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PLATFORM VALUATIONS IN EMERGING MARKETS:INDUSTRY SPECIFIC NETWORK EFFECTS MODEL

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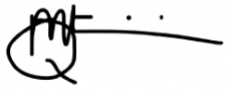
A research report submitted to the Wits Business School, University of the Witwatersrand in partial fulfilment of the requirements for the degree of Master of Management in Finance and Investment by combination of coursework and research

Johannesburg

2023

DECLARATION

I declare that this research report is my own unaided work. It is being submitted for the degree of Master of Management in Finance and Investment at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination at any other University.



Qhawekazi Mtini
4th day of June in the year 2023

DEDICATION

This body of work is dedicated to my heroes:
My late uncle, Thand'xolo Ramncwana, who was a diligent carpenter that taught me that ultimately it's the quality of your work and the joy you brought people that is remembered and not the mistakes you make along the way.

My late Aunt, Thandiswa Bambiso , a brave and dedicated police woman who taught me that continuous alignment with your principles, values and unwavering dedication to your vision can turn something very close to nothing into something unforgettable.

My mother, Noluthando Mtini, a formidable business woman and my role model who has changed and continues to change our family's trajectory through being audacious. You have continuously created spaces and opportunities for all of my potential.

Lastly, my favourite person in the whole world – my only nephew, Buhle-bemvelo Sonti; your constant curiosity and your inherent kindness inspires me daily.

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My colleague, Richmore Dzandza, for providing further support and guidance.

My clingy dog, Jazz, for leaving me alone… sometimes

And most importantly God for placing the desire in my heart and equipping me with the ability to fulfil on my desires.

I am because you are.

Thank you

ABSTRACT

Network effects are intangible assets that can create value in platform mediated businesses. Traditional accounting standards provide limitations to the ability to quantify the value created by these network effects, therefore, theoretical network effects laws, namely; Metcalfe's, Sarnoff's, Odlzyko's and Reed's laws are used as 'rules of thumb' to predict network value. Existing studies have largely verified the suitability of these rules of thumb by using data from developed markets with the use of overall company revenue as an indicator of the network value, albeit mixed conclusiveness and limited scope. In practice, Metcalfe's law is the most popularly used and although business models and revenue generation differs across various industries, it is used regardless of the industry that the platform business operates in.This empirical study makes use of actual platform generated revenue and monthly active user base data from companies in the Asia Pacific emerging markets and across social network, e-commerce and search engine industries to test the suitability of Metcalfe's law in emerging markets, regardless of industry. Theoretical value curves are derived using Metcalfe's, Reed's and Sarnoff's laws to conduct a comparative test using curve fitting and the least squares method across the industries.

The study finds that although Metcalfe's law is the most suited for e-commerce and search engines; it is not the most suited regardless of industry as Sarnoff's theory proves to be most suited for social networks. This proves that although Metcalfe's law is suitable for use in emerging markets; in practice, there should be consideration of industry when selecting the most suited network effects rule of thumb to be used to predict the value of a network. In addition, the adjustment from using overall company revenue to platform generated revenue proves that using overall revenue for companies that generate revenue through platform and non-platform activities can result in the use of a network effects law that overestimates the value of the network, as seen in the instance of Tencent where Metcalfe's Law was proven to be the best suited in the research by Madureira et al. (2013), Zhang et al. (2015) as well as Hove (2016). In this study the adjustment of revenue and improvement of the robustness of the model through use of quarterly data as opposed to annual data finds that Sarnoff's Law is best suited for social networks.

Keywords
Network effects; emerging market; Metcalfe's law; social network; e-commerce ; search engine

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LIST OF ABBREVIATIONS

MAU: Monthly Active Users
RMSD: Root Mean Square Deviations
SSE: Sum of Squares of the residuals
API: Application Programme Interface

CHAPTER 1: GENERAL INTRODUCTION

1.1 Background: The rise of the platform business model

Over the recent years the growth of the internet and global digitization has created opportunities for businesses to partake in the platform economy (Rietveld & Schilling, 2021). This growth has been supported by the increase in the availability of technology that supports innovative applications at a low cost, resulting in customers becoming digitally enabled and having access to convenience on various digital channels at a click of a button. Thelen and Rahman (2019) highlighted that platform business models have posed significant threat and disruption to traditional business models and as a result of this disruption it was noted that in 2020 companies with the largest market capitalisation were platform companies (Subramanian, Mitra, & Ransbotham, 2021). In an attempt to counter this threat many traditional companies have included the transition of parts or all of their business to incorporate on-platform strategies.

Platform businesses not only manage to provide similar goods or services more efficiently and conveniently where compared to traditional businesses; they can also unlock additional value through generating additional or new revenue streams such as advertising revenue and commission while managing cost efficiently, thus making them more profitable in the long term. The rise of platform business models has not only changed the way in which companies do business but according to Bernoff (2011), the growth in technology and globalisation has positively contributed to the information that customers have at their disposal when making purchasing decisions and increased optionality, therefore increasing the power of the customer.

The increase in the power of the customer necessitates businesses to not only consider business value creation in their strategies but also need to ensure that value is also created for customer as well. Businesses need to present the empowered customer with contextual products or services at the right time, place, price and in a manner that is appealing to customer in order to gain competitive advantage and meet their business targets. When users engage with platforms they share and generate information and data through explicitly sharing information, data and insights or through the platform tracking customer behaviour on platform. All that is gathered from platform engagement can be processed to assist businesses with improving customer intelligence. The superior ability for platform businesses to collect data from platform users enables these businesses to create more customised user and customer experiences.

Over the recent years regulations and governance regarding consent of the using and sharing of user and customer information have continued to evolve in order to protect the interests of platform users. An example of this in the South African context is the Protection of Personal information Act of 2013 (POPIA) that came into effect on 1 July 2020. It has been implemented in order to protect the customer's right to privacy as it prevents the unlawful sharing and use of personal information.

1.2 Value creation in platform businesses

The increased ability to extract data and information enables platforms to create value by serving as intermediaries and market makers (Thelen & Rahman, 2019). Schreieck et al. (2016) also highlighted that platform companies can be technology or market oriented, where technology orientated companies are considered as companies that develop building blocks for the infrastructure of other companies while market orientated platform companies focus on end-user interaction through enabling various users to interact on a common platform (Eisenmann,

Parker & Van Alstyne, 2011). Platform businesses have different business models that they utilize to ensure that value is created, delivered to customer through their value propositions and captured for investors by translating value creation and delivery into key revenue streams that are reflected in the business's income statement (Täuscher and Laudien, 2018). This may include the generation of advertising revenue by enabling third party advertisers to access the platform's user base as an audience of potential customers or the introduction of subscription fee for varying offerings and value propositions on platform which could consist of added benefits, premium user experience or access at a subscription cost to the user. Täuscher and Laudien (2018) further contribute that platforms can have varying ways of creating, delivering and capturing value beyond user base growth as businesses can create value through the strategic decision of selecting the most suitable platform type and activities conducted on the platform.

Unconventional measures such as network externalities are therefore considered when valuing platform businesses. The metrics often considered are typically the number of users of the platform as well as user enagement metrics such as user login frequency. Large user bases with high engagement are believed to be indicators of future revenue generation potential (Subramanian, Mitra, & Ransbotham, 2021).The understanding is that a platform becomes more valuable when there isan increase in the user base size and user engagement (Qiu, Tang, & Whinston, 2015). Dou, Niculescu, & Wu (2013) further explains that an existing user base is valuable as it can induce word-of-mouth (WOM) effects which organically and effectively distribute information regard the value proposition of the platform and propagate herd mentality; which positively contributes to platform adoption.

Social networks such as Facebook and dating sites such as Tinder create value through community building; they allow users to make use of these platforms at no charge in the form of a monthly prescription fee in order to access the community to the platform. This pricing strategy has been termed as "Freemium". Although this non-subscription paying user base does not generate immediate revenue; the strategy aids in growing the user base. This enables businesses to engage in market making or as an intermediary in order to generate revenue. The rationale behind most freemium business cases although businesses record initial economic losses or little profit, in the long term the business generates revenue from a large user base with high engagement through monetisation of the platform (Rietveld & Schilling, 2021). Monetisation efforts by a business can generate increased revenue, however, Subramanian, Mitra and Ransbotham (2021) argue that the value created and captured through user engagement has a dependency on the ability of the platform to monetise the engagements without users switching to alternate platforms. Given the observable low switching costs, in the event that monetisation efforts leads to poor customer experience or customer dissatisfaction, the intended value creating monetisation attempt by businesses can result in users switching platforms and platform user attrition. Therefore, platform businesses have an important task at hand of balancing user experience and monetisation in order to arrive at an optimal value creating model (Menell, 2019).

Platform activities such as review systems that allows for buyers to evaluate sellers on marketplaces can also have an indirect contribution to revenue generation. Reviews of goods and services that capture the user's evaluation of the quality of goods, services and the customer experience can inform the purchasing decisions of other platform users. On platforms such as Shein and Takealot, peer reviews enable customers that provide feedback on durability, quality and whether goods are true to size. Peer reviews are more common in platforms where services are exchanged that goods and on those platforms other users are able to make decisions on

which service provider to use based off peer reviews that comment on the quality of the service they received.

1.3 Network effects

Investors and analysts are mainly concerned with how business models translate network effects for the users and user utility into value for the business (Subramanian, Mitra, & Ransbotham, 2021) and the winner takes all dynamics in platform businesses are believed to be created by network effects. The presence of network effects makes it difficult for competitors to survive or new entrants to enter the market. Network effects are not merely created through growth the user base; but through the platform's business model enabling user base growth to create and unlock value for other platform users. An example in the context of Facebook; an additional user in the user base enables more communication and social engagement between the new user and the existing users that have a social connection with. With the introduction of Facebook marketplace, an additional user contributes to the marketplace buyers, sellers, or both. Being able to connect, communicate or buy and sell with more users creates increased usability and value for the user, thus improving the utility that the user gets from utilizing the platform.

Given the growing importance of understanding platform businesses, the value created through platform businesses models and the understanding that although there are many ways to create, deliver and capture value, network effects are the main concern for business stakeholders. Prior to 2013 the translation of network effects to business value was explored and Metcalfe's, Reed's, Sarnoff's and Odlzyko's network effects laws, which are explained and unpacked in chapter two of this research, were accepted as suitable theoretical laws that explain the relationship between user base size and the value of the network. Although the suitability of these theoretical laws has been debated amongst researchers, empirical studies were not conducted to validate these laws until 2013. Madureira et. al (2013) makes use of Digital Information networks (DINs) in the first attempt to validate Metcalfe's theoretical law that states that the relationship between the size of the network and the network value is a quadratic relationship not a linear one as proposed by Sarnoff's law or log linear as per Odlzyko's law. Metcalfe (2013) further contributed empirical evidence of the suitability and superiority of the theoretical law he proposed through making use of Facebook actual data. Zhang et al. (2015) make us of Facebook as well as Tencent data to further concur that Metcalfe's law is the most suitable law and Hove (2016) also makes use of the data from the two companies and includes a quality indicator to arrive at the same conclusion the existing empirical studies of network effects. This research focuses on further exploring the contribution of network effects to the value of market-oriented platform companies.

1.4 The research problem

Traditional accounting methods for valuations have been criticised for not fully capturing the value of firms that are underpinned by knowledge-based economies and characterized by increasing returns. The shortfalls regarding capturing value poses a challenge for investors that solely use traditional accounting and valuation models. Traditional models fail to capture the intrinsic value of companies built on intangibles and therefore analysts and investors need to go beyond financial statements in order to understand the underlying value drivers and unit economics for each business. Traditional accounting and valuation models consider intangibles such as goodwill but they display short-comings when intangible assets that do not meet accounting standards, such as network effects, are considered. These intangible assets are often

established through companies investing significant capital through their income statement rather than their balances sheet. These companies, therefore, create value without displaying profit in the income statement or through reflecting increased assets on the balance sheet in the short and medium run. Existing accounting models and practices for firm valuations do not fully capture the value created by intangible assets such as network effects which can create limitations for financial analyst and investors when decisions regarding the viability of an investment into platform-mediated firms needs to be made. There is therefore a need for models that enable the consideration of intangible assets and the value they create through either combining traditional models with models for intangible assets or adjusting traditional models to include variables related to intangible assets to derive a truer indication of intrinsic value.

