating Valuation Target Enterprise Value

In this model, the firms with the lowest comparison score are the closest firms to the valuation target. I utilize the five firms with the lowest comparison scores as the set of comparable companies. Then, I calculate the projected enterprise value or market capitalization for the company being valued based on the three traditional multiples (EV/Revenue, EV/EBITDA, Price/Earnings) and the EV/MAUs multiple, using both the mean and median of each set of multiples. After calculating the projected enterprise value and market capitalization, I calculate the absolute value of the percentage differential from the actual enterprise value (market capitalization) of the valuation target for each multiple. In Table 11, I report the results for Q3 2016, the most recent quarter within the dataset.

[Insert Table 11]

5.3 – Analyzing Findings

Table 11 shows that EV/MAUs, which has a mean differential of 118%, is more accurate than the EV/EBITDA, EV/Revenue, and Price/Earnings at 343%, 151%, and 181% respectively. In order to determine whether there is a significant difference between the accuracy of two multiples, I run a one-tailed t-test comparing the absolute value percentage differential of the two multiples. Since I use the absolute value percentage differential in the analysis, I am able to utilize a one tailed T-test to infer a significant difference. Table 12 demonstrates my findings.

[Insert Table 12]

In Table 12, the percentage differential from the market value projected through the Price/Earnings multiple is much greater than the percentage differential from the enterprise value projected from the EV/MAUs multiple. In order to determine whether there was a significant difference between these two multiple differentials, I run a one-tailed t-test that yields a p-value of 0.28. Thus, I am unable to reject the null hypothesis that both of these multiples yield similar valuations. On the other hand, when I run a one-tailed t-test between the percentage differentials in enterprise value as projected by the EV/EBITDA and the EV/MAUs multiple, at the 97% significance level there is a difference between the accuracy of these multiples, demonstrating that EV/MAUs is more accurate. Even though the differentials between the Price/Earnings and EV/EBITDA multiples and EV/MAUs multiple seem very similar, the Price/Earnings multiple does not yield a significant difference because some of these user based technology companies have negative earnings; thus, yielding inaccurate multiples. Thus, this limited sample size affects the significance of the value differentials of certain multiples. Additionally, in Table 11 and Table 12, EV/MAUs has a percentage differential in line with the EV/Revenue multiples. Thus, when performing a one-tailed t-test, the differential between these multiples is not significant.

5.4 – Takeaways & Further Research

This analysis suggests that EV/MAUs and EV/Revenue multiples are most accurate in valuing user based technology companies. However, all multiples deviate at least 70-80% from their actual enterprise value, and thus, multiples overall are rather inaccurate in estimating firm value. As I touched on earlier, multiples are integral in conducting valuation analyses and in performing the terminal value calculation for the discounted cash flow, venture capital, first Chicago, and Damodaran valuation methods. Thus, based on my analysis, I recommend utilizing the EV/MAUs multiple alongside the EV/Revenue multiple when valuing firms within the user based technology industry because these multiples tend to lead to the most accurate valuations.

Part 6 – Conclusion

In conclusion, along with the EV/Revenue multiple, the EV/MAUs multiple is most accurate in predicting the value of a firm in the user based technology industry. In this industry, traditional multiples such as the EV/Revenue, EV/EBITDA, and Price/Earnings multiples lack accuracy due to the negative earnings, low revenues, unavailability of transaction data, and unequal accounting principles across firms. These problems are alleviated when utilizing the EV/MAUs multiples because technology firms typically experience stable growth across their user base which often fails to (at least initially) positively reflect in revenue and earnings.

Initially, I look at whether a firm's monthly active users explains traditional valuation multiples. After running Fama-Macbeth regressions on this dataset, I report that monthly active users explains a significant amount of the variation in traditional multiples. Thus, the EV/MAUs multiple captures much of the variation contained in traditional multiple while also capturing a new aspect of a firm when valuating firms. Using these results as a springboard, I run a public comparables analysis in which I compare the accuracy of three traditional multiples to the sector specific multiple, EV/MAUs. The EV/MAUs yields a statistically significant improvement over the EV/EBITDA multiple. Furthermore, even though there is not a significant difference between Price/Earnings and EV/MAUs multiples, EV/MAUs yields a more accurate valuation. Finally, the EV/MAUs and EV/Revenue multiples yield very similar firm values.

