# Platform Valuation: Profit or User Base?

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**Abstract**

We represent a platform's valuation as its current profit plus its discounted next-period valuation, which is a function of its current user base. Wall Street emphasizes the current profit while the Silicon Valley emphasizes the user base, which represents the future value. We test the impacts of current profit and user base on platform valuation. We show that user base impacts platform valuation, but only slightly improve the explanatory power of the traditional accounting model which only uses financial data. It means that current profit and other financial data have already reflected most of the value of user base. Our findings support the Silicon Valley's method of valuation, but also remind the investors to pay attention to the importance of today's profitability of the platform, rather than only emphasize the value of the user base.

# 1 Introduction

We relate a platform's valuation to its current profit and user base. Seven of the ten most valuable public firms in the world are platforms[1]. In addition, many high valuation platforms are private firms. Venture capitals compete to provide them with sufficient funds. However, the profits of many platforms are small, sometimes even negative. Therefore, investors must expect the platform to have high profits in the future and tolerate the platform to sacrifice current profit. The reason is that the platform can promote the growth of user base by sacrificing current profit. A larger user base increases the platform's profit through two channels. First, it generates stronger network effects, which increase the price buyers are willing to pay. Hence, the profitability of the platform increases as the user base increases. Secondly, the platform' profit is positively related to its user base given its profitability. Hence, investors expect its profits to accelerate as user base increases.

In the 1980s, Robert Metcalfe proposed a model of network value for communication devices based on network size that has become known as Metcalfe's law [2], which states that the value of a network grows as the square of the number of its users: $V \propto n^2$. In late 2013, Metcalfe extended his argument to firms, using ten years of Facebook data fitting network size to firm revenues (Metcalfe 2013).

Based on the optimistic view that the user base can bring increasing profits of

[1] https://en.wikipedia.org/wiki/List_of_public_corporations_by_market_capitalization#2018. Accessed June 28, 2019.

[2] These formulations are not "laws" in a rigorous sense of maintaining their accuracy as scientists develop new theories. Rather they are descriptive models of empirical regularities. We adhere to conventional nomenclature in describing these heuristics as laws.

platforms, the valuation of platforms has risen sharply over the past several years. However, many platforms still cannot make money today. In the past year, Wall Street and Silicon Valley have huge different opinions on the valuation of platforms. Wall Street emphasizes the current profit while the Silicon Valley emphasizes the user base, which represents the future value. Not only the stock prices of FANG [3] went down, but also the valuations of other unicorns decreased in the public market and private market.

Who is correct? Wall Street or Silicon Valley? We test the impacts of current profit and user base on market value of the platform. We show that user base impacts platform valuation, but only slightly improve the explanatory power of the traditional accounting model which only uses financial data. It means that current profit and other financial data have already reflected most of the value of user base. Our findings support the Silicon Valley's method of valuation, but also remind the investors to pay attention to the importance of today's profitability of the platform, rather than only emphasize the value of the user base. A further interesting question is that why some platforms are very profitable while some are not profitable at all. Even platforms with a large user base, such as Uber, cannot improve their profits. It means that strong network effects do not help them make profits. If the investors expect them to have huge profits in the future, they might need to find other reasons.

The remainder of the paper proceeds as follows. Section 2 provides a review of related literature in network value, platform competition in two-sided markets, and internet stocks pricing. In Section 3, we provide models to calculate platform

[3]FANG is the acronym for Facebook, Amazon, Netflix and Google.

valuation. Section 4 uses empirical data to test the effects of current profit and user base on platform valuation. Section 5 concludes.

# 2 Related Work

Several branches of literature yield insight for this research, including network value, platform competition in two-sided markets, and Internet stock pricing.

## 2.1 Network Value

Farrell and Klemperer (2007) represent a platform's valuation as its current profit plus its discounted next-period valuation, which is a function of its current user base, but they do not propose an accurate form of this function.