Investments into new age businesses requires investors that can undertake risk and remain patient under the premise that the risk taken presents significant reward that is unlocked by network and learning effects and extracted through the dominance of their selected investment vehicle in the market (Thelen & Rahman, 2019). Platform mediated firms tend to display high P/E ratios and are fast growing across various industries. The high P/E ratios are driven by the optimism of the market regarding potential growth and profitability of these firms and one of the assumptions that drive the confidence in these firms is that investors expect that the growth of the platform's user base has a positive impact on a firm's network effects and that network effects can drive growth in future revenues.

The impact of network effects to the valuations of platform-mediated companies cannot be ignored as this may contribute to the undervaluation of companies. Network effect laws are currently being used to try to capture the impact of user base growth on the valuations of these; the most popular one being Metcalfe's Law. The use of these laws has in some instances contributed to the overvaluation of firms, whereby investments in platform -mediated firms have not produced returns in line with the expectations captured in their valuations. It is therefore important to ensure that the correct law can be applied to reduce both over and undervaluation of platform mediated companies. In instances whereby empirical studies have been conducted to validate these laws the focus has mainly been on firms in developed economies. Zhang, Lui and Xu (2015) observed this gap in research and in their research and in their study, they used Facebook and Tencent data to compare and validate the laws for developed and developing economies. The study uses actual revenue to represent network value and the monthly active user (MAU) data to represent network node to explore the relationship between user base size and the value of a network. In the study they found that Metcalfe's Law fits Facebook and Tencent's data best in comparison to the other three laws and that Metcalfe's law fits the data well. Although the use of Facebook and Tencent data meets the objective of the research to validate these laws on companies that include developing economies, the research does not consist of an industry specific lens as both Facebook and Tencent are predominantly social network companies. When conducting the study, they use topline revenue generated by Facebook and Tencent. Given that companies such as Tencent are companies that generate revenue that is from both on and off platform, there is an opportunity to adjust the revenue line considered to limit the contribution of off-platform operations to the revenue that is intended to be an indicator of platform value.

There is an opportunity to improve the approach to valuations of platform mediated companies to arrive at a more accurate indication of intrinsic value through considering the value created through intangible assets such as network effects; this can be done through complimenting or adjusting traditional valuation models. Currently, there is limited empirical evidence that validates network effects laws, existing studies find that Metcalfe's law is the most suited law

– however the companies that are used to validate this are in the same industry, social networks. Given that different platform industries have different business models, the nuances in various non- social network industries could be overlooked when using the conclusion that Metcalfe's law is the most suitable law due to the bias in the industry sample of previous studies. Empirical evidence to date mainly focuses on validating network effects laws through use of Facebook, a company in the developed world; the absence of inclusive research may result in the use of adjusted valuation method that are only suitable for countries in developed economies and given the growth of platform businesses in emerging market – it is important that valuations are suitable for emerging and developed markets or at least the economic aspects resulting in differences in outcomes is observed ,further unpacked and understood to enable the relevant adjustments to application. Zhang, Lui and Xu (2015), make the first adjustment to revenue considered to improve the robustness of the comparative network law tests, however, the opportunity to improve robustness through using data with higher frequency is overlooked in all studies; although quarterly data points are available for the relevant variables.

1.5 Research objectives

The objectives of this study:

- Contributing additional empirical evidence that validates the use of network effects laws theoretic laws in platform business valuations
- Testing if Metcalfe's law is the most suitable network effects law regardless of the industry that the platform operates.
- Contributing to economically inclusive research through focusing on companies in emerging markets
- Adding a new perspective that encourages consideration of the platform's industry when selecting a network effects law.
- Improving the robustness of the network effects law testing.

In validating the usefulness of network effects laws in emerging markets, the gap in the ability to provide valuations for new age businesses is reduced and, in the instance, whereby high growth in high-tech businesses is emerging markets can be observed, improving investor's abilities to evaluate investment viability in emerging markets can improve the confidence of investors and encourage investment.

1.6 Research questions

Given that Metcalfe's Law is the most utilized network effects law and has been empirically proven to be the most suitable law when conducting a comparative laws test for Facebook and Tencent, this study seeks to answer the following research questions:

i. Is Metcalfe's law the most suitable law regardless of the industry that the platform business operates in?
ii. Should the industry that a platform business operates in be considered when selecting the most suitable network effects law to use for platform company valuation?
iii. Are network effect laws suitable for use for valuation of companies in emerging markets?
iv. Does the use of overall company revenue as the measure to network value result in a change in the most suited network effects law and if it does, does it result in overestimation of network value?

1.7 Significance of the research

Many businesses are pivoting towards digital solutions, particularly platform solutions. As investment in platform companies continues to grow globally and knowledge-based firms tend to invest heavily in intangibles to remain or become competitive in an environment whereby "winner-takes-all" tends to be a theme within the competitive landscape, it is important to be able to understand the value that platforms and platform users can create for a firm and its shareholders. The study of intangible asset valuations is becoming an increasingly important area of research as it improves the ability of investors to assess the viability of an investment through establishing improved valuation models and methods.

Significant growth is being observed in the software industry in emerging markets therefore there is increasing importance for research to be inclusive of perspectives that not only focus on the dominant and developed market players and economies but also presents inclusive empirical evidence regarding the ability to use network effects laws for platform valuations in emerging markets. This research aims to contribute to the empirical work conducted on the use of the network effects laws with consideration of the industry a platform operates, the improvement of valuations of platforms and platform mediated businesses as well as provide more economically inclusive perspectives to the broader topic of the valuation of intangible assets.

CHAPTER 2: LITERATURE REVIEW

2.1. Introduction

In this chapter the changing world of business where the bulk material and industrial companies are being replaced by new- age businesses is explored. The knowledge-based economies that these businesses exist are further unpacked to understand the nuances with respect to the reliance of the creation intangible assets through high upfront research and development (R&D) costs and the creation of network effects to become or remain competitive in a competitive "Winner-Takes- All" landscape.

Network effects are defined at a topline level and a deeper dive into the various types of network effects is conducted before an understanding of how network value can be created, utilised and captured in platform businesses is outlined. The underlying theory of the network effects laws; Metcalfe's, Reed's, Sarnoff's and Odlzyko's laws is briefly overviewed prior to delving into the state of the arts with regards to the empirical studies that have been conducted to test these theoretical laws that were debated for 40 years, prior to 2013 ,without empirical evidence to validate them.

2.2. "New-age" businesses

The global landscape has been undergoing fundamental changes in which bulk-material and industrial companies that shaped the industrial age are being replaced by "new-age" businesses built on intangible assets (Arthur, 1996). Historical industrial businesses were understood to be subjected to diminishing returns where constant or decreasing economies of scale are expected. Conversely, Haskell and Westlake (2018) highlighted that new age companies built on intangible assets are subject to a phenomenon called "increasing returns". Increasing returns are driven by the presence of learning-curve effect and network effects; which are experienced through the improvement in efficiencies, product quality per unit produced and more value being derived from the growth of the users of a good or service (Rietveld & Schilling, 2021). In addition to the changes in economies of scale; the competitive landscape between industrial age and new age businesses differs; industrial age businesses typically displays price-based competition amongst competitors producing homogeneous goods and services (Thelen & Rahman, 2019), while new age businesses display "winner- takes-all" dynamics whereby one or a few firms have market dominance (Rietveld & Schilling, 2021). At face value, the winner-takes-all dynamics can be assimilated to classic monopolies but they differ due to the manner which market dominance is achieved and the nature of the dominance. Monopolies are more concerned with obtaining ownership of markets while new age companies are concerned with control (Thelen & Rahman, 2019).

The goal for companies in knowledge-based economies is to deliver "The next best thing" (Arthur, 2019), however, what makes new age businesses very interesting is that a company can have the best technology or quality offering but still not have control of the market and a company with inferior goods and services can become dominant due to early adoption that allows for the introduction of learning-curve effects which conversely contributes to the improvement of the quality of the good or unlocks cost efficiencies (Rietveld & Schilling, 2021). An example of this is in the early 1980's when CP/M, Mac and DOS were competing in the market for operating systems for personal computers. CP/M was first to market, Apple's Macintosh system was simple to use, and Microsoft's DOS operating system was ridiculed by computer professionals due to the perceived ill-assorted nature of the system , however, due to DOS being developed by Microsoft to provide an operating system for the IBM PC that had a

growing user base, software professionals wrote to DOS and DOS managed to lock in the market (Arthur, 1996). In the instance of CP/M whereby it was the first to market system and well adopted, it can be observed that although "winner-takes all" dynamics are prevalent in new age businesses, customer lock in is not permanent and is subject to change when a new wave of technology enters the market.

2.2.1 Knowledge-based economies

The concept of the knowledge-based economy is understood to date back as far as the early 1960s. The concept resurged in the 1990s and was given greater attention when it was better defined, and measurement metrics were established by the Organisation for Economic Co-Operation and Development (OECD). These definitions and metrics were established in response to the ongoing difficulty economists had highlighted with regards to integrating knowledge-based institutions into their theories and econometric models (Godin, 2006). Knowledge-based economies are defined as economies that are based on production, distribution and use of knowledge and information (Godin, 2006). The software industry can be categorized as a high-tech industry where knowledge economies can be observed.

Arthur (1996) highlights that there are various mechanisms that high-tech companies with knowledge-based economies utilise to remain or become competitive such as investing high upfront costs into R&D, the creation of network effects and increasing focus on driving customer groove-in/entrenchment. These mechanisms assist high tech firms derive competitive advantage. The software industry has become an interesting topic for discussion due to the high growth observed and the globalization of the industry. Over the past few years high tech growth was expected to come from the developed economies; however, since the 1990s, high tech growth has been experienced from non-G7 counties with consistent double-digit growth being experienced by countries such as India, Ireland and Israel (Arora & Gambardella, 2005). Within the software industry the subset of platform-mediated companies is becoming more and more topical as some of the largest firms on stock markets are platform-mediated and display high price-to-earnings ratios which is indicative of the optimism in the expectations of investors regarding the potential growth and profitability of these companies.

2.3 Network effects in platform-based markets

Some platform businesses have engaged in atypical business models; for example Uber has transformed the transportation industry by becoming a marketplace that facilitates transactions between a driver that owns or leases a vehicles and seeks to provide transportation services and customers that seek transportation. Unlike the traditional public transport industry such as the taxi industry, Uber has created this value without owning or leasing any of the transportation vehicles themselves which has resulted in them avoiding the risks as well as acquisition and maintenance costs associated with vehicle ownership or leasing as these risks and costs are carried by the supplier of the service. The value of the e-hailing business is not derived from fixed asset but rather the engagement of the Uber platform users. The basic e-hailing business model facilitates the relationship between a willing consumer and a provider, effectively creating value for all platform users. The addition of consumers of transportation services to the platform makes the platform more valuable for transport providers as it creates the market for their services and increases demand with the additional user that is a consumer. The increase in drivers on the Uber platform increases supply of transportation and creates value for customers. Platform value creation through network effects results in increased competition within the platform industry to attract and retain larger and more engaged user bases.

Gandal (1994) states that network effects can be observed when the value of the good or service being consumed increases with an increase in the number of customers or users of compatible products or services. According to Katz and Shapiro (1985) one of the key assumptions that underline the use of the size of the network as a driver of the value of the network effects is that all members of the network can transact with one another in order to extract equal benefit from the transaction, therefore, the more members in a network, the more benefit and value is extracted. One of the debates has been about whether the relationship between the size of the user base and the network value is linear or exponential for platforms. Metcalfe, Reeds, Sarnoff and Odlyzko's Laws have provided differing perspectives with regards to how the size of a firm's user base size translates into total network value and network value growth. Reed's Law and Metcalfe's Law argue that an exponential relationship exist between the size of the user base and the value of the network. Another key assumption of the Reed's law and Metcalfe's law is that each additional user to the platform user base contributes equal value.