Overall, utilizing the public comparables method to value a company in the user based technology industry does not lead to an accurate valuation (approximately 70-80% value differential). However, multiples are integral in the public comparables, precedent transaction analyses, and the terminal value calculation of many different derivatives of a discounted cash flow analysis. Therefore, multiples analysis will continue to be used as a valuation method in the future. Going forward, investment practitioners should consider EV/Revenue and EV/MAUs multiples first when valuing firms in the user based technology industry.

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Appendix of Tables

Table 1 – Characteristics of Social Media Technology Firms as they IPO

Through Table 1, I show that technology firms have many of the characteristics of start-up firms: low revenues, negative to minimal profit, and short operating history.

	IPO Characteristics of Technology Firms			
	LinkedIn	Facebook	Twitter	Snap, Inc.
IPO Date	5/19/2011	5/18/2012	11/7/2013	3/1/2017
Year Founded	2002	2004	2006	2011
Revenue	$ 161	$ 3,711	$ 449	$ 405
Operating Income	$ 13	$ 1,756	$ (93)	$ (521)
Net Income	$ 2	$ 668	$ (99)	$ (515)

*All financial data are the historical annual operating statistics as of each company's IPO date

Table 2 – R-Squared Statistics of a Simple Linear Fit Model

Through Table 2, I demonstrate that Monthly Active Users (MAUs) has a higher explanatory power of firm value, demonstrated through the higher R-squared, in comparison to other historical drivers of firm value (i.e. Revenue, EBITDA, and Net Income). This inference leads me to believe that MAUs may better explain technology firm valuations than historical drivers of firm value.

	Summary Table - R-Squared of Linear Model			
	Enterprise Value to MAUs	Enterprise Value to Revenue	Enterprise Value to EBITDA	Market Cap to Net Income
Facebook	0.95	0.91	0.89	0.82
Netflix	0.89	0.88	0.39	0.18
WebMD	0.78	0.84	0.90	0.66
LinkedIn	0.50	0.33	0.33	0.11

Table 3 – Listed Technology Companies within the Dataset

I utilized the 20 companies below throughout both parts of my analysis.

Company Name	**Country of Origin**
Alibaba Group	China
Facebook	USA
Friend Finder	USA
Groupon Inc.	USA
Kakao Corporation	South Korea
Line Corporation	Japan
LinkedIn Corporation	USA
MeetMe Inc.	USA
Momo Inc.	China
Netflix Inc.	USA
Pandora Media Inc.	USA
RenRen Corporation	China
Sohu.com	China
Tencent Holdings	China
TripAdvisor Inc.	USA
TrueCar Inc.	USA
Twitter Inc.	USA
WebMD Health Corporation	USA
Weibo Corporation	China
Yelp Inc.	USA

Table 4 – Control Variables Descriptive Statistics

Due to a skewness of 2.98 and a kurtosis of 11.15, I decide to log the value of total assets for the analysis, which creates a more normal distribution for this control variable. Other variables that have skewness and heavy tails are profit margin and EBITDA margin. However, these variables are difficult to interpret since these variables are percentages already, and thus, I do not log these variables within the analysis.

Control Variables	**Mean**	**Standard Deviation**	**Skewness**	**Kurtosis**	**Number of Observations**
Total Assets	$6,790,000,000	$13,800,000,000	2.98	11.15	328
Log of Total Assets	21.35	1.57	0.36	2.81	328
EBITDA Margin	13%	21%	-0.63	5.39	290
Profit Margin	-3%	53%	-5.55	43.38	319
Quarters since IPO	22	19	0.94	2.71	329
Return on Invested Capital	1.07%	10.35%	-0.21	2.81	322

Control Variables	**Minimum**	**1% Level**	**5% Level**	**Median**	**95% Level**	**99% Level**	**Maximum**
Total Assets	$90,400,000	$95,600,000	$112,000,000	$1,490,000,000	$46,500,000,000	$64,800,000,000	$70,700,000,000
Log of Total Assets	18.32	18.38	18.53	21.12	24.56	24.89	24.98
EBITDA Margin	-79%	-72%	-17%	12%	47%	54%	60%
Profit Margin	-455%	-261%	-36%	2%	38%	73%	127%
Quarters since IPO	1	1	2	15	60	70	73
Return on Invested Capital	-29%	-23%	-17%	1%	17%	22%	27%

Table 5 – Key Regressor Descriptive Statistics

In Table 5, I include key descriptive statistics of the key regressor, millions of monthly active users.

