Measure of Network Effect on Social Media Platforms

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Abstract. *Social media platform dramatically changed the world in the last 2 decades. From limited communication possibilities, the individuals found themselves in the posture of connecting with others at only few clicks distance. Those platforms rely on large networks of people and their operators benefit from their effect. The paper examines how network effects impact the financial performance of social media organizations, analyses the strength of these effects on various platforms, and suggests a methodology for calculating the money generated by each user. This comprehensive method seeks to analyze the correlation between user base expansion and income production, providing valuable insights into the strategic importance of network effects in the digital economy.*

Keywords: network effect, key financial indicators, social networks, value creation.

Introduction

Social media platforms hold large number of users, that individually subscribed to cover different needs: being in contact with friends (Facebook), watching friends' and persons of interest's personal photos (Instagram, Snapchat), producing / consuming entertainment (YouTube, TikTok, Douyin, Kuaishou, Josh, Twitch), real time communication (WhatsApp, Telegram, WeChat, Discord), microblogging (X former Twitter, Qzone, Threads, Weibo, QQ), information exchange (Reddit, Quora), interaction with professionals, promotion of professional information (LinkedIn), professional team collaboration (Teams, Skype), hobbies photos exchange (Pinterest), accommodation (Airbnb, Booking), travel (Waze). The number of users differs, in function of the individual needs covered by the platforms: from pure social, transposing offline networks (Facebook, Instagram) or entertainment (YouTube) to communication (WhatsApp), jobs or passions.

Facebook is the no.1 platform in term of users, according to Meta having 3.19 billion monthly active users, as can be seen in Figure 1:

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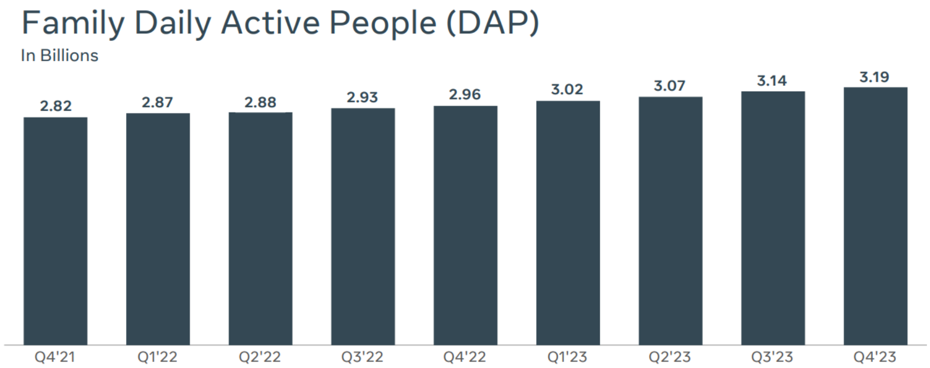

Figure 1. Family Dayli Active People (DAP)

Source: Source: Meta Investors Relations https://s21.q4cdn.com/399680738/files/doc_financials/2023/q4/Earnings-Presentation-Q4-2023.pdf

Structural analysis performed on data available in the first years of the platform existence when privacy rules were lighter (Dunbar et al, 2016), shown a strong correspondence between offline social relationships and those on the platform. In Facebook historical evolution, several stages were underlined by Niels Brügger, 2015: (1) 2004-2006 "Who are you?", (2) 2006-2008 "What are you doing and when?", (3) 2008-2013 "Where are you?". If we analyze the significance of the stages identified by professor Brugger, we observe that they reflect human interactions. We often want to show to acquaintance where are we, what we do, what we think of a subject etc. Therefore, Facebook could be considered the digital mirroring of the social human relationships. The platform practically relies on the most basic human relationships explained by Fiske A, Fiske S, 2010: "most important, people seek social belonging with their own kind, the most basic social motive of all". In consequence, Facebook, representing social belonging in a network of friends & acquaintance constantly increased the number of users since its beginning, showing strong resilience as compared with its competitors.

With the interpersonal relationships segment covered by Facebook, all remaining platforms go to other individual needs, as presented in the beginning of this chapter. By covering individual, but socially common needs (such as passions, communication, jobs etc.) development of platforms rely on the network effect, increasing the relevance for the group as new users subscribe. Studying the evolution of social media some questions may be risen.

Table 1: Questions arising from the study of social media

No.	Questions
(1)	Can we establish a hierarchy of the social needs based on platforms users' penetration?
(2)	Are there any individual or/and social needs that were not covered by those platforms?
(3)	Could new platform be created to cover those needs?
(4)	What is the defensibility of those platforms, based on already existing networks and their network effect? Could any new idea be quickly covered by existing platforms, that benefit of the existing network?
(5)	Is there a similar measure of network effect for all platforms in term of number of users, independent of the covered need or the it is a function depending on covered need and/or other parameters?
(6)	Can we assess the network effect on the value of the platform, independent from product improvements (data enabled learning) or any other parameters, such as market conditions, legislative constraints etc.?
(7)	Are the social media platform products with limited lifespan like any other product? Or, once a platform created it could adapt to remain forever in the "cash cow" segment.