Afuah (2013) recognises network size as the main determinant of network value but argues that size is not everything. The study criticises neoclassical economics for solely focusing on size and not exploring other variables such as network structure, the conduct of the network users and the basic conditions of the network. Exploration of these variables in addition to network size and their impact to revenues and probability can assist in enhancing firm valuations beyond accounting summary measures and existing network effects laws.

2.3.1 Types of network effects

The topic of network effects can seem generic at a high- level, however, it is more complex as different business models unlock nuanced cases of value creation through the presence of network effects. Within the business models, various types of network effects can create benefit to be able to gauge how businesses establish, utilise and capture value created on the platform.

Negative network effect can exist and persist; an example of negative network effects is when the size of the user base or a particular type of platform user has grown to a point whereby the quality of the experience on platform is reduced and with each additional user added to the platform, existing users get less value from it. It is important for platform businesses to be able to identify whether network effects are positive or negative as it enables them to build strategies that minimize negative network effects. Network effects can also be understood to be direct or indirect. Direct network effects, also known as same-side effects, are created by the growth in the size of a user in the network has direct value creation benefits for another user. Direct network effects can be observed in social networks where the increase in the community a user can engage with grows, thus adding value to existing users. Another example of direct network effects in the e-commerce industry would be in the instance whereby users heavily rely on user reviews to make their purchasing decision. A growth in the user that are in the consumer user base potentially results in more reviews on products and services– these reviews create value on the same side as they enable users to make purchasing decisions based off a significant sample of reviews (Voigt & Hinz, 2015).

Indirect network effects, also known as cross-side network effects (CNEs) can be observed in two-sided platforms when the growth in the user base of one group of users affects the value that the other user group experiences from the platform. There network effects are common amongst complementary goods (Subramanian, Mitra, & Ransbotham, 2021). In two-sided platforms network effects are unlocked through the platform mediating the relationship between

two groups of users (Rietveld & Schilling, 2021). These groups of users can be buyers and seller and in these markets two different products/services are provided to the different groups of users (Filistrucchi & Klein, 2013). One of the scenarios where this can be observed is on platforms that facilitate the sale of goods like Takealot or Amazon whereby additional buyers on the platform, increase the opportunity for their goods to be purchased or when suppliers on the platform increase; the increased competition may create downward price pressure for homogenous goods or services- to the benefit of the users that are seeking to consume goods or services. Another example of a two-sided platform in which acts as an intermediary between professionals and job seekers as well as recruiters is LinkedIn. On LinkedIn the recruiters seek talent, while job seekers connection with recruiters. A growth in the professionals on the LinkedIn platform with the right set of skills creates indirect network effects for the users that are recruiters as it creates recruitment opportunities and an increase in the recruiters creates indirect network effects for job seekers through increased job opportunities on the platform.

2.3.2 Network effects laws

There has been ongoing research into understanding the impact of the presence of network effect on a business's value. There have also been multiple laws that have been explored theoretically in an attempt to capture impact of user base growth on the value of the network.

Metcalfe's law is the most popular law that is used as a rule of thumb in estimating the value of a network. This law states that the growth of the value of the network is the square of its users ($V \propto n^2$). The rationale for the law is derived from the understanding that pairs of participants make n(n-1)/2 connections in the user base. These connections are directly proportional to the total value of the network and therefore the growth in value is said to be directly proportional to n^2. This law was validated through the use of Facebook and Tencent data. According to Reed's Law (1999), subgroups of users are important in the value of a network and that these groups can be formed through linking pairs of members. The value of the network is equal to the number of users in the subgroups to the power of the user base. Therefore, the growth in the value of the network is proportional to the subgroups in the network ($V \propto 2^n$). Sarnoff's law provides an opposing perspective to the two aforementioned laws, as it proposes that there is no net gain in value that is observed when two networks are combined therefore relationship between the growth in network value does not have an exponential relationship with the number of users, but rather a linear relationship ($V \propto n$). A shared assumption amongst the linear and exponential assumptions is that due to each new user generating equal value to the network, increasing returns can be observed as a new user is added to the network. Odlyzko's Law, on the other hand argues that exponential relationship overestimates the growth in value created by the user base but a linear relationship underestimates the value created. According to Briscoe, Odlyzko and Tilly (2005), assigning equal value to all users is not justified as some users such as spam and virus generators can reduce the value of the network and they also highlight that there is evidence of diminishing marginal returns in network effects and that there exists disparate discrepancies between the most valuable and least valuable users in a network. They make use of Zipf's distribution in order to propose that the network value grows in proportion to n log(n), ($V \propto n \log(n)$), which is a faster growth rate than Sarnoff's law as it recognizes the value generated through combining networks but also a slower growth rate than Reed's and Metcalfe's law as it also acknowledges that not all users contribute equal value to the network.

2.4 State of the art

For the 40 years prior to 2013, the debates regarding the most suitable network effects laws were theoretical and even to date, there are few empirical studies of network effects laws available. The studies that are available are also limited in scope as Metcalfe (2013), Zhang et al. (2015) as well as Hove (2016) all make use of annual actual data from Facebook to test the validity of Metcalfe's Law. Madureira et al. (2013) was the first empirical study that validated Metcalfe's law through use of Digital Information Networks (DINs). The study made use of 13 capabilities that enable DINs users can convert their access information on the DIN such as the internet into economic value through revenue or income creation. An example for the perceptibility capability, a user of the internet can access information regarding a potential employer in preparation and use that information to secure employment, thus generating income through earning a salary. The increase in value of the capability was found to be dependent of the size of the network as per the theory of network effects laws. In this study Metcalfe's law was compared to Briscoe's law using data from predominantly developing markets between 2002 and 2009 and it was found that both Briscoe and Metcalfe's law fit well but Metcalfe's law is the most suitable law to describe the relationship between the size of the DIN and the value of the capabilities.

Metcalfe (2013) mentions that of all of the theoretical arguments that claim that Metcalfe's Law overestimates network value, Odlyzko and Tilly (2005) makes a fair argument regarding the over estimation but proved the criticism that although Odlyzko's Law captures less network value growth due to the log-linear relationship of the law's function; both his law and Odlzyko's law have not been empirically validated and do not have an upward bound. In this study Metcalfe makes use of ten years of annual revenue for Facebook and a slider on the Python programme to fit Metcalfe's value function. The curve fitting by Metcalfe, however, only validates that his law fits the actual data but does test the suitability of the law relative to other network effects laws.

Metcalfe's use of the python programme slider was acknowledged by Zhang et al. (2015) as a step in the right direction as it provided additional empirical evidence to the validity of the law, however, provides critic to the accuracy and robustness of the method. In their study they also make use of the Python programme but instead of manual curve fitting, they make use of the least squares function to improve accuracy. In addition to the objective of improving the accuracy of the Metcalfe (2013)'s test using Facebook data the study also makes use of real data from China's largest social network, Tencent, to test the validity of the law in developing countries. Given that the size of Facebook and Tencent differ significantly, the study is able to test the validity of the network effects laws to companies of varying sizes. Metcalfe's Law is also tested in comparison to other network effects laws in this study and is found to be the most suited law relative to other network effects laws for Facebook and Tencent, regardless of the company size difference or whether the company is in a developed or developing economy.

The focus of the state of art thus far has been on Metcalfe's revenue value function, however, Metcalfe's law also consists of a cost model. The formulation of the cost function for Metcalfe's law contains more complexity than what is observed in the revenue function (Zhang, Liu, & Xu, 2015). In formulating cost function in accordance to the understanding of the researchers in the study, they find that the Tencent and Facebook's data demonstrates that the cost of the network has a quadratic relationship with the size of the network and not a linear one. Hove (2016) challenges the interpretation by Zhang et al. of the cost component of Metcalfe's law by proposing that the correct interpretation of cost is not costs of the network, but rather the average cost per user/node (CNP) that have a linear relationship with the network's size. This study is the first study that attempts to complement Afuah (2013)'s argument that size is not

everything through empirical testing. Hove brings forward the notion that the quality of network services is an additional driver of network value. To test this, Hove amends Zhang et al.'s model to include a quality indicator which is derived by the year on year difference in CNP. The premise behind the use of the difference in CNP is the assumption that constant cost indicates a constant level of quality for the users of the platform and for companies that continue investing in their platform and investment above the constant CNP would translate to quality improvements. Hove also highlights how the assumption of constant cost per note indicating constant quality could be flawed given that economies of scale are expected and could be impacting cost per node, however, the assumption was maintained to enable the derivation of the quality indicator. The second, and most valuable adjustment to Zhang et al.'s model in the context of this study is the adjustment of the revenue used to validate the network effect's law. Metcalfe and Zhang et al.'s study does not adjust Facebook and Tencent revenue to consider revenues only relating to the social network, in adjusting the revenue and removing revenue lines such as ecommerce revenue for Tencent, some mixed conclusiveness introduced by the use of overall revenue can be reduced. The value functions for the network laws becomes:

$$V_{network} = \alpha \times SIZE + \beta \times QUALITY$$

Where:

- $V_{network}$ – Network revenue adjusted to remove revenue that is not associated with the social network
- Size - Number of nodes in the network
- Quality- Quality indicator that is the difference between CNP_t and CNP_{t+1}.

This adjusted function implies that there is no relationship between quality and network size and that network can still have value even when there are few or no users of the platform and that even if there are no users of the network or are very few users of the network, there can still be network value, there are arguments regarding these implications and the implication for no interaction between quality and network size is admittedly acknowledge to be too radical. Through regression it was found that the quality variable was significant for Sarnoff's and Odlyzko's law and suitability and fit can be seeing to increase as indicated by the decrease in the RMSDs and an increase in the R^2 of the laws when Tencent data was used, but the quality variable is not significant where Facebook data is concerned. Although it is significant for Sarnoff's and Odlyzko's law where Tencent is concerned, the coefficient of size becomes negative thus implying that the presence of network users destroys value, therefore, the inclusion of the indicator collapses the laws. In the instance of Metcalfe's law, the inclusion of the quality variable does not collapse the law, the variable is found to not be significant, and the inclusion of the quality indicator does not improve the model. With the modifications to Zhang et al.'s model of introducing a quality indicator and adjusting the revenue used, Hove finds that the conclusion that Metcalfe's law is the most suited law is still valid and in fact further outperforms the other network effects laws.

The empirical studies found in literature to date have focused mainly on validating the models using Tencent and Facebook's actual data and have not included companies in other industries. Hove (2016)'s adjustment of Tencent data focuses on social network revenue and the Tencent e-commerce revenue is not explored to understand e-commerce networks value. This is understandable as Tencent's industry is mainly social networks, through observing social network revenue it is also comparable to Facebook; however, there exists a gap in research to

understand the suitability of Metcalfe's law to companies in industries other than social networks.

CHAPTER 3: METHODOLOGY

3.1 Overview of methodology

The actual data from listed companies is used to test if Metcalfe's Law is the most suited network effects law regardless of industry in emerging markets. The actual data is collected over a seven-year period, from December 2015 to December 2022, therefore only companies that were operational and listed prior to 2015 are considered for sampling.
The three industries that are considered in the research are social networks, electronic commerce (e-commerce) and search engines. The empirical studies found in literature have focused on companies that are market leaders, Facebook as the largest social network and Tencent as the largest social network in China, to conduct their research although the sizes of the companies may differ. To contribute comparable views for emerging markets and reduce the potential impact of market position on revenue and user base size, the companies that are market leaders. Given that the intention is for the selected company to represent an industry and contribute to studies on platform valuation, the selection criteria of the company is based on market capitalisation; the company with the highest market capitalisation in each industry at the time of conducting the study was selected. The social network, ecommerce and search engine industries are therefore represented by Tencent, Alibaba and Baidu, respectively.