Key Regressors	**Mean**	**Standard Deviation**	**Skewness**	**Kurtosis**	**Number of Observations**
Monthly Active Users (Millions)	296.60	543.68	2.34	7.31	329

Key Regressors	**Minimum**	**1% Level**	**5% Level**	**Median**	**95% Level**	**99% Level**	**Maximum**
Monthly Active Users (Millions)	0.73	0.83	4.76	72.30	1,724.10	2,287.40	2,395.80

Table 6 –Non-Winsorized Dependent Variables Descriptive Statistics

Since some P/E and EV/EBITDA multiples are negative, I set these values to missing so these observations are not used in the regressions. Additionally, since there is a large skew on the right side of the dependent variables, I winsorize the EV/EBITDA and EV/Revenue multiples at the 1% level and winsorize the P/E multiples at the 2% level.

Multiple Ranges	**Minimum**	**1%**	**5% Level**	**Median**	**95% Level**	**99% Level**	**Maximum**
P/E	-4,209.5x	-1,724.8x	-201.1x	23.x	435.1x	974.9x	5,186.8x
P/E Diluted	-4,447.3x	-1,714.4x	-183.8x	24.8x	466.1x	1,008.x	5,555.2x
EV/EBITDA	-6,612.8x	-2,539.x	-165.3x	23.6x	160.3x	573.1x	1,693.2x
EV/EBITDA Diluted	-6,906.3x	-2,499.7x	-186.5x	24.3x	173.4x	619.7x	1,655.8x
EV/Revenue	.35x	.41x	.86x	6.02x	19.13x	25.38x	51.22x
EV/Revenue Diluted	.34x	.41x	.87x	5.96x	18.6x	25.87x	47.27x

Table 7 – Cleaned Dependent Variable Descriptive Statistics

After winsorizing and setting negative multiples to missing, I show the descriptive statistics below of the variables used within my dataset. Furthermore, since the multiples and their diluted counterparts are very similar, I solely utilize the traditional multiple (i.e. P/E, EV/EBITDA, and EV/Revenue) in my analyses.

Multiple Ranges	**Mean**	**Standard Deviation**	**Skewness**	**Kurtosis**	**Number of Observations**
P/E	132.x	200.2x	2.50	8.44	183
P/E Diluted	135.2x	198.6x	2.39	7.75	184
EV/EBITDA	67.1x	157.5x	7.57	69.96	232
EV/EBITDA Diluted	68.9x	156.1x	7.41	67.40	232
EV/Revenue	7.28x	5.85x	0.91	3.22	319
EV/Revenue Diluted	7.38x	5.97x	0.95	3.33	318

Multiple Ranges	**Minimum**	**1% Level**	**5% Level**	**Median**	**95% Level**	**99% Level**	**Maximum**
P/E	7.4x	7.9x	16.6x	53.x	709.1x	851.7x	851.7x
P/E Diluted	8.x	8.5x	17.2x	56.9x	729.1x	812.8x	812.8x
EV/EBITDA	2.9x	3.9x	6.7x	30.4x	202.5x	573.1x	1,693.2x
EV/EBITDA Diluted	2.9x	3.9x	6.7x	31.x	216.4x	619.7x	1,655.8x
EV/Revenue	.35x	.41x	.86x	6.02x	19.13x	25.38x	25.38x
EV/Revenue Diluted	.34x	.41x	.87x	5.96x	18.6x	25.87x	25.87x

Table 9 – Fama Macbeth Regression Results using Total Assets

Due to concerns of serial correlation over time, I utilize a Fama Macbeth regression to address this concern. In this Fama-Macbeth regression, I utilize total assets in nominal form as a control variable, and then determine the effect of millions of monthly active users on these three traditional multiples. When both EV/Revenue and EV/EBITDA are used as dependent variables, millions of monthly active users significantly explains these multiples. Millions of monthly active users most likely loses significance in the Price/Earnings regression since over 43% of observations are eliminated due to their negative values. Due to multicollinearity concerns, I utilize EBITDA margin as a control variable for Price/Earnings regression and net income margin for EV/Revenue and EV/EBITDA regressions.