Metcalfe's law states that the value of a network grows as the square of the number of its users: $V \propto n^2$. In late 2013, Metcalfe (2013) extended his argument to firms, using ten years of Facebook data fitting network size to firm revenues. However, not everyone agrees with Metcalfe's law. Odlyzko and Tilly (2005) and Briscoe, Odlyzko, and Tilly (2006) argue that Metcalfe's law is a significant overestimate of network value. They propose Odlyzko's law which states that the value of a network grows in proportion to $nlog(n)$. The logic for Odlyzko's law is that the most valuable contacts are much more valuable than the least valuable one. According to Zipf's distribution, the ranked value of the Nth item is roughly 1/n. the sum of this series approaches log(n), therefore, the value summed across all members of a network is $nlog(n)$. This growth is slower than the square growth of Metcalfe's law, but faster

than the linear growth of Sarnoff's law, which states that the value of a network is proportional to the number of users.

## 2.2 Platform Competition in Two-sided Markets

Armstrong (2006) sets up a symmetric and linear utility model to analyze competition in two-sided markets. He shows that the equilibrium profit of the platform is related to a platform's user base, market power and the magnitude of the cross-group externalities.

Mitchell and Skrzypacz (2006) study the dynamic competition of duopoly platforms when there exist network effects. They show the relationship between the current profit of the platform and the current and previous user base.

Parker and Van Alstyne (2005) study strategic pricing behavior in network markets. They show that the platform can provide a discount price for one side user to attract more users in the other side and make a larger profit.

## 2.3 Internet Stocks Pricing

Trueman, Wong, and Zhang (2000) (2001) study the valuation of Internet stocks by combining fundamental accounting information and web traffic data. They incorporate web traffic as a linear variable in their empirical model. They show that web traffic has significant predictive power of the revenues of the e-commerce firms, but little predictive power for the revenues of the portal/content firms.

Rajgopal, Venkatachalam, and Kotha (2003) show that network effects created

by web traffic can be considered as an important intangible asset which impacts the market value. They also show that web traffic is nonlinearly associated with market value, which is consistent with the functional form suggested by Metcalfe's law or Odlyzko's law of network value.

In this paper, we use the user base instead of web traffic to estimate market value since the profit of a platform is directly related to the user base according to the theories of network value and platform competition in two-sided markets while web traffic is only a proxy of the user base of the platform.

# 3 Model of Platform Valuation

The traditional accounting model represents a firm's valuation as its current profit plus its discounted profits in the future (Gordon and Shapiro 1956). Let the interest rate be $r$ and the growth rate of profit be $g$. The firm's valuation is as follows.

$$V_t = \frac{\pi_t}{r - g} \tag{1}$$

Farrell and Klemperer (2007) represent a platform's current-period valuation $V_t$ as its current profit plus its discounted next-period valuation $V_{t+1}$. $V_{t+1}$ is a function of the size of its current-period user base $n_t$. $1 + r$ is the discount rate. We first assume that $V_{t+1}$ is linear to $n_t$ in our baseline model and regress equation (2) to get

naive results.

$$V_t = \pi_t + \frac{V_{t+1}(n_t)}{1+r} = \pi_t + \alpha n_t \tag{2}$$

Secondly, we notice that user base is not randomly assigned to the platforms and it is endogenous to other factors. We need to include the exogenous variables that determine the user base in the model. Mitchell and Skrzypacz (2006) show that profit in period t is a function of user base in period $t$ and $t-1$, i.e. $\pi_t = f(n_t, n_{t-1})$. We have its inverse function as $n_t = g(\pi_t, n_{t-1})$. Since we already have $\pi_t$ in the model, we only need to add $n_{t-1}$ into the model. Armstrong (2006) show that the platform profit is determined by market power and user base of the platforms, i.e. $\pi_t = g(\sigma_t, n_t)$. $\sigma_t$ represents the market power of the platform. We have its inverse function as $\sigma_t = h(\pi_t, n_t)$. We are worried that platform's market power in period $t$ and $t-1$ affects the current user base. Therefore, we need to include $n_{t-1}$, $\pi_{t-1}$, $n_t$, $\pi_t$ in the model. Since we already have $n_{t-1}$, $n_t$, $\pi_t$ in the model, we only need to add $\pi_{t-1}$ into the model. Another concern is that the platform may take strategic approaches to increase network effects (Parker and Van Alstyne 2005). We expect that these strategic approaches are reflected in its operating expense, including $R\&D$ expense (RDX) and marketing expense (SGX). Furthermore, since book value (BV) might affect the market power of the platform, we also have it in our regression.