Metcalfe, Sarnoff and Odlyzko's law are transformed into network effects value functions to enable the comparison of the expected outputs from the theoretical models with the actual data. In Zhang et al. (2015), it can be observed that the Root Mean Squared Deviation (RMSD) of Reed's law relative to the other laws both for Tencent and Facebook data is significantly larger, this empirically proves this law is the least suitable law. Theoretically, arguments around the plausibility of the law have been made as it is said that although Metcalfe's law results in an overestimation of the value of a network, Reed's law is even more of an overestimation (Odlyzko & Tilly, 2005). The study places emphasis on the impact of the extreme threshold effect which states that for smaller values below a certain user base size, the network value would be a portion of the value of the entire global economy but due to the network value growing proportionally to 2^n, after exceeding a certain threshold whereby the network value becomes equal to total economic value; an additional user has the ability to double total economic value. This is not realistic and does not fit expectations of network values. Overby and Audestad (2021) also realized this issue with Reed's law and proposed to modify the law to use Dunbar's number and this modification would result in more moderate increases of network value, however, when attempting to plot Reeds law and the modified Reed's law with the other three laws, it was noted that it is not possible to plot them on the same graphs as the other laws because they increase so rapidly that they almost overlap with the vertical axis. Given the design of this study and the use of top companies with large user bases, it is expected that the use of the Reed's law tends towards the unrealistic scenario stated above, therefore, Reed's law is excluded from the laws that are tested in this study.

Curve fitting of Metcalfe's, Sarnoff's and Odlyzko's laws are conducted using the least squares method and the Root Mean Square Deviation (RMSD) is observed for each value function to determine the most suited value function across the three industries.

3.2 Description of the data

For the selection of the companies in the various industries Bloomberg's company classification browser is used to categorise companies into their industries and the filter for Asia Pacific

emerging was used to limit this study to companies in emerging economies in Asia Pacific. On the company classification it is possible for companies to appear under various classifications, however, for the purposes of this research companies are only considered in their primary classification. The classifications that were considered were Internet and Media services, Marketplace, and Internet advertising portals. The companies whose classification was their primary classification were ordered by US Dollar market capitalization and the company with the highest market capitalization was selected. For ease of reference regarding industry, these industries are renamed as social networks, e-commerce, and search engine industries.

In the literature, it can be observed that for previous empirical studies annual data was used to test the suitability of the laws. Given that a larger data set and increased observations improve accuracy of models and the data for the listed companies and the required variables for the study are available quarterly, this study makes use of quarterly time series data to improve the robustness of the models. If higher frequency data was available for the variables concerned, the robustness of the results could be better improved. The quarterly data is gathered for these companies using Bloomberg and company financial statement. Table 1 displays the variables that are collected for use in the network law functions. Revenue is used as a proxy of network value (V) and the platform's monthly active users (MAU) gives us an indication of the size of the network is therefore used to represent the number nodes of a network (n).

Table 1: Variable definitions

Symbol	*Unit*	*Definition*	*Data Source*
V	USD	Value of a network	Quarterly revenue from Bloomberg
n	MAU	Number of nodes of a network	Company quarterly financial statements

3.2.1 Revenue and MAU variables

In the research conducted by Metcalfe (2013) and Zhang et al. (2015), overall company revenue was utilized to test the suitability of the laws but given that this research seeks to take on an industry focused approach, only revenue and user data lines related to the platform mediated operations are considered where possible. Tencent is a multinational conglomerate business with operations in the social network, music, gaming, artificial intelligence, entertainment, and technology solutions industries. In their financials revenue is split between value -added services, games, social networks, online advertising and Fintech and Business services and their MAU are split between Wexin and WeChat users and mobile device of QQ users. For the purposes of understanding the relationship between user base size and the value of social network networks, the social network revenue and the Wexin and WeChat monthly active user base are considered. As observed in Appendix 1A, data using the Bloomberg terminal and the Tencent's quarterly financial statements was collectable from December 2015 until September 2022 for social network revenue and MAU.

Alibaba reports on seven revenue segments based on their operations, namely, China commerce, international commerce, local consumer services, Cainiao, Cloud, Digital media, and entertainment as well as an innovation and others segment. China and International commerce segments consist of retail and wholesale business such as Taobao Deals, Tmall, Taocaicai, Freshippo, 1688.com, Lazada, AliExpress, Trendyol, Daraz and Alibaba.com.

When reporting on MAUs, it is limited to mobile MAUs which access their China retail marketplaces. Given the restriction on the MAUs reporting, this research utilises China retail commerce revenue and mobile MAUs data to study the relationship between user base size and the value of e-Commerce networks. As observed in Appendix A1, the MAU quarterly data was obtained between December 2015 and September 2021; therefore, this period is used for Alibaba data.

Baidu is no different from Tencent and Alibaba as it also has multiple operations and streams of revenue. Historically, Baidu only had one combined reporting segment but in March 2017 the decision to split into two reportable segments: Baidu Core and iQiyi was implemented. Baidu Core consists of reporting on search services and transactional services while iQiyi reports on revenue generated from online entertainment services. Baidu is the leading Chinese language search provider that offers their services through Baidu App and Baidu.com. Baidu App is the flagship app and the main channel to access Baidu services. It allows users access to search, feed, and other services and through the Baijiahoa (BJH) accounts, Smart Mini Program and Managed AI as the API building blocks. Baidu reports on Baidu App's Daily active users (DAU), MAU and iQiyi's subscriber base but not on the user traffic on their website, Baidu.com. Due to limitations in the data and for the sake of user base data consistency, Baidu App's MAU and Baidu core revenue is used to explore the relationship between MAU's and search engine networks. Given that the revenue segmentation only came into effect in March 2017, data for Baidu core is only available from then, as seen in Appendix A1. Prior to September 2018, data on the MAU was not collectable using Bloomberg and Baidu's financial statements, therefore the period of September 2018 to December 2022 is used for Baidu's data.

3.3 Research design

Zhang et al. (2015) critics Metcalfe (2013) for using manual curve fitting to validate the network effects law as the method used introduces possible inaccuracies. They make use of the least squares method for curve fitting to improve the accuracy. In their study Zhang, Lui and Xu (2015) makes use of the least squares function found in an open-source Python library, but the similar objectives can be achieved through using Microsoft excel solver add -in. This study makes use of excel solver add-in to enable the least squares method for curve fitting by using actual company data and the data is derived from the network law value functions.

Network law value functions are derived from the theoretical laws, thereafter actual revenue is used alongside the network law value functions to establish the proportionality constant. Once the proportionality constant is established for each network effect law, the companies actual MAU is used to derive the theoretical revenue based on the network effect value function. This data is visualised through plotting the actual data against the derived values, however, for more accurate interpretation the variability of the actual and theoretical data of the network effects law value functions are assessed using the root mean squared deviations (RMSD) to find the most suitable network effects law.

This is repeated across all three industries to establish whether Metcalfe's law is the most suitable law across all industries.

3.3.1 Value functions

The three network effects laws examine the relationship between the value of network effects and user base. From these laws the value functions in Table 2 are established. Within all three

of the value functions the presence of the proportionality constant can be observed. This value is the constant value of the ratio between the number of nodes in network and the network value. Where the proportionality constant is greater for one network relative to the other, the network with the greater proportionality constant generates more value per user.

Table 2: Network laws value functions

Value functions	Model	Unit of parameters
Metcalfe's function	$V = \alpha \times n^2$	$\alpha: \mathrm{USD/MAU}^2$
Sarnoff's function	$V = \alpha \times n$	$\alpha: \mathrm{USD/MAU}$
Odlyzko's function	$V = \alpha \times n \log(n)$	$\alpha: \mathrm{USD/MAU}$

For all other functions besides Metcalfe's function, the unit for the constant USD/MAU, however, for Metcalfe's function it is $\mathrm{USD/MAU}^2$. For consistency in the observations, all network values are displayed in US dollars. The proportionality constant's unit of parameter indicates the value of US dollars that is added per additions monthly active user for Sarnoff and Odlzyko's function and for every additional squared monthly active user in case of Metcalfe's law. When holding the assumption that revenue is the proxy for value and the value of the network being proportionally attributed to the number of nodes of a network, when there are no users in the network there value of the network should be zero.

3.3.2 Curve fitting

Given that the network laws consider that the relationship between network size and network value as linear and non-linear, the most appropriate method for testing the hypotheses is to use the non-linear least squares method for curve fitting.

3.3.2.1 Finding the proportionality constant.

When using the least squares method for curve fitting, the best fitting curve can be obtained by minimizing the sum of squares of the residuals (SSE). The sum of squares residuals is a measure of the amount of the variance between the theoretical data that is outputted by the network law functions and the actual company data and this variance is not explained by the theoretical model.

The SSE can be calculated using this formula:

$$SSE = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

Where:

- y_i – the observed (actual) network value
- $\hat{y}_i$ – the theoretical network value

As highlighted above, the solver function on excel enables that minimising of the RSS through the adjustment of the proportionality constant for each network effects value function.

3.3.2.2 Deriving the theoretical expected value

Once the proportionality constant is established through minimising the RSS for each function, the derived proportionality constant is plugged into the network effects value function. The MAU is the independent variable that is used in the function to derive the theoretical expected revenue for the time series for each of the network effect laws. Wherever there exists an actual MAU data point on then the quarterly time series, a theoretical revenue can be derived. Both the theoretical and actual revenues can be plotted per industry using a scatter plot to observe the variability between the actual and derived data.

3.3.2.3 Measuring variability between actuals and derived values

For more reliable results, a statistical approach is used in conjunction with the visualized data. The RMSD is calculated between the actual and theoretical data. The RMSD can be calculated using this formula:

$$RMSD = \sqrt{\frac{\sum_{i=1}^{N}(y_i - \widehat{y_i})^2}{N}}$$

Where:

- y_i – the observed (actual) network value
- $\widehat{y_i}$ – the theoretical network value
- $N-$ number non-missing data points

The theoretical model with the smallest RMSD is considered as the best fit model for the industry.

CHAPTER 4: RESULTS AND DISCUSSION

4.1 Introduction

In this chapter we engage in the result and a discussion regarding the finding of the empirical study using social network, e-commerce and search engine industry actual data and using the theoretical models to derive data for Metcalfe, Sarnoff and Odlyzko's value functions to test and discover if Metcalfe's law is the most suited law across these industries. For each industry we visualise the outputs of the curve fitting as shown in Figures 1 to 3, using the actual and the derived data that can be found in Appendix A1 to A4. To ensure that the observation of the visualised data is statistically sound, we use Root Mean Squared Deviations found in Tables 3 to 5 to make the conclusive decision on which law is most suited for each industry. After reviewing the results, discussions regarding the results at an industry level are conducted and in conclusion of this chapter, the results are summarised and the research questions are answered based on the findings.

4.1.1 Social Networks data

Figure 1 visualises actual data from Tencent based on MAU and Social Network revenues. This data represents the view for the social network industry. As observed in Appendix A2, the minimum theoretical revenue outputted by Metcalfe's value function is US$ 814 Billion, therefore, due to the disparate difference between that value and the other values in the diagram, the theoretical values are not visible in Figure 1 as the inclusion would alter the revenue scale and prevent the ability to visualise the actual data relative to Odlyzko's law and Sarnoff's law. The theoretical revenue derived from Odlyzko and Sarnoff's law are more in line with the actual data and therefore it is important to assess these laws to establish which of the two is a more suited to establish Social Network value.

In the visualised data, it can be observed that Odlyzko's and Sarnoff's law underestimate the actual values until around the 1,04 Billion monthly active user base mark, beyond that mark we observe these value curves underestimating the actual values and a growth in the deviation until actual revenue peaks at approximately 1,27 billion monthly active users in December 2021. When compared to the results for e-commerce and search engine, no trend or explanation for this can be observed at face value, however, for social networks and e-commerce the over estimation is observed for smaller monthly active user bases but in search engines, underestimation is observed for the smaller user base.