Fama Macbeth Regression using Total Assets in Model			
	EV/Revenue	**EV/EBITDA**	**Price/Earnings**
Monthly Active Users (Millions)	0.004***	0.23**	1.60
	-	(0.11)	(1.14)
Total Assets	-	-	-
	-	-	-
EBITDA Margin	-	-	-525.60**
	-	-	(245.60)
Profit Margin	-8.58**	-2626.67*	
	(3.42)	(1,520.51)	
Quarters Since IPO	-0.18***	-2.65***	12.08
	(0.03)	(0.89)	(15.25)
International Dummy	-1.50*	-73.19	-50.45
	(0.88)	(46.21)	(37.50)
ROIC	28.79***	3,109.69	-921.81*
	(5.81)	(2,056.77)	(535.04)
Constant	10.13***	190.86***	638.12***
	(0.92)	(43.92)	(142.68)

* p < .1, ** p < .05, *** p <.01

Table 10 – Fama Macbeth Regression with Log of Total Assets

Similar to the prior regression with the nominal value of total assets, I find that millions of monthly active users significantly explains EV/Revenue and EV/EBITDA, but not Price/Earnings. I hypothesize that Price/Earnings is not significant since there are significantly less observations due to negative multiples.

Fama Macbeth Regression using Log of Total Assets in Model			
	EV/Revenue	**EV/EBITDA**	**Price/Earnings**
Monthly Active Users (Millions)	0.004***	0.14*	-0.13
	-	(0.08)	(0.27)
Log of Total Assets	-0.29	-29.24	117.37
	(0.29)	(17.13)	(173.90)
EBITDA Margin			-869.20**
			(327.59)
Profit Margin	-6.95**	-2,367.76*	
	(2.75)	(1,264.29)	
Quarters Since IPO	-0.18***	-2.35***	-8.90**
	(0.03)	(0.66)	(4.11)
International Dummy	-1.19	-44.46	69.67
	(0.76)	(30.51)	(140.57)
ROIC	29.78***	2,740.08	606.71
	(6.31)	(1,702.43)	(1,095.87)
Constant	16.12**	797.90*	-2,048.06
	(6.22)	(392.12)	(3,700.61)

* p < .1, ** p < .05, *** p <.01

Table 11 – Percentage Differentials of the Median Multiples for Each Company

In Table 11, I show the percentage differentials from the actual enterprise value of the company, utilizing both Q3 2016 multiples and enterprise values. In the table, the EV/Users multiple has the lowest average percentage differential and the second lowest median percentage differential of all multiples.

Median Differentials By Company				
Company	**P/E**	**EV/EBITDA**	**EV/Revenue**	**EV/Users**
Sohu.com	NA	878.65%	1,942.87%	70.50%
Groupon Inc.	NA	73.17%	624.23%	54.29%
Pandora Media Inc.	NA	1,178.93%	107.39%	10.95%
TrueCar Inc.	NA	1,002.85%	55.23%	76.90%
WebMD Health Corporation	236.83%	1,657.85%	101.23%	327.48%
MeetMe Inc.	532.89%	248.10%	0.56%	54.82%
Yelp Inc.	NA	75.97%	34.61%	177.55%
Kakao Corporation	44.97%	17.67%	114.36%	62.76%
Netflix Inc.	70.18%	8.99%	7.10%	90.51%
Twitter	NA	72.97%	25.71%	51.20%
TripAdvisor Inc.	70.31%	386.70%	27.38%	104.93%
Linkedin	NA	269.97%	35.42%	90.06%
Momo Inc.	96.07%	46.05%	13.40%	128.20%
Tencent Holdings	112.58%	11.27%	11.82%	17.68%
Alibaba Group	297.91%	14.01%	14.64%	74.52%
RenRen Corporation	NA	100.00%	15.29%	434.97%
Facebook	1.45%	80.68%	59.12%	76.40%
Weibo Corporation	56.74%	67.56%	70.61%	222.78%
Mean	151.99%	343.97%	181.16%	118.14%
Median	83.19%	78.33%	35.01%	76.65%
Minimum	1.45%	8.99%	0.56%	10.95%
Maximum	532.89%	1,657.85%	1,942.87%	434.97%
Standard Deviation	162%	492%	462%	110%