$$V_t = \alpha_0 + \alpha_1\pi_t + \alpha_2 V_{n+1}(n_t) + \alpha_3\pi_{t-1} + \alpha_4 n_{t-1} + \beta_1 BV_t + \beta_2 SGX_t + \beta_3 RDX_t \tag{3}$$

Finally, what is the accurate form of $V_{n+1}(n_t)$? According to the research of two-sided marketsthe equilibrium profit of the platform is proportional to $an + bn^2$ (Armstrong 2006) (Mitchell and Skrzypacz 2006). Since the valuation is the sum of discounted profit, the platform valuation is proportional to $an + bn^2$. Furthermore, this form of $V_{n+1}(n_t)$ can represent all of the three famous laws. The reason is that $an + bn^2$ is a combination of Sarnoff's law and Metcalfe's law, which state that the network value is proportional to $n$ and $n^2$ respectively. If $a$ is positive and $b$ is negative, $V_{n+1}(n_t)$ grows with $n$, but the growth rate decreases, which is similar with Odlyzko's law. Therefore, we represent $V_{n+1}(n_t)$ as $an+bn^2$ and include $n_t^2$ and $n_{t-1}^2$ in the model.

$$V_t = \alpha_0 + \alpha_1\pi_t + \alpha_2 n_t + \alpha_3 n_t^2 + \alpha_4\pi_{t-1} + \alpha_5 n_{t-1} + \alpha_6 n_{t-1}^2 + \beta_1 BV_t + \beta_2 SGX_t + \beta_3 RDX_t \tag{4}$$

# 4 Data and Empirical Results

## 4.1 Data Description

Our sample consists of 15 US firms, 13 Chinese firms and 154 firm-years. We have three criteria to select the sample firms. First, the firm should be internet companies that enable value-creating interactions in two-sided markets. Secondly, they should be public firms because we need to get financial data. Thirdly, we only include firms that publish their user base data. The second and third criteria greatly limits our sample size. We get financial data from Compustat. For user base data, we get from

firms' annual financial reports and Statista. Table 1 provides statistics on both the dependent variable and the explanatory variables included in our regressions.

Table 1: Descriptive Statistics for the Regression Variables

| **Variable** | **Number of Firms** | **Obs** | **Mean** | **Std. Dev.** | **Min** | **Max** |
|---|---|---|---|---|---|---|
| V($M) | 28 | 154 | 41492.41 | 88921.51 | 204.3554 | 512792.8 |
| $\pi(\$M)$ | 28 | 165 | 735.1781 | 2363.283 | -3445.07 | 15934 |
| n (M) | 28 | 166 | 236.9519 | 392.1071 | .151 | 2129 |
| BV($M) | 28 | 161 | 5504.02 | 11528.37 | -1440 | 74347 |
| SGX($M) | 28 | 164 | 2248.935 | 4260.981 | 33.65335 | 32951 |
| RDX($M) | 28 | 164 | 735.1779 | 1635.426 | 0 | 12540 |

## 4.2 Market Value and User Base

In Table 2, we show the effect of user base on a platform's valuation. Column 1 and Column 3 show the results of traditional accounting model without and with controls. Column 2 shows the correlation between the platform's valuation and user base without controls. The relation is significant and positive. One additional user is associated with $ 150.9 increase in valuation. Column 4 shows the correlation between the platform's valuation and user base with controls. The relation is still significant and positive. One additional user is associated with $ 322 increase in valuation. The relation between valuation and the square of user base is significant and negative, it has two implications. First, the impact of one additional user on valuation is smaller than $ 322 and depends on the number of user base. If we use