Figure 1. Social Networks: Actual vs Value curves

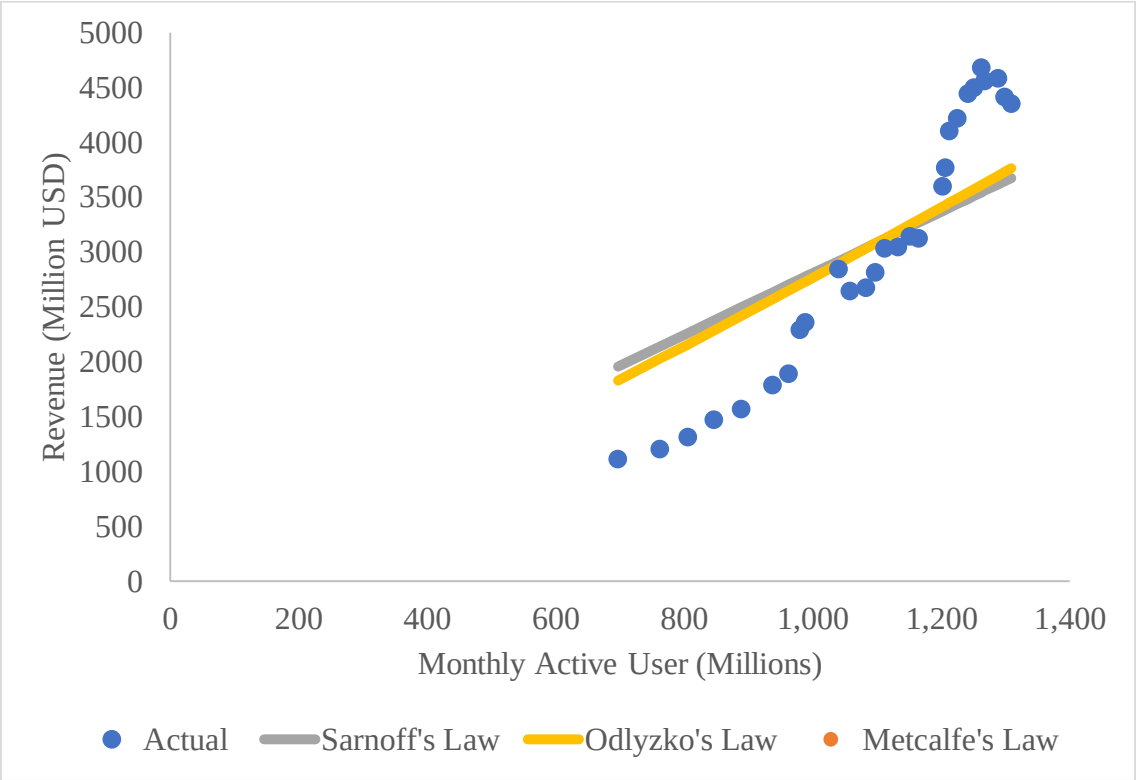


Table 3 displays the statistical fitting results whereby one can confirm through the Metcalfe's law RMSD that the theoretical outputs of Metcalfe's law deviate significantly from the actual data and that Metcalfe's law is the least suitable law to use to predict Social network networks using MAU. It is interesting to observe that the results present a difference to the empirical findings by Zhang et al. (2015) that Metcalfe's law is the most suited law in developing and developed economies. Although the time period as well as the frequency of the data differs, it is also important to note the differences between the objective of this study and the revenue selected to test the laws. The study by Metcalfe (2013) and Zhang et al.(2015) uses these value functions using overall company revenue and MAU, it does not consider the revenue linked to the MAU. When MAU is linked to the applicable revenue line and takes on an industry lens, Metcalfe's law overestimates the value of the network.

Visually it is also possible to see either Sarnoff or Odlyzko's law function is the best-fitted value function and therefore the statistical test become important to enable a view of the most suitable law beyond what is visualised. In Table 3, we observe that both the RSMD of Sarnoff and Odlyzko's laws value functions are almost zero which indicates that both functions are good fits, however, Sarnoff's law function produces that least variability to the actual data when compared to the other two laws**.** Therefore, it is not only a good fit for the data but the most suitable law for establishing social network value.

Table 3: Fitting results of network effects laws for Social Network industry data

	Value function	RMSD
Metcalfe's law	$V_{Social\ Network}$=1.3279 × n^2	1.07× 10^7
Sarnoff's law	$V_{Social\ Network}$=1.7633 × n	2.75× 10^{-7}

Odlyzko's law	$V_{Social\ Network}$=0.5442 × $n \log n$	0.0003

4.1.2 E-commerce industry data

Alibaba's data represents the e-commerce industry view in Figure 2. Unlike what was observed in the social networks industry, the plotting of the actual and theoretical values for all three network effect laws can be visualised on the same graph. Visually it seems that the Metcalfe's curve law is best fit to the data but for accuracy it is important to verify this statistically. The RSMD in Table 4 for all three laws is almost zero which indicates that all three functions are good fits for the data. Therefore all three laws are good fits for the e-commerce industry, however, the RMSD for Metcalfe's law is the least at 0.00080. This statistically proves that although all laws can be good fits, Metcalfe's law is the most suitable law for the eCommerce industry. These findings cannot be contrasted to empirical studies at an industry level as Metcalfe's law has not been tested on e-commerce businesses yet. It can be compared to empirical studies when industry specific nuances are ignored as it agrees with the findings of the prior research that find that Metcalfe's law is the most suitable law.

Figure 2. E-commerce: Actual vs Value curves

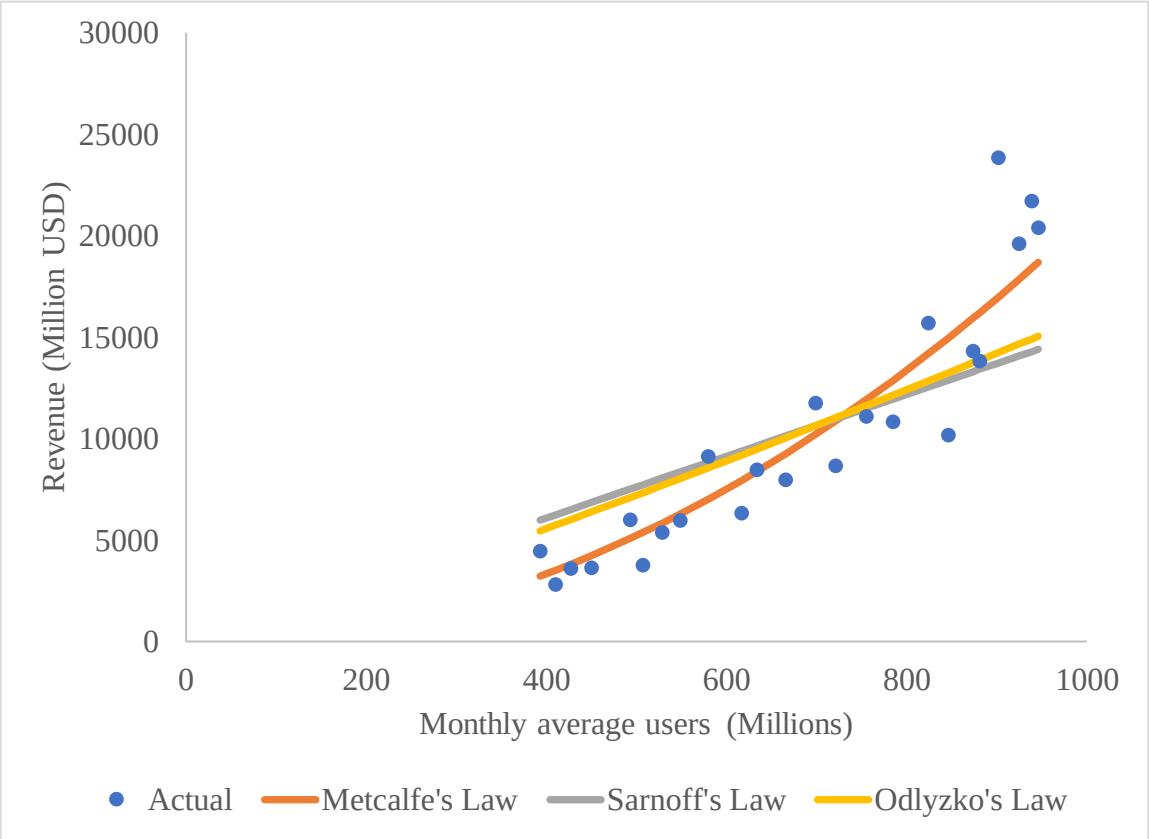


Table 4: Fitting results of network effects laws for e-commerce industry data

	Value function	RMSD
Metcalfe's law	$V_{e-commerce}$= 0.0209 × n^2	0.00080
Sarnoff's law	$V_{e-commerce}$= 15.2272 × n	0.00084

Odlyzko's law	$V_{e-commerce} = 5.3447 \times n \log n$	0.0015

4.1.3 Search Engine industry data

The search engine industry views make use of Baidu's Baidu core revenue and MAU actual data and the network effect value functions. The actual data and the derived data are displayed in Appendix A3 and is visualised in Figure 3. For 342 million MAU and less, it can be observed that all of the value curves overestimate the actual value of the network and for over 544 million MAU, all the value curves overestimate the revenue. This trend cannot be explained at face value or through comparison with the other industries in this study- it would require greater unpacking.

Visually, it can be assumed that Sarnoff's value curve is the better fit curve given that it seems to underestimate the values by the least amount before the 342 million MAU mark and overestimate the value the least after the 544 million MAU mark, however the visual observation needs to be verified statistically.

Figure 3. Search engine: Actual vs Value curves

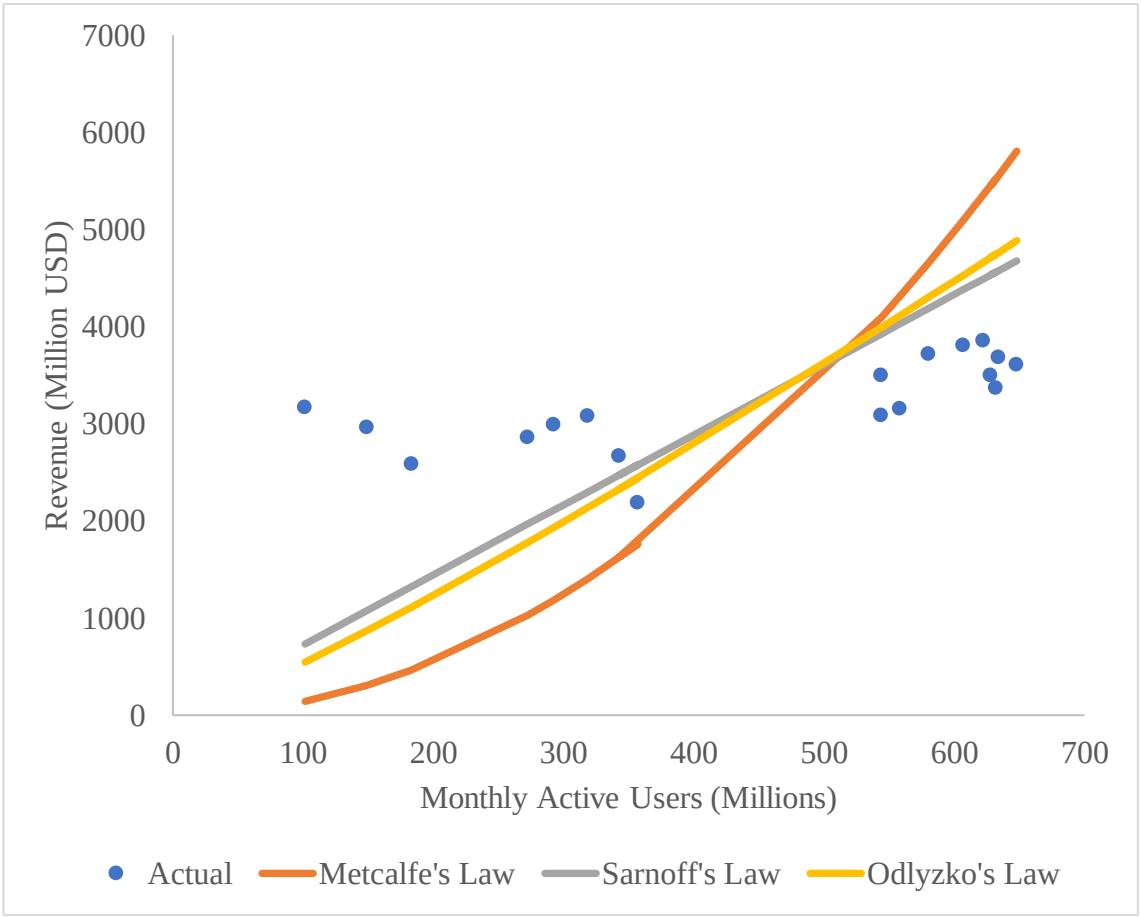


Table 5 confirms the importance of statistically verifying visual curve fitting observations and the RMSD indicates that Metcalfe's law value function is the most suitable law for the search engine industry and not Sarnoff's law as assumed through visual observation. Similar to what was observed in the eCommerce network , although Metcalfe's law is the most significant law

for search engine industry, Sarnoff and Odlyzko's law's RMSD are close to zero and are therefore also good fits for the industry.