Table 12 – One Tailed T-Test for Median Percentage Differentials

In Table 12, I calculate the p-value for a one-tailed t-test between EV/Users in all traditional multiples to determine whether there is a significant difference in percentage differentials. From these tests, I determine that EV/Users has a significant difference from EV/EBITDA, proving that EV/Users is the more accurate multiple. Though, I am unable to prove that EV/MAUs is more accurate than P/E and EV/Revenue.

	Accuracy of Multiples One-Tailed T-Test			
	EV/Users	**P/E Difference**	**EV/EBITDA Difference**	**EV/Revenue Difference**
Sohu.com	70.50%	NA	808.15%	1,872.37%
Groupon Inc.	54.29%	NA	18.88%	569.94%
Pandora Media Inc.	10.95%	NA	1,167.98%	96.45%
TrueCar Inc.	76.90%	NA	925.95%	-21.67%
WebMD Health Corporation	327.48%	-90.65%	1,330.36%	-226.26%
MeetMe Inc.	54.82%	478.07%	193.29%	-54.26%
Yelp Inc.	177.55%	NA	-101.57%	-142.94%
Kakao Corporation	62.76%	-17.79%	-45.09%	51.60%
Netflix Inc.	90.51%	-20.33%	-81.52%	-83.41%
Twitter	51.20%	NA	21.77%	-25.49%
TripAdvisor Inc.	104.93%	-34.62%	281.76%	-77.56%
Linkedin	90.06%	NA	179.91%	-54.64%
Momo Inc.	128.20%	-32.13%	-82.15%	-114.80%
Tencent Holdings	17.68%	94.90%	-6.40%	-5.86%
Alibaba Group	74.52%	223.39%	-60.51%	-59.88%
RenRen Corporation	434.97%	NA	-334.97%	-419.68%
Facebook	76.40%	-74.94%	4.29%	-17.27%
Weibo Corporation	222.78%	-166.04%	-155.22%	-152.17%
Mean	118.14%	35.98%	225.83%	63.03%
Median	76.65%	-26.23%	11.58%	-54.45%
P-Value (One-Tailed T-Test)		0.28	0.03	0.30

Appendix of Figures

Figure 1 – Enterprise Value and MAUs Growth Overtime

In these graphs, both MAUs and Enterprise Value seem to be trending upwards in very similar proportions over time. Thus, I hypothesize that MAUs explains changes in Enterprise Value over time showing that this multiple may better explain firm value than traditional multiples.