the mean of user base, which is 237 million, to calculate the effect of user base on the valuation, we have one additional user is associated with $ 204 increase in valuation. Secondly, the impact of one additional user on valuation decreases with the growth of user base. Column 4 also shows that the impact of one additional user in last period on valuation is significant and negative. The reason is that after we control the current user base, a higher user base in last period means a slower growth of user base, which has a negative impact on the valuation. The significant and positive relation between the valuation and the square of one additional user in last period means the investor has a lower expectation of the growth of user base when the user base gets larger. Column 3 shows the relations between valuation and financial variables are significant, but Column 4 shows that after we include controls in the regression, the relations are insignificant except for the relation between valuation and book value. The reason may be that the user base fully reflects the profit when we have the accuracy form of $V_{n+1}(n_t)$. By comparing adjusted $R^2$ in column 1 and 2 as well as column 3 and 4, we find that the increases in adjusted $R^2$ are 7% without controls and 9% with controls, which means most of the impact of user base has already been reflected in platform profit and other financial variables. Our findings show that the user base has an impact on market value, but only slightly improve the explanatory power of the traditional accounting model which only uses financial data. They support the Silicon Valley's method of valuation, but also remind the investors to pay attention to the importance of today's profitability of the platform, rather than only emphasize the value of the user base.

Table 2: The Effect of User Base on Platform's Market value

| VARIABLES | (1) Traditional model | (2) Include user base | (3) Traditional model with controls | (4) Include user base and controls |
|---|---|---|---|---|
| Profit | 26.87*** | 14.00*** | 7.132** | -1.735 |
| | (2.250) | (2.783) | (2.720) | (2.026) |
| User base | | 150.9*** | | 322.0*** |
| | | (23.25) | | (104.6) |
| User base$^2$ | | | | -0.249*** |
| | | | | (0.0520) |
| Profit in last period | | | 4.183 | -2.847 |
| | | | (2.950) | (2.200) |
| User base in last period | | | | -408.1*** |
| | | | | (104.5) |
| User base$^2 inlastperiod$ | | | | 0.411*** |
| | | | | (0.0553) |
| Book value | | | 5.813*** | 3.597*** |
| | | | (0.909) | (0.674) |
| Marketing expense | | | -17.49* | -0.185 |
| | | | (10.06) | (7.131) |
| R&D expense | | | 60.84** | 16.67 |
| | | | (25.77) | (17.89) |
| Marketing expense in last period | | | 44.95*** | 11.52 |
| | | | (12.74) | (9.502) |
| R&D expense in last period | | | -127.0*** | -29.85 |
| | | | (32.93) | (24.88) |
| Constant | 21,133*** | -5,803 | -14,840*** | 748.2 |
| | (3,983) | (5,400) | (4,332) | (5,459) |
| Observations | 154 | 154 | 134 | 134 |
| Adj R-squared | 0.533 | 0.57 | 0.838 | 0.914 |
| Number of firmid | 28 | 28 | 28 | 28 |

Standard errors in parentheses
*** p$\leq 0.01, **p \leq 0.05, *p \leq 0.1$

### 4.3 Robustness Tests

First, we assume $V_{n+1}(n_t)$ is linear to $n$ in the baseline model. Now we use $nlogn$ and $n^2$ to represent $V_{n+1}(n_t)$ in the baseline model based on Metcalfe's law and Odlyzko's law. The reason is that different platforms may have different types and strength of network effects. Then we include $n$, $log(n)$, $n^2$ and all the controls in the model. Finally, we use non-parametric method in our regression because the accurate form of function $V_{n+1}(n_t)$ might not follow any of the above laws. Table 3 shows the results, which are very similar with the results in Table 2.