Table 5 : Fitting results of network effects laws for search engine data

	Value function	RMSD
Metcalfe's law	$V_{Search\ engine}$=0.01382× n^2	0.0014
Sarnoff's law	$V_{Search\ engine}$=7.2170× n	0.0065
Odlyzko's law	$V_{Search\ engine}$=2.6815× $n \log n$	0.0193

4.2 Discussion of results

When discussing the results, they are discussed per industry to enable the interpretation of the results with consideration of industry specific nuances, especially regarding how the different industries operate and how they generate revenue which is used as a source of network value quantification in this study.

4.2.1 Social networks industry

The finding of this study that states that Sarnoff's law is the most significant law contradicts the research by Zhang et al. (2015) and Hove (2016) that both found that Melcalfe's law is best suited for Tencent data. In the instance of Zhang et al. it may be assumed that this may be caused by the discrepancies in revenue used as Zhang et al makes use of overall revenue for Tencent but the study uses revenue that can only be attributed to social networks. When selecting a more specific revenue segment, social network revenue and MAU for WeChat and Wexin, we find that although Metcalfe's law could be applied at an overall company level, using Metcalfe's law at a social network industry level results in a significant overestimation of the social network value. This can be due to the attribution of non-social network related revenue to the social network MAU base, which inflates the true revenue impact of an additional user and their relationship with other users in the network.

Hove uses a similar adjustment to revenue, however, still finds Metcalfe's law as the most suited law for social networks. Given that the same company was used and revenue was adjusted in a similar manner, the deviation in outcome can potentially be attributed to Hove's inclusion of the quality indicator (CNP) but according to Hove (2016), the quality indicator is not significant variable for explaining network value and should therefore not be the driver of the discrepancies in the findings. Therefore other factors such as difference in time periods that the actual data is considered for Hove's study and this study can be considered as Hove makes use of Tencent data from 2007 to 2014 in his study and this study makes use of data from 2015 to 2022. In addition to the differences in the time periods for the studies, the differences in frequency of the data used in the studies can explain the discrepancies as Hove makes use of annual data, while this study improves accuracy by making use of quarterly data.

The results by industry demonstrate that both Sarnoff and Odlzyko's law fit the Social Network data well, however Sarnoff's law is the most suited law to use predict the value of a social network by using the nodes of a network. The underlying assumption of the Sarnoff's law is that there is a linear relationship between the number of users in the network and value, each additional user adds equal value to the network and that there is no net gain that is observed

when two nodes or users in the network are combined. Given the nature of this study, no net gain would refer to no net gain in revenue. It not possible to speak to engagement, entrenchment and user utility as a net gain through using revenue as the metric of value. It is important to note that when we say that the relationship is linear and each additional user adds equal value, it does not imply that with each additional MAU $1 in value is added. When we observe the proportionality constant, we can see that US$2.8 in value is added to the social network value through each additional MAU.

When observing how social networks generate revenue, it is possible that the relationship is linear or log-linear when revenue is the metric used to determine social network value as the assumption under Metcalfe's law is that additional actual revenue would be generated through engagement between two users in the same network. The current key driver of social network revenue is advertising revenue (Yang, Kim, & Dhalwani, 2007). Advertising revenue through third parties being able to advertise on the platform to the platform's users. For third party advertisers being able to access large user bases is valuable and therefore, they are typically more willing to pay more to advertise on larger social networks. Advertisers pay to have access to active users on a platform and not necessarily the engagement between the users – unlike on platforms like market places or eCommerce whereby additional revenue such as commission revenue can be earned through the platform facilitating the purchase and sale of goods between two users.

Social network industry companies are continuously evolving in their capability offering to customers and their pricing structures. In some instances some social networks are starting to generate revenue through offering paid engagements between users of the platforms, for example some online dating applications charge for access to users in different geographical locations or additional ability to indicate interest in other users through likes.

Some social networks have also started using affiliate programs to generate revenue through enabling their users to seamlessly be directed to the advertiser's site to complete their purchases. Affiliate programs are typically underpinned by a contract between the platform company and the advertiser based off the actions that customers fulfil on the page they are redirected to by the platform company (Yang, Kim, & Dhalwani, 2007). In addition to this we have started seeing social networks build streams of revenue through the connection of two or more users of the network through enabling gift purchasing of one user for the next and charging an administration fee or payment fee to the purchaser of the on-platform gift.

Twitter ticketed spaces are also examples of additional ways that social networks are attempting to generate revenue through the engagement of two or more platform users. Ticketed spaces enable users to monetise live online conversations amongst multiple platform users through the host user being able to charge a ticket fee to the attendees of the ticketed space and Twitter gains revenue as a percentage of the ticket fee revenue that would be paid to the host. Given that advertising revenue is still the dominance source of revenue, Sarnoff's law is currently the most suitable network effects law for establishing and projecting social network value.

4.2.2 e-Commerce industry

Although all three of the value functions seem to fit e-Commerce actual data, the most suited law is the Metcalfe's law. It does not come as surprise that Sarnoff's law is not the most suited law in e-commerce as revenue generation in eCommerce differs from what can be observed in social networks. Where advertising revenue is the primary source of revenue in social networks,

transactional revenue is the primary source for e-commerce. Transactional revenue can be earned through the commission earned from the facilitation of sales of goods by the buyer to the seller is the main source of revenue for e-commerce (Maio & Re, 2020).

Platforms for e-commerce also have hybrid revenue models where over and above the transactional revenue e-commerce businesses also enable advertising revenue. Affiliation revenue, however, may not be as common as the sole objective of the e-commerce business is to enable the completion of the sales journey on the e-commerce platform. Metcalfe's law differs from Sarnoff's law as it attributes some of the value creation in a network to the connections between user in the network's user base. E-commerce businesses generate commission through being the intermediary between a willing buyer and a willing seller. Therefore comes as no surprise that there is value created through the relationships between uses that our buyers and sellers in the form of commission revenue.

For the purposes of this study, given that revenue is used to quantify the value, the creation of the commission revenue is what is considered as value in the network. In some instances, for example where product reviews are enabled by the platform owner it is possible for value to be created by same side platform uses such as buyers who can create value for each other by engaging in reviewing products that they have bought in order to assist other buyers with their buying decisions, this can result in indirect revenue generation for the platform. Based on the empirical evidence of the study when uses of network effects laws for valuations make use of Sarnoff's and Odlyzko's law, under the assumption that the user base continues growing, it is possible that at a certain point making use of these laws results in an under estimation of the value created by the additional user in an e-commerce platform. Given the dominance of transactional revenue in e-commerce businesses, Metcalfe's law is the most suitable law for e-commerce networks valuations.

4.2.3 Search engine industry

When one notes the discussions around the findings with regards to social network valuations as well as e-commerce valuations one tends to assume that the correct or suitable network effects model can be determined by the primary revenue generated by the industry. The search engine research in the study provides an opposing view to this assumption. When viewing revenue from search engines one observes that similar to social networks the primary revenue generated for search engines is advertising revenue.

According to Yao and Mela (2011) at the core of the business functions of search engines, they price custom information, deliver auctioning mechanisms and also design webpages that clarify or summarise information around products and services. Unlike in the instance of social networks where the users in a social network are on the same side of the platform and the advertiser is the third-party; in a search engine the users are on opposite sides. The consumer of the information and the advertisers are on the other side of the platform. Advertising revenue in a search engine is generated in a different way to advertising revenue in a social network. In search engines advertising revenue is generated through advertisers bidding for keywords and for search priority. Through bidding for keywords and search priority advertisers are able to actively target customers who search information relating to their products. Although in some instances uses on search engines could merely be browsing prioritising product based of searches is valuable to the advertiser as it in enables advertiser to position their products to some customers that are actively shopping for the products advertisers seek to offer.

The connections and conversions between searchers and advertisers using keywords or search priority enables for search engines to be able to set prices for keywords and search priority auctions, thus driving revenue. The revenue between the search engine platform and the advertiser is not only limited to auctioning of search for keywords and prioritisation but there is also revenue that is generated through affiliation programs such as rates paid to the search engines based off the number of customers that click to be redirected to the desired page by the advertiser. Although social networks also generate their revenue through advertising revenue, the difference in the role and the types of revenue generated through advertisers results in a different outcome regarding the most suitable network effects law for search engine network valuation.

From the empirical results of the study we observe that all three network effects laws are good fits for the search engine network value, however given the revenue generated through the connection between two or more network users we observe that the most suitable law is Metcalfe's law meaning that the relationship between MAU and the value of a search engine network is not linear or log linear as assumed by other laws, but exponential.

4.3 Summary of results

The main research question underpinning this study is whether the most widely used law in practice, Metcalfe's law can be proved to be the most suitable law regardless of the platform industry. The study would have had to prove that Metcalfe's law is the most suitable law across all three of the industries sampled in order to affirm that it is the most suitable regardless of industry. Although Metcalfe's law was empirically proven to be the most suited law for e-commerce and the search engine industries, it is not the most suitable law for social networks. In the data we observe that Metcalfe's law significantly over-estimates network value for social networks, therefore, Metcalfe's Law's suitability is observed as industry specific.

CHAPTER 5: SUMMARY AND CONCLUSION

5.1 Introduction

In this final chapter we conclude the findings of this study, unpack the implications and limitations of the findings, and provide recommendations for further research.

5.2 Conclusion

In this study it was observed that the relationship between MAU and social network value is linear and can be represented by the following Sarnoff's model, $V_{Social\ Network}$=1.7633 $\times n$.

It was also observed that the relationship between MAU and e-commerce network value as well as MAU and search engine network value is exponential and can be represented by the following Metcalfe's models $V_{e-commerce}$= 0.0209 $\times n^2$ and $V_{Search\ engine}$=0.01382$\times n^2$, respectively. Indicating that although search engine's and e-commerce both have exponential value creation, where an additional squared MAU adds \$0.01 to network value, e-commerce additional squared MAU doubles that by adding \$0.02 to e-commerce network value. Given these observations, the popular Metcalfe's law is not the most suited network effects law regardless of industry and therefore, it can be concluded that Metcalfe's law is industry specific.

Industry specific discussions regarding the suitability or lack of suitability of Metcalfe's law has been facilitated through the empirical outcomes of this research and it can be rationalised through the understanding of the dominant business models within each industry. The use of these laws can inform value creation expectations based on current operations or business models in platform businesses, inform opportunities into new or expansionary ventures or drive platform and digital strategies in businesses.