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Finding answers on the questions above would establish a framework to better estimate the chances of potential new platforms and the value of existing one. The outcome of this framework could translate into business decisions related to Capital Expenditure (CAPEX) / Operational Expenditure (OPEX) budgets and strategic directions to acquire value for the platforms.

In this paper we will focus on the network effect reflected in the business value of social media platforms. We will propose a model of the individual value of each user in the social media platform and by taking into consideration two relevant data: (1) number of monthly active users as trigger and (2) platform turnover, as a value effect, we will search for numeric data of the model. We will the use data related to evolution of the number of customers and make comparation between several platforms.

Literature review

Network effects is defined in numerous sources as the increase in value or utility of a product or service as the number of users increases. The concept become more relevant once the development of online social media platforms, where the interactions between users or between users and content created by others can increase their relevance and consequently their value.

The first referral on the network effect was made by Katz and Shapiro in 1985, introducing the concept of “network externalities” and presenting their implications for competition. They classified the effects in two categories (a) positive network effects, giving the example of the utility of a consumer that acquire a telephone; the utility of the product, increase with the number of telephone users. Such definition perfectly aligns with our days use of online platforms. (b) indirect network effects, providing the example of hardware / software relation, with increase in sales for compatible software.

Other studies, split the effects in function of benefits for customers: positive network effect, as a result of increasing number of users (as in social media platforms) and negative network effects (such as overcrowding of city streets, spam, interruptions in sites functionalities due to over accessing).

The measure of network effects was evaluated though several models (1) Metcalfe law, stating that the value of network, increase by a quadratic function: value = n2; (2) Sarnoff’s law stating that the value of network, increase proportional with the number of users: value = n; (3) Reeds law, stating that the value of the network, increase exponentially with every new user: value = 2n. On all cases, “n” represents the number of users.

Apart of those models, Yoo, 2020 mention a fourth model, Zipf’s law, stating that the value of a network increases by a logarithmic function value = n*log(n). He also states that a single model to be applied to all types of sites (ie. Search engines, social media, e-commerce, software, streaming) would be impossible.

Network effect was studied by Hagiu and Wright (2021) relating on Bertrand competition between two infinitely lived firm and their capacity to learn from experience (data enabled learning), their willingness to offer discounts, the quantity of existing data and the regulation effects. They also studied the impact of data learning in the value of a product. They supposed that learning curve is S shaped, being 0 until a minimum data volume is acquired, then the value increase on constant rate until a capped value, as a limit of learning. In the model below, we took into consideration this hypothesis, that seems to be plausible.

The same S shaped approach is taken into consideration by Dixon on the platform adoption. As soon as the platform is adopted by users and developers, the become more valuable up to a certain point, where the platform relationship with users become zero-sum. The author considers that this is a limitation of centralized platforms and advocate for decentralized platforms "cryptonetworks", with opensource, multiple contributors and higher rate of development. As an example of an early open network is Wikipedia that outperformed versus Encarta, a centralized information platform.

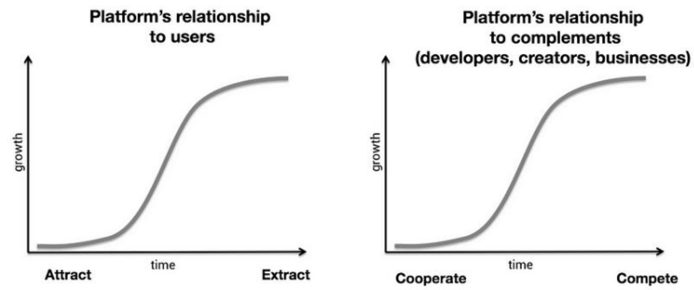

Figure 2. Relationship between platform and users / complements.

Source: https://onezero.medium.com/why-decentralization-matters-5e3f79f7638e

Researchers and market specialist studied the network effect theory on most known platforms. Hariharan presented the mechanism that led to this effect on Facebook. The initial product (1) was an online student directory information that was useful even for a single user. This platform permitted students to connect each other in multiplayer mode. To grow (2), they accessed the entire Harvard directory, aspect that led to early organic adoption in the students' network. An important aspect of the platform survival was user retention. The creators observed that the engagement trigger (3) was represented by the number of friends subscribed to the platform. If more than 10 friends subscribed during next 2 weeks, user remained active. To cover this need, they used the email contact imports to suggest friends. To rely on network effects, they developed the product adding other information to be registered such as relationship status, timelines, location etc. This led to increasing usage as number of users increased. In my opinion, an important step in developing the product was the transpose of an existing offline networks (students of Harvard) in online platform. To start the platform, creators seized the tumultuous student life, with people willing to show off and interact with others, disposed to adopt a new platform. We saw the same adoption path for TikTok, where mostly young generation easily subscribed in the first stages.