Secondly, our sample firms are public firms, which are large and mature firms. It is possible that user base plays a more important role in estimating the valuation of young firms because their user base grows much faster than these mature firms. We address this concern by divide the firms into two groups. One group has a growth rate of user base higher than the average while the other group has a growth rate of user base lower than the average. We include the dummy that represents the higher growth rate, the interaction of the dummy with $n$ and $n^2$ in the model. Column 1 in table 4 shows the results are robust. We also want to test whether the impacts of user base are different on firms with a large user base and firms with a relatively small user base. We divide the firms into two groups based on the size of average user base. We create a dummy that represents the firm with a large user base and include the dummy, the interaction of the dummy with $n$ and $n^2$ in the model. Column 2 in table 4 shows the results are robust. Finally, we run the regression based on data of US firms and Chinese firms. Table 4 shows the results, which is still robust and

Table 3: Competitive Laws

| VARIABLES | (1) Traditional model | (2) Include nlogn | (3) Include $n^2$ | (4) Traditional model with controls | (5) Include n, logn,$n^2$ and controls |
|---|---|---|---|---|---|
| Profit | 26.87*** | 13.43*** | 9.539*** | 7.132** | -1.583 |
| | (2.250) | (2.886) | (3.400) | (2.720) | (2.095) |
| User base | | | | | 286.9** |
| | | | | | (124.8) |
| Log use base | | | | | 10,917 |
| | | | | | (19,949) |
| Use base * log use base | | 19.78*** | | | |
| | | (3.115) | | | |
| User base$^2$ | | | 0.0839*** | | -0.240*** |
| | | | (0.0134) | | (0.0554) |
| Profit in last period | | | | 4.183 | -2.786 |
| | | | | (2.950) | (2.266) |
| Use base in last period | | | | | -368.2*** |
| | | | | | (121.8) |
| Log use base in last period | | | | | -10,000 |
| | | | | | (15,070) |
| Use base$^2 inlastperiod$ | | | | | 0.398*** |
| | | | | | (0.0590) |
| Book value | | | | 5.813*** | 3.610*** |
| | | | | (0.909) | (0.680) |
| Marketing expense | | | | -17.49* | -0.0531 |
| | | | | (10.06) | (7.235) |
| R&D expense | | | | 60.84** | 16.14 |
| | | | | (25.77) | (18.15) |
| Marketing expense in last period | | | | 44.95*** | 12.27 |
| | | | | (12.74) | (9.670) |
| R&D expense in last period | | | | -127.0*** | -31.45 |
| | | | | (32.93) | (25.22) |
| Constant | 21,133*** | 793.7 | 15,836*** | -14,840*** | -5,685 |
| | (3,983) | (4,725) | (3,588) | (4,332) | (28,716) |
| Observations | 154 | 154 | 154 | 134 | 134 |
| Adj R-squared | 0.533 | 0.565 | 0.562 | 0.838 | 0.911 |
| Number of firmid | 28 | 28 | 28 | 28 | 28 |

Standard errors in parentheses
*** p$\leq 0.01, **p \leq 0.05, *p \leq 0.1$

similar with the results in Table 2.

# 5 Conclusions

Platforms are the largest firms in the stock market and of rising importance. Wall Street and Silicon Valley have different opinions on the valuation of platforms. Wall Street emphasizes the current profit while the Silicon Valley emphasizes the user base, which represents the future value. We test the effect of current profit and user base on market value of the platform. We have two findings. First, we show that user base has an positive impact on market value of the platform, but the impact decreases, which implies the value of additional users decreases. Secondly, including user base in the traditional accounting model only slightly improve the explanatory power. It means that current profit and other financial variables have already reflected most of the value of user base. This finding reminds the investors to pay attention to the importance of today's profitability of the platform, rather than only emphasize the value of the user base.

Our findings have important implications not only for investors, but also for researchers. Our paper relates a platform's market value to its financial data and non-financial data. Hedge funds use non-financial data to estimate the firm valuation for a long time, but they do not have any theoretical support. Meanwhile, many research of information systems provides insights of the impact of non-financial data on platform's performance. We hope our paper is a start to bridge information systems research to platform valuation.