For investor's seeking to make investment decisions, given that in most instances MAU information is becoming more accessible, these valuations can be used to amend or to complement existing traditional valuation models.

5.3 Implications of findings

This study has found that Metcalfe's law is industry specific, and the implication of that network effects laws should not be assumed to be industry agnostic. What this practically means for network effects law users is that when valuing a platform business, while using the laws in their current state, the industry that the platform operates in should be considered to select the suitable network effects law.

Although there is some mixed conclusiveness regarding why the research by Hove (2016) and this study have conflicting outcomes regarding the suitability of Metcalfe's law for modeling the value of social networks, the adjustment of using overall revenue to only use network specific revenue to represent network value has a noticeable impact on the outcomes of the model and should therefore be adjusted when these laws are used.

Higher frequency data was used in this study and due to the increase in observations, more accurate findings were produced. When data with a higher frequency is available, it is advisable to re-run the models for more accurate views on model suitability.

It is also important to note that the underlying business models that generate the revenue, which indicates network value in this study, are evolving as platform businesses seek better ways to monetise their platforms. It is therefore important to note that the outcomes of this study are not static. It is encouraged especially when there are significant changes in industry specific business models and the revenue that they generate that these models are re-run and tested to ensure that they remain suitable to the industry.

5.4 Limitations of the study

Limitations of the study can be broken down into limitations caused by underlying theory of the network effect laws, the research methodology and limitations due to company reporting standards. Through the unpacking of the limitations, we can identify areas of improvement in network effects laws and methodology as well as company reporting standards that can improve the ability to conduct platform valuations in the future. Limitations in the methodology, in most instances can be resolved through making amendments and introducing additional considerations to the methodology used in future studies, these can influence changes to how network effect laws are modelled going forward. Company reporting standards, however, may not be immediately resolved by future research but continued research in network effect valuation may influence changes in reporting practices through the sharing of research recommendations to relevant and impactful stakeholders.

5.4.1 Limitations of the network effects laws

Afuah (2013) and Hove (2016) make the "size is not everything" argument when it comes to network effects laws as Metcalfe's, Sarnoff's and Odlzyko's laws as consider size of network as the only determinant of network value. In their studies they discuss the limitations of the laws not exploring other variables such quality of network service, conduct of network users and network structure and the relationship that they have with network value. In addition to the contributions of Afuah and Hove regarding the variables considered in network value modelling, this study finds Metcalfe's law to be industry specific and therefore brings in the perspective of company industry type being a variable that impacts the suitability of a network effects law that is not considered in network effects laws. Literature also unpacks other aspects of network effects that could impact network value such as network type. Network effects laws do not take into consideration whether the network effects are direct or indirect and positive or negative, this limitation assumes that all types of network effects have the same impact to network value, and this is particularly concerning in the instance of positive and negative network effects as one type adds to value while the other detracts from network value. The limitation of the variables considered in the network effects laws limits the users of the model to be able to explore the relationships between other factors that can create network value other than network size, and this creates an over-reliance on network size when trying to understand how to create and capture network value. The emphasis on network size as the only determinant of network size can result in the neglection of other variables that create value. The implication for businesses is that as network effects laws become more widely used and used to inform strategic objectives, the over reliance on network size can drive strategic drives for user base growth without focusing on other aspects that result in the monetisation of the user base such as network service quality and other conditions on the network. The limited consideration of network type can create over and under estimations of the potential impact of direct or indirect network effects as they are assumed to have the same impact on network value. The limited consideration of the split between positive and negative network effects implies that all network

effects are positive; not considering the network value destruction by negative network effects can over-estimate network value.
For network effect functions, the implication of network size being the only variable determining network value is that when there are no network users, the network does not have value. Hove (2016) makes the argument that the implication of having a quality indicator would mean that even when there are no or few network users, the network still has value because networks have value that is independent of network size. Hove uses the argument that users can gain value from the network regardless of their ability to interact with other users. Although I agree with the argument in principle, given that the determinant variable in monthly active users and not a measure of connection between users, the network effects laws in their current state would cater for value created outside of user interactions. If there is one user of the platform that engages in activity that does not require interaction with other users, the monthly active user number will be one and not zero as assumed in Hove's justification. When considering the function that includes a quality indicator as proposed by Hove, calculating network value when there are no users of the platform will not be possible because the calculation of CPN make use of monthly active users and therefore, cannot be established as it would be an undefined value when the method of calculating CPN and the quality indicator is used. In the instance whereby the value of the network is not only represented by revenue, or the network size is represented by connections and interactions between users, the limitation that network value is zero when there are zero users would need to be re-evaluated.

Another limitation of this research is that although the study focuses on finding network value based on industry segments within multi-industry companies it does not explore how one would bring together the various value views and uses of models to provide an overall company view. This study is limited to only three industries whereby there are many other platform mediated industries that are relevant and can be explored. There exists an opportunity to test the suitability of Metcalfe's law across a broader base of platform mediated industries.

5.4.2 Research methodology limitations

The limitations regarding methodology include the methodology that is utilised to conduct the study, how the data is sampled, the method used for sampling the data, the variables considered in the study and the method followed. Some of these limitations were intended as they enabled the study to be conducted successfully and some of the limitations were consequential given the selected research methodology and availability of information.

Although the title of the research refers to a network effects model, the methodology utilised in this study is a comparative laws test. The comparative laws test was intended to be the first step to deriving a network effects model with consideration of traditional valuations and the outcome of the test. While conducting the test, the gap in network effects empirical research necessitated a deeper dive into the network effects laws and their applicability. In conducting a network effects comparative law test that has proven that the suitability of network effects law is industry specific, it enables that starting point for necessary considerations for model building.

The objective of the study was to provide a study related to emerging markets and this was conducted with a geographical sampling limitation to consider companies in the Asia pacific region. In selecting to focus on emerging markets only, given that the isn't an empirical study that compared the suitability of laws in developed countries or comparing emerging and developed countries, the applicability of the findings of this study to companies in developed markets is yet to be tested. Large emerging market platform businesses can be found in the Asia

pacific region, however, emerging market span across more geographical locations outside of the Asia pacific market. The focus on Asia pacific emerging markets to represent emerging markets can unintentionally capture biases that exist within that market and not emerging markets wholistically, the replication of this study to include other emerging geographical regions such as Middle East and Africa emerging markets can better represent emerging markets.

When sampling for industry only three industries were selected: social network, e-commerce, and search engines. Within those industries, the company with the highest market capitalisation was used to represent each industry. The selected industries are big players in platform businesses; however, they do not represent all industries. The findings of this study may be relevant to only the industries selected and this would create concern in the instance when different industries are used and social networks are excluded and the conclusion was that Metcalfe's law is the most suitable law, regardless of industry in emerging markets. A statement of that nature would require to be validated in industries outside of those selected and tested in this study. The conclusion that Metcalfe's law is industry specific is fair given that it was demonstrated to not be suitable for social networks but given the exhaustive nature of the industries selected, the question of "To what extent?" would need to be answered through testing more industries as the finding may be that social network industry is the only industry it is not the most suited for.

Within the three industries, only one company was selected to represent the industry. Although specific selection criteria are applied in selecting the companies, it is possible for company specific nuances to impact the industry view. More robust findings could be achieved through using multiple companies to represent an industry. In addition to this, the selection of companies with the highest market capitalisation and market leaders in each industry results in companies of relatively larger size to be considered. Given that industries are typically made up of companies of varying sizes, the sampling of one large company does not consider the nuances that may apply to small and medium size businesses to enable a user of the findings to make necessary adjustments for the use of the model on smaller companies. It would also be interesting to be able to see if these laws are applicable to companies in the same industry of varying sizes. The size of these companies also created a limitation on utilising Reed's law due to the concerns around the threshold effect. When conducting a similar study for smaller size companies it would be interesting to see in which instances Reed's law or modified Reed's law can be included in the laws to be tested. Only listed companies were considered in this study as the data for public companies is accessible and are standardised due to the need to meet accounting standards. In limiting the sample to only public companies, privately held prominent industry leaders such as ByteDance Ltd. that owns Tiktok have been excluded from the study and given the broad user base and difference in the business model for Tiktok, it would have been valuable to contrast it to other platform businesses is the same industry.

The study uses a December 2015 to December 2022 data collection period and within this period, for certain Alibaba and Baidu some data was missing or unavailable especially for the quarterly MAU variable, however, this period was maintained for comparability between the three industries over a similar period. This sampling period is not aligned with the sampling period in the study by Hove (2016). Network effects laws empirical studies prior to Hove (2016) consider overall revenue and do not adjust inputs to only consider revenue and cost related to the network. Given that similar adjustment to revenue was conducted by Hove and in this stud, the use of a similar sampling period for Tencent would have enabled the observation of the impact of using data with a higher frequency to improve the model's robustness. The difference

in the sampling period results contributes to the mixed conclusiveness regarding why Hove's study found Metcalfe's law as the most suited law for social network and why this study found it to be the least suited.

In this study and other empirical studies, revenue is used to represent network value. Value for stakeholder's, particularly, shareholders is generated through profitability of the company. Focusing on revenue alone without considerations of costs limits the ability to readily utilise network effects laws as a compliment to traditional valuation models. The methodology selected in this study does not consider cost as per Metcalfe's law (2013) and Zhang et al. (2015). Although there does seem to be disagreement between Zhang et al. and Hove, understanding and the consideration of the overall operational cost of a network is important in understanding value from a net revenue perspective and understanding if it is a significant variable in understanding network value.

Curve fitting on actual data enables the research objective of testing the suitability of Metcalfe's law when compared with other laws, however, it does not test the significance of industry as a determinant variable of network value as would be possible through use of a similar methodology used by Hove which includes the establishment of an industry variable and using regression to comment on its significance and compare the difference in the R^2 of a model that only has network size as a variable and a model with network size, industry with consideration of the relationship between network size and the industry variable. In being able to test the significance of the variable and the impact of the inclusion of the model to the fit, one would be in a better position to determine the importance of including this variable in network effects models.

5.4.3 Reporting limitations

Tencent, Alibaba and Baidu are large market-capitalised, multi-industry listed companies, however, there are significant differences in the financial and non-financial data, their contribution to industries, their business models, and the way that they approach financial reporting. In treating these companies individually when testing the suitability of the network effects laws, these differences have not prevented the achievement of the objective of the study, but they have unavoidable impact on the comparability of the tests across industries as there is impact on the standardisation and availability of user base data, the period the data is observed for each company, the ability to adjust revenue to only consider revenue linked to the MAU and the percentage of overall company revenue considered in the study.

Although platform companies have started reporting on monthly active users, this reporting is not standardised and is not always available. In the context of Alibaba, monthly active users were only reported on for mobile users that use the platform for China retail commerce. In the monthly active user base international retail commerce and China and international wholesale commerce was not accounted for. This limitation resulted in the study limiting the revenue line to be considered to only China retail commerce. From December 2021, the information of monthly active users was not made available on Alibaba's financial statements, therefore, limited the period that was used to test the suitability of the network effects model. Historically Baidu also did not report on monthly active users and only reported on daily active users, this therefore limited the period the study could be conducted on Baidu data. From the revenue reporting perspective there were further limitations imposed by how companies compile and segment revenues. For Alibaba although revenues were split into seven segments for China retail commas and the rest of the segment it was not possible to decipher between revenues

generated on platform and revenues generated off platform. Baidu only started splitting revenues between Baidu core and iQiyi from 2017 – this has further limited the period that was available for use for this study for search engines. Unlike Tencent, even in the split of IQiyi and Baidu core, it is not possible to link the industry specific revenue to the user base based off their current reporting. Baidu core is the main revenue driver for Baidu but it contains revenue from other industries that are not search engine revenues such as their cloud services. The impact of the additional unrelated revenues can overestimate the value of revenue generated by mobile search engine users.