An in-depth analysis of the network effect was performed by the business community, strongly interested by the economic impact and return on investments. Coolican & Jin, market specialists proposed in their analysis three types of network effect curves: (1) S shaped, with the exemplification of ride sharing, considering that expecting more than 5 minutes to take the car, will lead to indifference of final user related to the number of cars sharing in the platform. (2) Bell shaped, as in the example of social lending platform "Frank", where a group of more than 7 friends decreased the chances to use the platform for lending (exceeding the trust circle of someone). (3) From positive to negative slope as in the case of social media. As the number of users increased, the effect was positive, but constant interactions eroded relationship among users, finally leading to weakening the network. As a personal note, we observed a change in strategy for Facebook after the pandemic, that limited interactions among users, especially on opinions.

Methodology

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Starting from the network effect definition, we considered that from the business perspective, it should create higher revenues for a company offering the goods or services, without any additional product or service development, meaning that no improvements in product/service quality have been performed.

In the social media platforms, the business owner is the platform provider, while the sold product is the user itself. Most of social media platform generate their revenues from the sale of the advertising space, more concretely through targeted advertising. All major social media platforms, such as Facebook, Instagram, YouTube, X, TikTok post results that are formed especially advertising, and more recently some of them oriented toward offering "freedom" from undesirable advertising to the users through monthly subscriptions (YouTube, Facebook). Contrarily, TikTok approach is to create a marketplace, in order to benefit of numerous trends created on the app[1].

In our analysis, from social media business figures, we took into consideration 2 data that we consider they have strong relevance: the number of monthly users, measuring the volume and implicitly the complexity of the network and the sales generated by the network, as measure of the platform value. We took into consideration that in the development of the social networks, the large amount of data generated by users' interactions constituted a strong base of increasing the advertising campaigns efficiency and the developments were done in steps, with trial and errors. Not once, in the beginning a user was invaded by advertising with rather limited or no relevance, while more recently, their relevance increased.

To observe and model the value of social media, we collected aforementioned data for Facebook, Instagram, Tiktok, Youtube and Linkedin. As a limit, the public data for the very first years of platforms' existence are not available, as at that time the companies were not public and had no disclosures obligations. In the first stages of platform development, companies focused on creating the network, adopting new users (see Brugers), while revenues were expected to be created in the future. As a result, we took into consideration public quarterly data for the platforms, starting with the first quarter it was available.

We collected data from different sources, out of which the site www.businessofapps.com and www.statista.com were the main source. We also completed with data from articles presenting key figures of platforms before the public listing. Most of specific sites presents the information under the form of graphs that show data by passing over the mouse on the chart column and cannot be downloaded as files. We therefore collected data, figure by figure, by passing through the mouse on charts. For some platforms, in the first year's data was presented on a yearly basis. We recomposed data, by using the methods presented in the table below.

Table 2: Source of quarterly data

No.	Platform	MAU [2]	Sales	Sources of data
1	Facebook	Quarterly data, in million users, since Q2.2008	Quarterly data, in million dollars, since 2010.	https://www.businessofapps.com /data/facebook-statistics/ - For sales, data contained common sales of FB and Insta, starting the year of Insta incorporation. We therefore deducted Insta sales from total Meta sales to obtain FB figures.
2.	Instagram	Quarterly data, in	Quarterly data, in	https://www.zdnet.com/article/instagram-passes-50-million-users/ - data for Q4.2010 to Q1.2011 no of users

[1] TikTok Shop Emerges as Amazon Rival, Powered by Indonesian Boom - Bloomberg
[2] Monthly active users

		million users, since Q4.2010.	million dollars since Q1.2015	https://www.investopedia.com/articles/investing/102615/story-instagram-rise-1-photo0sharing-app.asp - data evolution Q1 and Q2.2012 For Q3 and Q4.2012 data was linearly approximated (starting from Q2.2012 to Q1.2013. https://www.businessofapps.com/data/instagram-statistics/ - No. of users from this site starts from Q1.2013; sales data from Q1.2015. Sales of Insta were deducted from FB, as sales of FB contains the Insta .
3	Tiktok	Quarterly data, in million users, since Q4.2017	Quarterly data, in million dollars, since Q4.2017	https://www.businessofapps.com/data/tik-tok-statistics/ - data collected manually from the graphs on the site.
4.	Youtube	Quarterly data in million users since Q1.2010.	Quarterly data, in million dollars since Q1.2010	https://www.businessofapps.com/data/youtube-statistics/. Quarterly revenues from 2010-2014 are missing, only yearly sales were found in a specific graph. For Q1.2010 to Q4.2014 we estimated quarterly sales by extrapolating seasonality of 2015 to yearly revenues of 2010 to 2014, considering that sales follows the same partern.
5.	Linkedin	Quarterly data in million users since Q2.2009.	Quarterly data, in million dollars since Q2.2009	https://www.businessofapps.com/data/linkedin-statistics/ - for number of users since Q2.2009, and revenues since Q1.2015. https://www.statista.com/statistics/274018/quarterly-net-revenue-of-linkedin/ - for sales since Q2.2009 to Q1.2015.