Table 4: Robustness Tests

| VARIABLES | (1) Dummy of growth rate | (2) Dummy of size of user base | (3) US firms | (4) Chinese firms |
|---|---|---|---|---|
| Profit | -1.627 | -1.826 | 3.244 | -7.970 |
| | (2.068) | (2.086) | (2.072) | (6.037) |
| User base | 229.8 | 243.3 | 697.4*** | 84.93 |
| | (148.4) | (191.6) | (258.4) | (135.9) |
| User base$^2$ | -0.224*** | 0.270 | -0.549*** | -0.0808 |
| | (0.0605) | (0.575) | (0.152) | (0.0880) |
| Profit in last period | -2.880 | -2.849 | 6.258** | -6.472 |
| | (2.231) | (2.261) | (3.016) | (6.143) |
| User base in last period | -300.8* | -415.0*** | -709.9*** | -201.2* |
| | (158.0) | (105.2) | (260.7) | (107.9) |
| User base$^2 inlastperiod$ | 0.377*** | 0.411*** | 0.679*** | 0.218** |
| | (0.0674) | (0.0557) | (0.192) | (0.0977) |
| Book value | 3.556*** | 3.740*** | 2.756** | 8.771*** |
| | (0.690) | (0.689) | (1.047) | (2.226) |
| Selling, general and | 0.604 | 0.507 | -12.77 | -21.49 |
| administrative expense | (7.274) | (7.234) | (8.479) | (13.24) |
| R&D expense | 15.35 | 13.79 | 28.09 | 146.3** |
| | (18.33) | (18.25) | (18.45) | (62.34) |
| Selling, general and administrative | 10.65 | 10.58 | 10.60 | 37.43** |
| expense in last period | (9.675) | (9.699) | (10.55) | (15.25) |
| R&D expense in last period | -28.62 | -28.70 | 1.861 | -218.1*** |
| | (25.50) | (25.23) | (26.25) | (72.08) |
| Growth rate of use base | -1,074 | | | |
| | (7,929) | | | |
| Growth rate of use base * user base | 11.91 | | | |
| | (81.07) | | | |
| Growth rate of use base * user base$^2$ | 0.0436 | | | |
| | (0.159) | | | |
| Size of user base | | - | | |
| Size of user base * use base | | 75.93 | | |
| | | (164.8) | | |
| Size of user base * use base$^2$ | | -0.515 | | |
| | | (0.570) | | |
| Constant | 427.6 | 2,938 | -5,777 | 7,983 |
| | (7,353) | (6,809) | (8,914) | (6,372) |
| Observations | 134 | 134 | 76 | 58 |
| Adj R-squared | 0.912 | 0.913 | 0.932 | 0.975 |
| Number of firmid | 28 | 28 | 15 | 13 |

Standard errors in parentheses
*** p$\leq 0.01, **p \leq 0.05, *p \leq 0.1$

The limitation of this research is the small sample size. Private firms do not publish their financial data and not all public firms provide user base data in their financial reports. Fortunately, the sample size may increase greatly because more and more platforms are going to be listed in the capital market. Furthermore, some third party data companies can provide high quality use base data as well as user behavior data. As the data grows richer, I am optimistic about the future research on this topic.

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Table 5: The Sample Firms

| **Firm Id** | **Firm Name** | **Country** | **Firm Id** | **Firm Name** | **Country** |
|---|---|---|---|---|---|
| 1 | Amazon | US | 1 | Alibaba | China |
| 2 | Ebay | US | 2 | Jingdong | China |
| 3 | Wayfair | US | 3 | Dangdang | China |
| 4 | Etsy | US | 4 | Jumei | China |
| 5 | Zulily | US | 5 | Vipshop | China |
| 6 | Facebook | US | 6 | Tencent | China |
| 7 | LinkedIn | US | 7 | Weibo | China |
| 8 | Twitter | US | 8 | Momo | China |
| 9 | Snapchat | US | 9 | YY | China |
| 10 | Netflix | US | 10 | Xnet | China |
| 11 | Pandora | US | 11 | Cmcm | China |
| 12 | Yelp | US | 12 | Qunar | China |
| 13 | Zillow | US | 13 | Soufun | China |
| 14 | Groupon | US | | | |
| 15 | PayPal | US | | | |