There are also additional reporting limitations brought about by how different entry points onto platform have been treated, with the growth in use of Application Programming Interfaces (APIs) in technical solutioning, the interface entry point becomes negligible as the backend technology is the same and therefore has the same capabilities. What this essentially means, is that a platform user does not need to be considered differently based on whether they engage with the platform using a mobile app or desktop. For the search engine industry there are multiple entry points such as mobile, mobile app and desktop. When looking at the reporting by Baidu, one observes the mobile app user reporting but the absence of user traffic reporting on Baidu.com. Website user traffic and mobile app users have historically been tracked and reported on differently, when considering that the user's intent is to access search capabilities or advertise, intent regardless of entry point, it becomes important to standardize how we view users regardless of entry point. In instances whereby companies still report web traffic and MAU separately, where MAU only represents mobile app users, it creates the limitation of being able to capture the full network size and the user base can be understated if only mobile app users are used to capture MAU and over-stated if web traffic is simply added to mobile app users as web traffic captures foot flow and cannot decipher pre-login if the multiple entries on the platform belong to one user accessing the website multiple times or if it is different users.

The highest frequency that this study uses is quarterly reporting, however, in increasing the reporting frequency by either accessing monthly or weekly revenue as well as monthly or weekly user base information for modelling may improve the robustness.

5.5 Recommendations

The recommendations from this study can be grouped into three themes: Recommendations to improve model robustness, recommendations to reduce mixed conclusiveness and comparability constraints as well as recommendations for future studies.

5.5.1 Recommendations to improve model robustness

Based on the study by Hove (2016) and this study we observed that adjusting the revenue to only consider network revenue makes a difference in the findings. For Hove, the adjustment for Tencent further proved the significance of Metcalfe's law relative to other laws and in this study the combination of changes in the frequency of the data, the sampling period and adjustments to revenue resulted in Sarnoff's law being found to be the most suitable law, closely followed by Odlzyko's law. Given that these differences, for future research I would recommend the continued adjustment of revenue line for more accurate observations. The robustness of the models and research can be improved by increasing the frequency of the data observation. The increase in the frequency can be achieved through using monthly revenue and monthly active users reported on monthly where available or weekly or daily data where available.

As highlighted in the study limitations, there is an ability to improve on the data sampling selection to present more representative view of emerging markets and for the industry views. For emerging markets, I would recommend that the sampling of geographical location is represented by the geographical distribution of platform businesses. Depending on the objective of the study this can be done by number of platform businesses or market capitalisation by region and companies in the sample can be selected by means of weighting or potentially selecting representation across all emerging market regions. This will improve the accuracy of the observations relating to emerging markets. To achieve a more representative industry view, modelling methods that enable an industry view that considers multiple companies and is diversified by size are recommended to be used. Modelling methodologies such as multi-level modelling may need to be considered to enable more accurate industry representative views.

It is recommended that when more company data becomes available, these models are run and re-run to ensure are improved through the increase of available observations and are maintained, especially in the instance that industry and company businesses models are continually changing, the suitability of the model may also become impacted.

5.5.2 Reducing mixed conclusiveness and comparability constraints

Hove used the same method to adjust revenue and found Metcalfe's law to be most suited for this study, it was found to be the least suited. Given that there are multiple differences between Hove's study and this study, to reduce the mixed conclusiveness regarding what is contributing to the differences in the finding, it is recommended that the impact of change in frequency is tested with the necessary controls and the inclusion of the quality indicator is also tested with controls. The main control recommended is a control for the period of sampling. To test whether it is due to the change in frequency, the Hove method can be used on Tencent annual data over the same period of this study and to test whether it is the inclusion of the quality indicator-quarterly data can be used to run Zhang et al.'s method without the quality indicator modification over the same period of this study. The outcomes can be compared with the outcomes of this study to gain the relevant insight and conclusiveness.

Inconsistencies in reporting standardisation and data availability in financial and non-financial metrics used for network effects models would require policy changes that would be influenced by the increased use of the variables in research and in practice. In the interim it is recommended that research continues making use of what is currently available to expand the body of studies relating to network effects laws and share the limitations and recommendations that can motivate for changes in reporting standard that enable better informed investment decision making.

5.5.3 Recommendations for future studies

The outcome of the comparative laws test was intended to be the starting point for building a network effects model which can be compared with traditional valuation models. From the outcome of this study, there are still recommendations to narrow and deepen the research regarding network effects, improve the robustness and broaden the industries and other variables considered. The recommendation would therefore be to deepen and narrow the current research prior to broadening the scope and once done, use the insight to still develop a valuation model that takes into consideration the value generated by network effects as well as other

intangible assets. Once this has been completed, the outcome of the new model can be compared with traditional valuation model.

To gain a view of the global applicability of the study findings it is recommended that the methodology of the study is replicated in developed markets as well as other geographical regions in emerging markets. Comparisons of this study with the replications enables the identification of potential new answers based off geographical region and developed markets.

For future studies, I would recommend further exploration of the significance of industry as a determinant variable of network value through the derivation of an industry indicating variable and testing its significance through regression against network value and observing the difference in a model's explanatory power when industry in included. I would also recommend similar significance testing of the inclusion of the variables highlighted by Afuah as value creating revenues beyond network size and give that differences in business models leaned on in this study to substantiate the differences in the suitability of Metcalfe's law, a variable that considers business model and revenue generation within the business model should be considered. Hove (2016) also starts to explore the quality indicators in networks and there is opportunity to further expand on the inclusion of that perspective in network effects modelling through finding relevant and improved quality indicators for inclusion in the model.

For the benefit of being able to translate the value of networks into shareholder value and to be able to consider network effects laws alongside traditional valuation models, it is important to consider how cost impacts the value of the network. Further study into unpacking the implications of cost on network value is recommended. In the instance whereby cost is considered it is also important to consider the best approach for the treatment of development costs as they are often upfront costs. In addition to the consideration of development costs, it is recommended that the ability to use other sources of network value are explored for example, profitability. It is also recommended that existing valuation models are considered in conjunction with network effects models to ensure that overestimation of network revenue or cost does not due to double counting when models are used in conjunction to derive company value.

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Appendix A1: Actual quarterly data of Tencent, Alibaba and Baidu

QUARTER	Tencent data		Alibaba data		Baidu data	
	Monthly Active Users (Millions)	Revenue (Millions USD)	Monthly Active Users (Millions)	Revenue (Millions USD)	Monthly Active Users (Millions)	Revenue (Millions USD)
31/12/2015	697	1110	393	4433	N/A	N/A
31/3/2016	762	1205	410	2805	N/A	N/A
30/6/2016	806	1310	427	3579	N/A	N/A
30/9/2016	846	1472	450	3617	N/A	N/A
31/12/2016	889	1569	493	5971	N/A	N/A
31/3/2017	938	1786	507	3750	N/A	2
30/6/2017	963	1888	529	5357	N/A	2426
30/9/2017	980	2293	549	5936	N/A	2752
31/12/2017	989	2358	580	9098	N/A	2892
31/3/2018	1040	2846	617	6318	N/A	2536
30/6/2018	1058	2642	634	8455	N/A	3136
30/9/2018	1083	2677	666	7948	102	3171
31/12/2018	1098	2813	699	11721	149	2967
31/3/2019	1112	3031	721	8658	183	2585
30/6/2019	1133	3046	755	11084	272	2865
30/9/2019	1151	3140	785	10804	292	2995
31/12/2019	1165	3126	824	15682	319	3082
31/3/2020	1203	3600	846	10158	357	2187
30/6/2020	1206	3769	874	14296	342	2670
30/9/2020	1213	4103	881	13803	544	3091
31/12/2020	1225	4220	902	23844	544	3499
31/3/2021	1242	4442	925	19589	558	3159
30/6/2021	1251	4498	939	21699	580	3723
30/9/2021	1263	4683	946	20392	607	3811
31/12/2021	1268	4556	N/A	26300	622	3861
31/3/2022	1288	4585	N/A	21420	632	3368
30/6/2022	1299	4415	N/A	20702	628	3500
30/9/2022	1309	4351	N/A	19161	634	3685
31/12/2022	N/A	NA	N/A	23318	648	3609

Appendix A2: Actual data vs Derived value from value functions for Tencent

QUARTER	Actual (Millions USD)	Metcalfe's function (Millions USD)	Sarnoff's function (Millions USD)	Odlyzko's function (Millions USD)
31/12/2015	1110	813897	1956	1828
31/3/2016	1205	973800	2140	2027
30/6/2016	1310	1087554	2261	2160
30/9/2016	1472	1199354	2375	2285
31/12/2016	1569	1324954	2496	2419
31/3/2017	1786	1473413	2632	2571
30/6/2017	1888	1553017	2702	2650
30/9/2017	2293	1609001	2751	2704
31/12/2017	2358	1637364	2775	2732
31/3/2018	2846	1812053	2919	2895
30/6/2018	2642	1874257	2969	2951
30/9/2018	2677	1963179	3038	3030
31/12/2018	2813	2018331	3081	3079
31/3/2019	3031	2070520	3120	3124
30/6/2019	3046	2149483	3179	3191
30/9/2019	3140	2219498	3231	3250
31/12/2019	3126	2273039	3269	3295
31/3/2020	3600	2422559	3375	3417
30/6/2020	3769	2437086	3385	3429
30/9/2020	4103	2464237	3404	3450
31/12/2020	4220	2514064	3438	3490
31/3/2021	4442	2582662	3485	3544
30/6/2021	4498	2623593	3512	3576
30/9/2021	4683	2670765	3544	3612
31/12/2021	4556	2694509	3560	3631
31/3/2022	4585	2780598	3616	3696
30/6/2022	4415	2827413	3646	3732
30/9/2022	4351	2870232	3674	3764

Appendix A3: Actual data vs Derived value from value functions for Alibaba

QUARTER	Actual (Millions USD)	Metcalfe's function (Millions USD)	Sarnoff's function (Millions USD)	Odlyzko's function (Millions USD)
31/12/2015	4433	3224	5984	5449
31/3/2016	2805	3509	6243	5725
30/6/2016	3579	3807	6502	6003
30/9/2016	3617	4228	6852	6381
31/12/2016	5971	5074	7507	7095
31/3/2017	3750	5366	7720	7330
30/6/2017	5357	5842	8055	7700
30/9/2017	5936	6292	8360	8038
31/12/2017	9098	7023	8832	8566
31/3/2018	6318	7948	9395	9201
30/6/2018	8455	8392	9654	9495
30/9/2018	7948	9260	10141	10050
31/12/2018	11721	10201	10644	10627
31/3/2019	8658	10853	10979	11013
30/6/2019	11084	11901	11497	11613
30/9/2019	10804	12865	11953	12146
31/12/2019	15682	14175	12547	12842
31/3/2020	10158	14942	12882	13236
30/6/2020	14296	15948	13309	13740
30/9/2020	13803	16204	13415	13867
31/12/2020	23844	16986	13735	14247
31/3/2021	19589	17863	14085	14664
30/6/2021	21699	18408	14298	14919
30/9/2021	20392	18683	14405	15046

Appendix A4: Actual data vs Derived value from value functions for BAIDU

QUARTER	Actual (Millions USD)	Metcalfe's function (Millions USD)	Sarnoff's function (Millions USD)	Odlyzko's function (Millions USD)
30/9/2018	3171	142	733	546
31/12/2018	2967	307	1075	868
31/3/2019	2585	464	1321	1111
30/6/2019	2865	1024	1964	1777
30/9/2019	2995	1182	2110	1934
31/12/2019	3082	1404	2299	2139
31/3/2020	2187	1762	2576	2444
30/6/2020	2670	1621	2471	2327
30/9/2020	3091	4092	3926	3991
31/12/2020	3499	4092	3926	3991
31/3/2021	3159	4305	4027	4110
30/6/2021	3723	4651	4186	4298
30/9/2021	3811	5095	4381	4530
31/12/2021	3861	5349	4489	4660
31/3/2022	3368	5523	4561	4746
30/6/2022	3500	5453	4532	4712
30/9/2022	3685	5558	4576	4764
31/12/2022	3609	5806	4677	4885