Starting from primarily gathered data (number of users and quarterly sales), we calculated an indicator that we consider relevant, namely quarterly sales per user, considering its value as the equivalent of product value in the model proposed by Hagiu and Wright.

As a first step in analyzing the data, we translated series into a graph, to observe and estimate if any path is followed. To create the graph, we used Microsoft Excel 2016. Furthermore, data was further analyzed using RStudio platform, version 4.0.2. For debugging errors, we used ChatGPT 4.0, an excellent source of evaluating errors and providing the right solutions. We also used ChatGPT 4.0. for identifying the major releases of social media platforms to identify possible correlations between releases and revenues evolution.

(1) After observing data patterns, a first analysis was the rolling covariance, between number of users and revenues per user, computed with a window of 3. We used the function rollapply(), from "zoo" library. We use the syntax "rollapply(cbind(users_[platform], sales_user_[platform]), width = window_size, FUN = function(x) cov(x)[1,2], by.column = FALSE, align = "right", fill = NA)". For each output of rolling covariance, we generated graphs using "plot()" function. Off note, if the social media network was created more recently, data for the first periods was completed with 0, in order to have the same number of observations.

(2) The resulting data of the first analysis, was used to identify the data with stronger interdependency. Rolling covariance with higher fluctuations, suggested that there are other factors that influences the revenues generated by each user. For the platforms we identify strong correlation, we constructed a linear regression, using the function lm(). We used the syntax "lm_model_[platform] <- lm(sales_user_[platform] ~ users_[platform], data = head(data, [first n

figures]))”. To summarize we used “summary(lm_model_[platform])” function. Graphs were obtained by using function plot(), while the regression line was displayed using “abline()” function. In our model, we used first 27quarters of LinkedIn, 15 quarters of FB and 19 quarters of YouTube.

(3) From the regression model, we considered the intercept as the intrinsic value of a user, while the slope of equation as the network effect.

(4) Starting from the next quarter of the analyzed regressions, we considered that the value of the revenue per user is influenced by data enabled learning (creation of better product, based on learning from data generated). To understand the development, we generated via ChatGPT the list of the analyzed platforms releases. We did not model this function in this paper, as we concentrated on network effect.

(5) To further deep dive into data, we applied a seasonality test, as we observed on the graph on the (1) a seasonal type of data. To verify, we used Augmented Dickey-Fuller (ADF) test. Data was transformed into time series using ts() function with the following syntax “sales_user_[platform]_ts=ts([table, column],frequency = 4)” and we performed the ADF test with the syntax “adf_test <- adf.test(sales_user_[platform]_ts, alternative = "stationary")”. Results were printed using the function print(), with the sytax “print(adf_test)”. 4

(6) We completed the ADF test with the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test for the null hypothesis that x is level or trend stationary. Syntax used “result[platform] <- ur.df(sales_user_[platform]_ts, lags = 3, type = "trend")”. Results were printed using “print(summary(result[platform]))”.

(7) Observing the 2 peaks of revenues per user in 2016 and 2020, we performed a possible white noise test. We chose Ljug Box test, with the syntax “ljung_box_test_[platform] <- Box.test(sales_user_[platform]_ts, lag = 10, type = "Ljung-Box")”. Results were printed using “print(ljung_box_test_[platform])”

(8) Using the results of the performed tests, we propose a model inspired from Hagiu and Wright, for value of product under data enabled learning.

Results and discussions

The graph generated by the collected data show increasing no. of users and revenue per user.