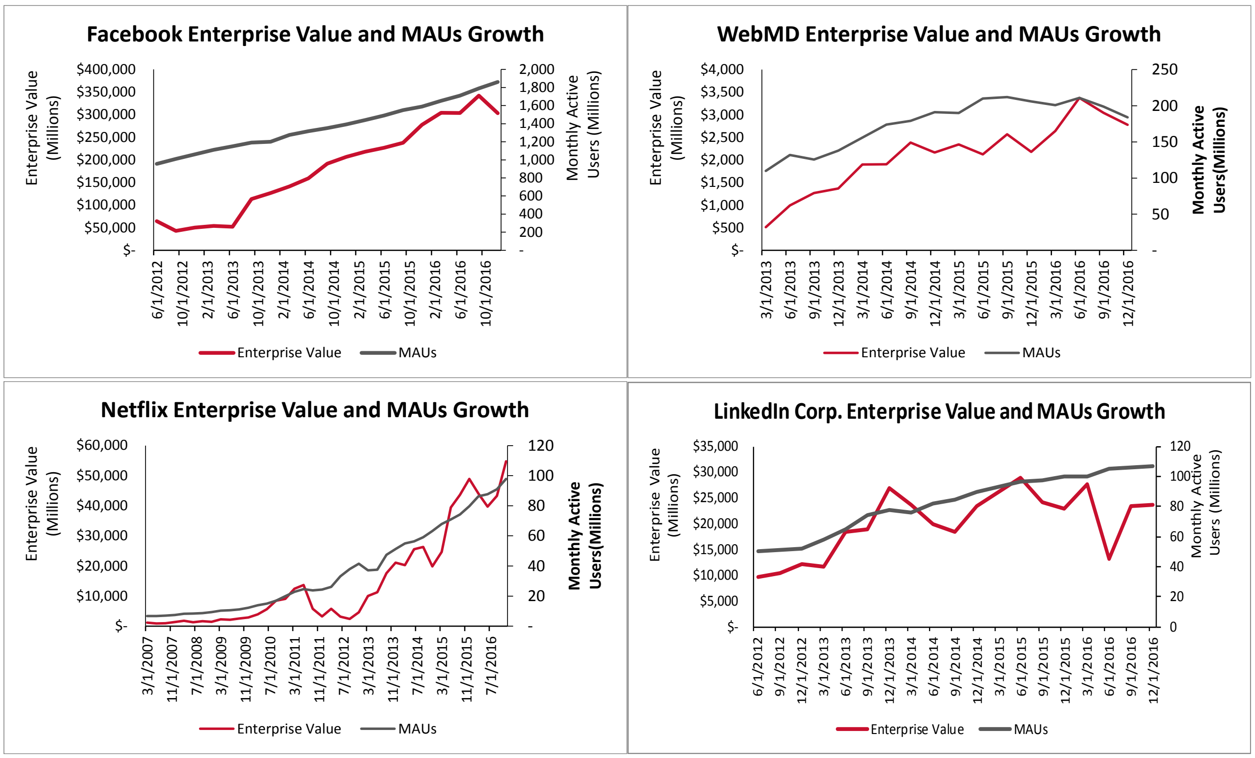

Figure 2 – Traditional Value Drivers and Firm Value over Time

In Figure 2, I show graphically that traditional multiples (EV/Revenue, EV/EBITDA, and Price/Earnings) don't have as strong of a relationship between firm value and the value driver as firm value and MAUs.