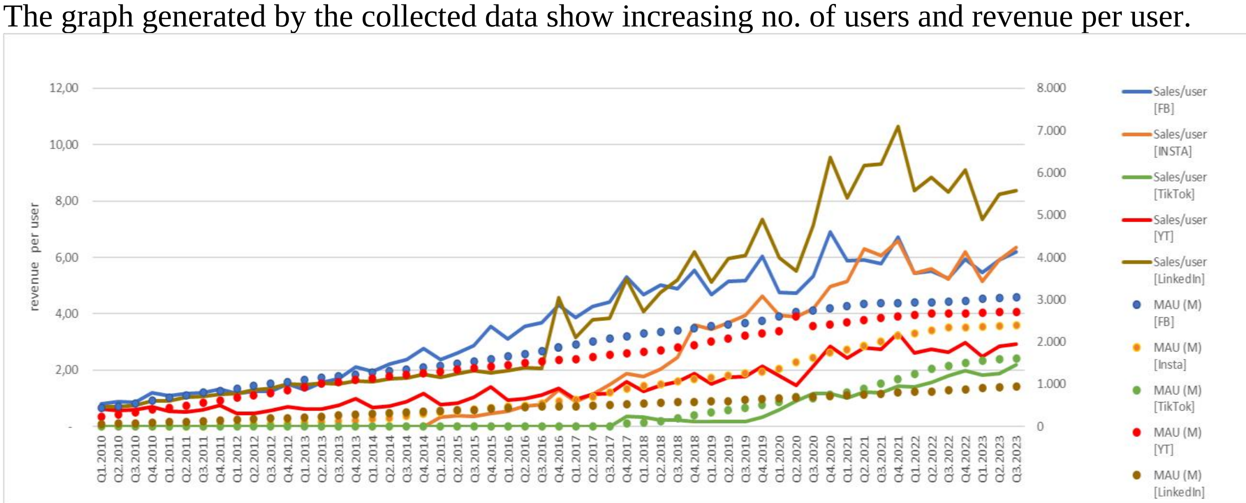


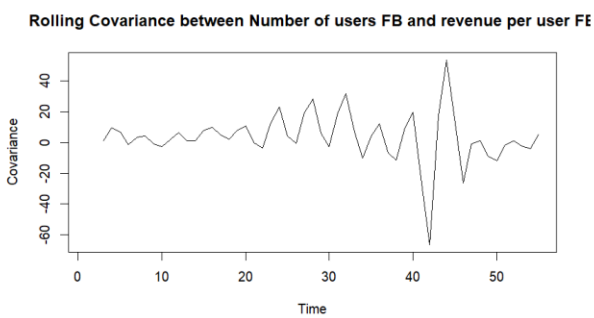
Figure 3. Number of users evolution (millions, dots, right scale) combined with revenue per user ($ generated per user, lines, left scale).

Source: authors analysis

Findings: With the exception of Tiktok, revenues per user increased in line with network expansion, with exception of Tiktok that had a strong increase in number of users. We concluded that the increase could be the result of network effect (the willingness of advertising companies to spend more money per user, as the network increases, or higher advertising demand as more individuals can be targeted via digital platforms. The strong increase in number of users generated a decrease of revenues per user Tiktok, meaning that if there is a too high network increase, it could generate a short-term negative network effect – the advertising companies, with campaign budgets established for a specific interval have no budget to allocate on strongly enlarged the number of users.

TikTok and Instagram, created after Facebook, relying on the FB experience, show a limited relationship between number of users and price per user, suggesting that price per user evolution was influenced also by another factors. We note a short period of time with relatively stable rolling covariance for TikTok (between Q1.2018 and Q3.2019) period of strong development of the network, followed by adding new functionalities.

The results in analyzing the rolling covariance were displayed in graphs.



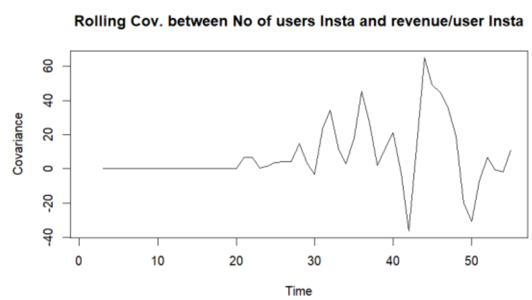
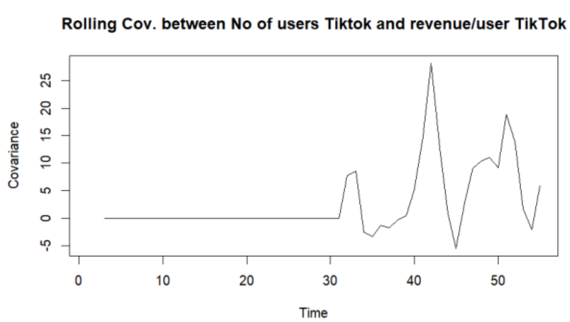


Figure 4 and Figure 5. Rolling covariance between number of users and revenuer per user FB / Insta

Source: authors analysis.



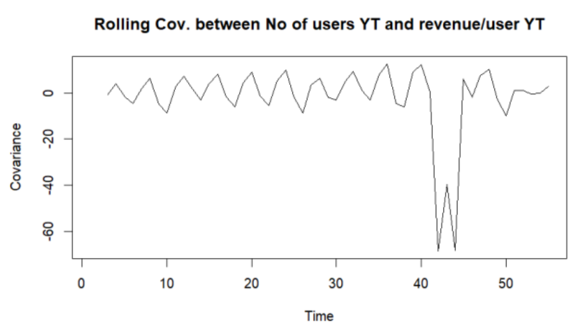


Figure 6 and Figure 7. Rolling covariance between number of users and revenuer per user TikTok /Youtube

Source: authors analysis.

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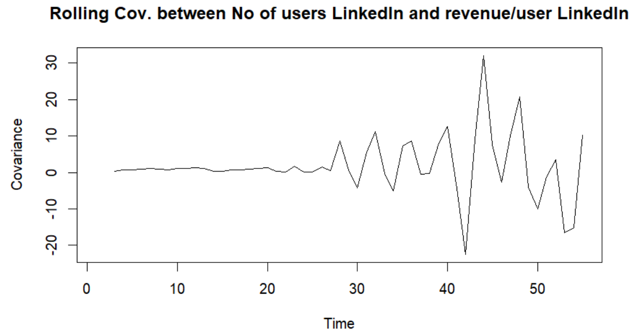


Figure 8. Rolling covariance between number of users and revenuer per user LinkedIn

Source: authors analysis.

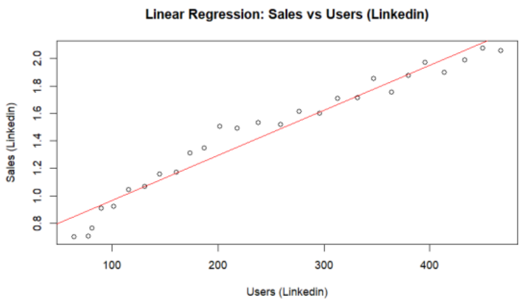
YouTube maintained a relatively stable rolling covariance, with the exception of Covid19 pandemic. In fact, YT is the platform with the most limited interactions between users, having creators that post videos and a comment sections, but the advertising rolls only during video watching. Therefore, YT sales relates mostly on the number of users, with lower particularization as compared with FB, Insta, TikTok and LinkedIn. We can consider that YT reflects most the network effect, having limited room to improve the quality of advertising. We also observed that there is a rolling covariance with limited amplitude on the first years of Facebook and LinkedIn. For the remaining years, the evolution of the indicator (higher amplitude) suggests that there is another factor that influence the value of revenue per user. We even observe a linear rolling covariance for the first years of LinkedIn, which can suggest a strong link between number of customers and price increases.

To estimate the network effect, we calculated the regression for the first 27 quarters of LinkedIn, 15 quarters of Facebook and 19 quarters of YouTube, using the number of customers the independent variable and revenues per customers the dependent variable. The outcome is:

Table 3: Regression on fist 27q of Linkedin , first 15q of FB, fist 19q of YT

Coefficients	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept Linkedin)	0.6360325	0.0406593	15.64	2.02e-14 ***
users_Linkedin	0.0032839	0.0001459	22.50	< 2e-16 ***
(Intercept FB)	0.4421749	0.1026010	4.310	0.0518
users_FB	0.0009304	0.0001183	7.866	2.69e-06 ***
Intercept	0.4874	0.06867	7.098	1.79e-06***
users_YT	0.0002232	0.00008524	2.618	0.018*

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1



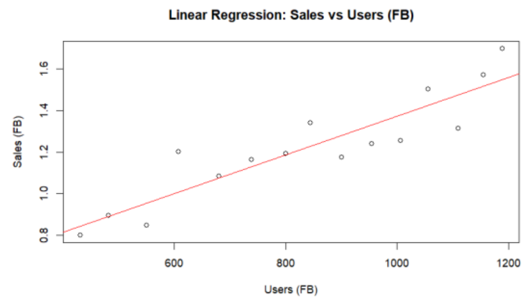


Figure 9. Linear regression: sales vs users Linkedin. Figure 10. Linear regression sales vs users Facebook.

Source: authors analysis.

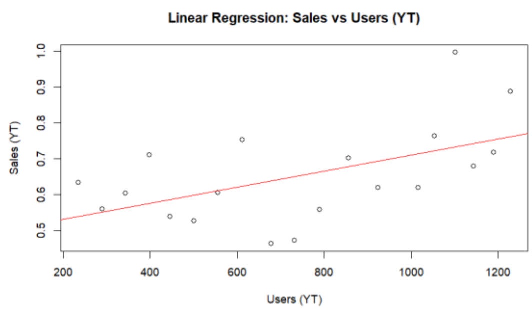


Figure 11. Linear regression: sales vs users Youtube.

Source: authors analysis.

The equations for the three calculated regression is:
Sales/user [LinkedIn] = 0.6360325 + 0.0032839 × Users LinkedIn (millions)
Sales/user [Facebook] = 0.4421749 + 0.0009304 × Users Facebook (millions)
Sales/user [YouTube] = 0.4874000 + 0.0002232 × Users YouTube (millions)

The intercept, signify that an advertiser is ready to pay 0.63$/quarter to reach a person from the LinkedIn, 0.44 $/quarter for Facebook and 0.49$ /quarter for YouTube without any development (network effect or data enabled learning. We note the close value per user on Facebook and YouTube (0.11-0.12 $ per month) and the average can be considered intrinsic value of a user, without personalized advertising and network effect. From the regression equation, we can consider the slope of equations as the network effect for the three networks. By comparing the slopes, we find that: (a) Network effect of LinkedIn is 3.53 times higher than Facebook; (b) Network effect of Facebook is 4.17 times higher than YouTube; (c) Network effect of LinkedIn is 14.71 times higher than YouTube. From this perspective we can provide an answer to the question "Is there a similar measure of network effect for all platforms in term of number of users, independent of the covered need or the it is a function depending on covered need and/or other parameters?". We can see that professional relationships are 4.17 times more important in term of network value than the friendship, and 14.7 times more important than leisure and less interactions. Moreover, we can conclude that higher the social interactions are, higher the network became.