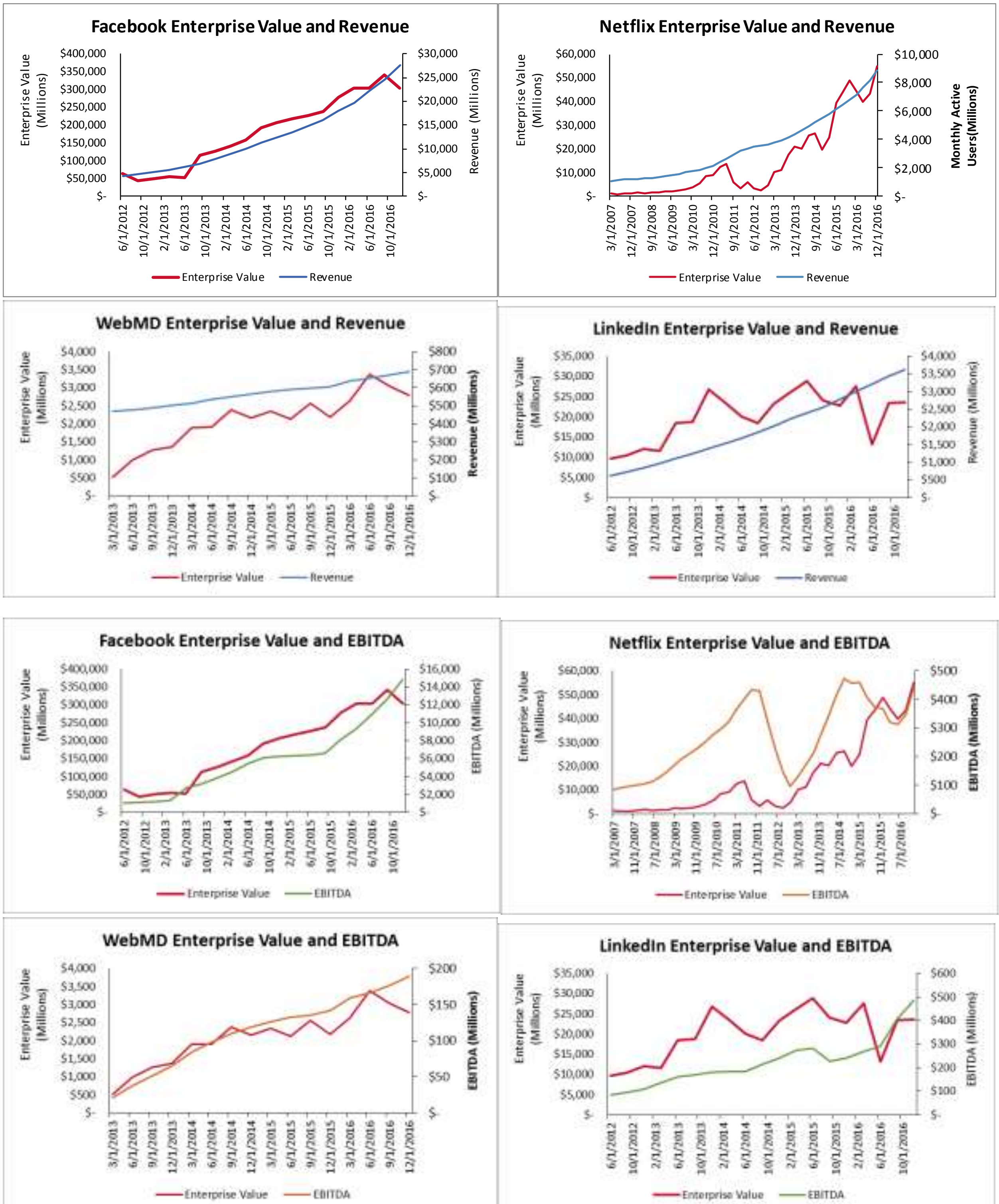

Figure 3 – Histogram of the Nominal Value of Total Assets

Through Figure 3, I demonstrate that total assets is right skewed and has a heavy tail.

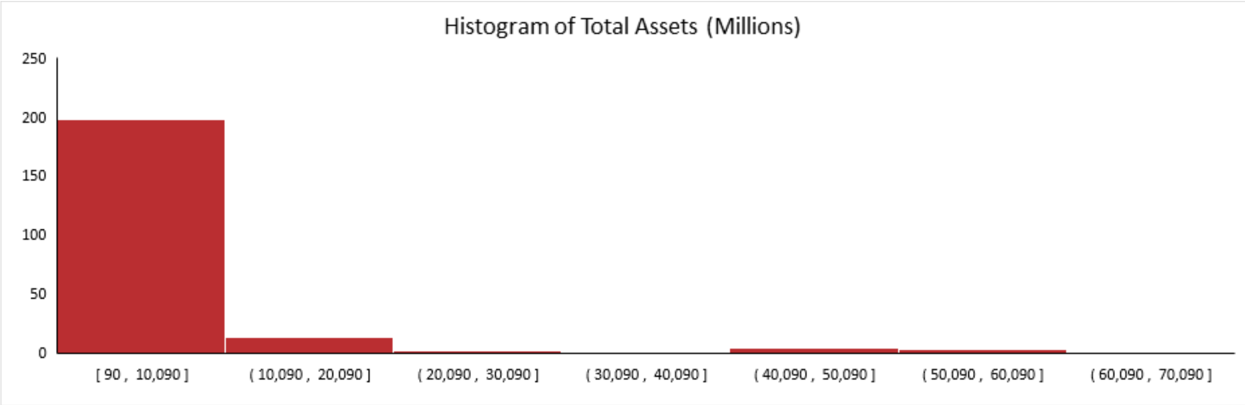

Figure 4 – Histogram of the Log of Total Assets

After taking the log of total assets, the distribution becomes similar to a normal distribution.