Based on those conclusions, we consider that Microsoft took a good business decision to acquire LinkedIn, leveraging on higher degree of human interaction of the network. Of course, this kind of decisions might have also other types of knowledge at base (Bratianu & all, 2020).

Starting a certain point, the increase in value of revenue per user accelerated. Based on Hagiu & Wright model, we concluded that the value of revenue per user increased as a result of data enabled learning, as a second component of value increase. To interpret, we asked Chat GPT to provide a list (see Table 4) with main releases of social media that could influence the revenues. Results were used only as an indication of data enabled learning. We can see the historical development of platform involved several releases of functionalities aimed to increase sales. The most visible effect can be seen on LinkedIn, after the acquisition of Microsoft. The value of sales/user strongly increased as an effect of product development.

Table 4. Major releases of social media platforms (source ChatGPT 4.0)

Platform	Release
Facebook	2007: Introduction of Facebook Ads, opening up revenue through targeted advertising. 2009: Launch of Facebook Pages monetization through ads, expanding revenue opportunities. 2012: Facebook's IPO; significant growth in mobile advertising revenue following. 2013: Introduction of video ads, boosting advertising revenue. 2014: Acquisition of WhatsApp and Oculus, diversifying revenue sources. 2015: Launch of Facebook Instant Articles, aiming to keep users on the platform longer and increase ad revenue. 2017: Introduction of Facebook Marketplace, expanding into e-commerce.
Instagram	2012: Acquisition by Facebook, leading to the introduction of advertising on the platform. 2013: Launch of sponsored posts, Instagram's first major revenue-generating feature. 2016: Introduction of Instagram Stories ads, significantly increasing engagement and ad inventory. 2018: IGTV ads and the expansion of shopping features, opening new revenue channels. 2020: Introduction of Instagram Reels and its eventual monetization strategies.
TikTok	2018: Introduction of ads, marking the start of TikTok's revenue generation. 2019: Launch of the TikTok Creator Marketplace, facilitating brand partnerships and influencer marketing. 2020: Expansion of e-commerce capabilities and introduction of TikTok For Business for ad solutions, significantly boosting revenue potential.
YouTube	2007: Launch of the Partner Program, allowing creators to earn revenue from their videos through ad sharing. 2013: Introduction of paid subscriptions (later rebranded as YouTube Premium), offering ad-free viewing and additional revenue. 2015: Launch of YouTube Gaming and Super Chat, creating new revenue streams from live streams. 2018: Expansion of YouTube Music and YouTube Premium, enhancing subscription revenues.
LinkedIn	2008: Introduction of LinkedIn's first revenue-generating product, Job Listings. 2013: Launch of Sponsored Content, LinkedIn's major advertising revenue stream. 2014: Introduction of Sales Navigator, targeting sales professionals and contributing significantly to revenue. 2016: Acquisition by Microsoft, leading to increased integration and product development aimed at boosting revenue.

The most visible effect can be seen on LinkedIn, after the acquisition of Microsoft. The value of sales/user strongly increased as an effect of product development.

In addition, we observe a seasonality in revenues per user for most of the platforms, with emphasis in Q4. Under these circumstances, a 3rd component of the revenue per user would be the seasonality. We tested the seasonality by ADF and KPSS, with the following results:

Table 5 Results of ADF test

Platform	**Dickey-Fuller**	**Lag order**	**P-value**	**Alternative h**
Facebook	-0.48357	3	0.9794	stationary
Instagram	-1.8753	3	0.6248	stationary
TikTok	0.31448	3	0.99	stationary
YouTube	-2.0049	3	0.5726	stationary
LinkedIn	-1.6561	3	0.7131	Stationary

Table 6 Results of KPSS test

Platform	KPSS
Facebook	0.201
Instagram	0.3128
Tiktok	0.3436
Youtube	0.2883
LinkedIn	0.2432

ADF analysis shows strong evidence not to reject the null hypothesis, meaning that the data is seasonal. KPSS test results show that we cannot reject null hypothesis that the series is stationary around a seasonal pattern.

The Liung Box test for punctual events (white noise), shown the following results:

Table 7 Ljung Box test

Platform	**X-squared**	**Df**	**P-value**	**Alternative h**
Facebook	348.39	10	< 2.2e-16	**Autocorrelation**
Instagram	347.61	10	< 2.2e-16	**Autocorrelation**
Tiktok	239.71	10	< 2.2e-16	**Autocorrelation**
Youtube	295	10		**Autocorrelation**
LinkedIn	333.81	10		**Autocorrelation**

Results suggest strong evidence of no autocorrelation, therefore there is significant autocorrelation. Apparently, the effects of elections arise on top of peak of season, the model interpreting as a seasonal data.

Starting from the analysis performed, we propose the modelled the value of user, and subsequently the platform capacity to generate value. This is not a real market value of the platforms, but the global value of period sales. The real value of platforms should use the classical approaches (such as future cash flows, times x EBITDA etc.).

We note with S the overall value of a service (platform), with U the number of users of the service and su the average value generated by each individual user. Our first hypothesis is that advertisers are interested to reach any new customer with their campaign. In our model, we consider that advertising budgets destinated to social media are not caped and can increase with the number of new users. In case the budgets are caped, a negative network effect may occur (as in the case of TikTok).

The value of the platform (social media service) at one moment will be then:

$$S = s_u \times U$$

This formula results that if s_u maintain its value, meaning that the company will sell any new user at the same value as existing users, the value of the platform will increase, with the subscription of the new user. We define this as "intrinsic network effect" – the value of a platform increase, with the increase of the number of users.

The value of individual user take as a product sold by platforms to advertisers, can be breakdown into four components: (1) Standalone value of the service, noted s_0. (2) Increase of the product value (efficiency of advertising) through data enabled learning (interpretation of data generated by user interactions, sociological studies etc.) during each period (t) noted f(t). According to Hagiu and Wright, the learning function is S shaped, with a minimum set of data necessary to increase the product value (minimum threshold), while the learning function will be finite (maximum threshold). (3) Network effect, defined as the increase of the value of individual user, caeteris paribus in the context of the number of users increase, noted with n(U). (4) Market seasonality φ (with peak on q4, when higher advertising budgets are thrown in the market). We note ε the measure of unexpected market events and potential market turbulences (such as US elections, when important budgets are used).

$$s_u = s_0 + f(t) + n(U) + \varphi(t) + \varepsilon$$

Each component of s_u represents a function that could differ from the peers in function of: learning capacity of each platform and volume of data acquired (see Hagiu & Wright), network effect that rely on typology of interactions.

Conclusion

Recognizing the constraints of a study is crucial for putting its results into perspective and directing future research. Using publicly accessible data for research may not fully capture all user interactions and the dynamic nature of social media sites. This constraint might result in an inadequate comprehension of the network effects being studied.

Another important constraint arises from the time frame of the data examined. Social media platforms are always evolving, introducing new features and experiencing changes in user behaviours. The study's conclusions are limited to the current era of the data analysed and may not fully represent previous or future network impact dynamics.

Moreover, the study's quantitative methodology, albeit strong, can fail to include the qualitative elements of user engagements and community behaviours on social media platforms. These qualitative elements are difficult to quantify but significantly influence network effects and, as a result, the economic results of the platforms.

The study's results may not be easily applied to other social media sites due to concerns over generalizability. The analysed platforms feature unique business structures, user demographics, and operational regulations that may not be typical of other platforms. This constraint implies that the results may not be widely relevant across the varied terrain of social media.

Additionally, the research may not completely include platform-specific variables and external factors that might greatly affect network effects. These include content recommendation algorithms, user interaction methods, global events, market trends, and regulatory changes. These aspects are crucial for comprehending the intricate dynamics of network effects yet can be beyond the present analysis's scope.

Measuring the degree and impact of network effects has inherent obstacles. The metrics used in this work may not completely capture the complex nature of these impacts, emphasising the need for more research to provide more comprehensive assessments.

Considering these constraints in the conversation enhances the study's depth and the dependability of its findings. This highlights the challenge of quantifying and understanding the impact of network effects on social media platforms and suggests potential directions for future study to expand on the results.

Online social networks have had a profound influence on society in the last twenty years, acting as crucial venues for worldwide communication and engagement, as well as generating substantial revenue for its shareholders. Our examination of data from prominent social networks highlights the crucial importance of every engaged user. Users generate platform money by using network effects, data-driven insights, seasonal patterns, and market events like elections. Our analysis highlights Facebook's consistent high value creation compared to Instagram, which has started to adjust its income per user by using insights from its related platform. LinkedIn is considered the most beneficial site due to its distinct emphasis on professional contacts and organisational networking. YouTube's per-user revenue enhancement has plateaued, indicating that transitioning to subscription models might be advantageous for long-term revenue growth.

A multimodal approach in a future research might provide more profound insights into the behaviour of social media platforms. An analysis comparing the effects of subscription models vs. standard advertising income sources might provide important insights into platform monetization strategies. Studying market prospects, such as the impact of U.S. elections or the launch of new platforms like Threads that use current networks like as Instagram and Facebook, might reveal the characteristics that boost user engagement and platform expansion. Furthermore, examining the sustainability and defensibility of current systems would help determine their long-term viability. A crucial area for future investigation is whether social media platforms exhibit a lifecycle analogous to traditional products, which could lead to innovative strategies for platform development and user retention.

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