Essays on digital markets

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Abstract

This thesis consists of five essays that relate to digital platforms/markets. The first essay provides a literature survey on digital platform competition and relevant competition policy. The second and the third essays study the indirect effect of software/application quality on hardware/tablet demand in the asymmetric competition between the closed platform (Apple iOS) and the open platform (Google Android), and analyze the effects of possible policies by platforms/regulators. While the second essay develops a theoretical model to set up the predictions, the third essay tests these predictions empirically using product-level data on tablet PCs and applications in five European countries. In a similar context of a closed platform versus an open platform, the fourth essay investigates the trade-off between quality and variety that platforms face when choosing the software quality standard. Finally, the fifth essay examines the merger strategies and evaluates the ex-post effects of mergers and acquisitions on innovation measured by patents in the cloud computing market.

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Chapter 1

Introduction

The booming of digital technologies in the last two decades has attracted a large number of economic researchers, leading to an extensive literature on digital platforms/markets. However, there are still many aspects of digital platforms/markets that we have not understood or investigated (Katz 2019). In this thesis, we aim to tackle the area in the literature on digital platforms/markets where there has been little attention from economic researchers.

In the first chapter, we will present an introduction to the literature on digital platforms with a focus on competition and competition policy. The aim of this chapter is not to deliver an exhaustive literature review of all related topics in digital platform literature. Instead, our target is providing to the readers an overview of platform markets and the most important research topics related to competition issues and competition policy, as well as the key gap in the literature. Specifically, the chapter will analyze the special features of digital platforms, which make them different from traditional firms. Then we will discuss how these features affect the competition in the platform market and the recent debates about three main areas of competition policy: market definition, market power, and merger policy.

The next three chapters will focus on the hardware-software market and exploit the role of software quality. The previous literature on digital platforms has largely ignored the impact of quality in digital platform markets, even though this is one of the competitive strategies of platforms (Rysman 2009). These three chapters also contribute to the small branch of the literature on competition on the platform, where platforms play a role as regulators. In Chapter 3, we will develop a simple theoretical model of the hardware-software market where there is oligopoly competition between a closed platform, which produces the hardware and controls the software (Apple iOS) versus an open platform, which licenses the operating system (Android) for free to many other hardware producers and only control the application store. Using the Hotelling and Salop model of horizontal product differentiation, we exploit the asymmetry between the two platforms and examine whether this causes an asymmetric impact of software quality on platform demands, prices, and profits. We find that the software quality has larger impacts on the hardware demand, prices, and profits of the closed platform than the open platform. Thus, it suggests that the closed platform has a higher incentive to control for software quality. This will set up the hypotheses, which will be tested empirically in Chapter 4.

In Chapter 4, to test the hypothesis proposed in chapter Chapter 3, we study the impact of application quality on the competition between Apple and Android producers in the tablet PC market. we construct a structural discrete choice demand model following Berry et al. (1995) and Grigolon & Verboven (2014). We model the competition in a nested structure where there are three segments: Apple products, Android products, and outside goods. Our model, by incorporating the interaction between consumer income and prices, also allows for the heterogeneity in consumer taste towards prices. Our main objective is to identify the impact of application quality on tablet demand with application quality is measured by the average user rating as in previous literature. We estimate this model using the combination of tablet characteristics data, application data, and demographic data in five European countries: France, Germany, Italy, Spain, and the UK. Then we take the advantage of the structural approach to conduct two counterfactuals of two policy interventions: 1) Platforms control quality by removing 10% of the lowest quality apps, 2) Platforms impose interoperability/compatibility by allowing all the applications to be available in two stores. Our main findings are: first, there is a significant positive indirect effect generated by application quality on tablet demand. Second, the exclusion of the lowest quality applications has positive impacts on the demand and profit of the tablets on the own platform but negative impacts on the tablets of the competing platform, and these impacts are larger for Apple than Android. Third, imposing interoperability/compatibility will favor the tablet producers in the platform with lower average application quality, and enhance consumer welfare.

While in the two above chapters, application/software quality is treated as exogenous, Chapter 5 contributes to the literature by allowing software quality to be determined endogenously by the platform. In this chapter, we investigate the trade-off between software quality versus variety in the similar context of the second chapter, where a closed platform is competing with an open platform. Consumers are of two types: low-income, who are price-sensitive and care only about software variety but not quality, and high-income, who are not price-sensitive and value quality over variety. Platforms may have an incentive to tighten their quality control to attract more high-income users, who care more about quality than variety. This leads to the reduction of software variety, thus forming the trade-off. We adopt a similar model of horizontal product differentiation as in Chapter 3 and find that when consumer valuation for software quality is sufficiently high, the closed platform would choose a higher software quality standard, and attract more higher-income users than the open platform. The opposite is true for the open platform when it would choose a lower software quality standard and attract more software variety than the closed platform.

The final chapter contributes to the emerging literature on the impacts of mergers on competition and innovation in digital platform markets. The biggest five firms running platform business, Google, Amazon, Facebook, Apple, and Microsoft (GAFAM) have undertaken a large number of mergers in recent years, which raises significant concerns about potential negative impacts of these mergers on competition and innovation. Although there are several theoretical works, which provide great insights into these merger activities and how they affect the incentive to innovate, there has been a lack of empirical analysis addressing the exact question of how mergers affect innovation in digital markets. This chapter will tackle this gap by providing an ex-post analysis of merger and innovation in the cloud computing market, which is one of the fastest-growing and innovative digital platform industries. The cloud computing market is also peculiar since there are three of the biggest tech firms competing aggressively: Amazon, Microsoft, and Google. We exploit the combination of data on mergers, firms characteristics, and patents, and aim at first investigate the mergers strategies by big tech firms in the market, then second empirically analyse whether mergers promote innovation in the market. The descriptive evidence shows that there is a difference in the merger strategies by the two groups of firms in the market. While the leading firms are less active in acquiring other computing firms and tend to buy young start-ups, the niche firms are more active and prefer to acquire well-established cloud computing firms. In the next analysis, we employ the DiD (difference in difference) estimator combined with propensity score matching to estimate the causal impacts of mergers on the innovation of merged entities measured by patents. The results suggest that there is no evidence that merger activities have negative impacts on the innovation activity by merging firms. Additionally, we examine the heterogeneous impacts of mergers on the innovation by different groups of firms: leading firms vs niche firms, and multi-sided platform (MSP) firms vs non-MSP firms. We find that mergers have positive and significant effects on the innovation measured by patents of leading firms and MSP firms compared to niche and non-MSP firms. This is consistent with the theoretical literature on the relationship between mergers and innovation, which states that in some specific cases, mergers can lead to a higher level of innovation.

Chapter 2

Competition and competition policy in digital platform markets: a literature survey

2.1 Introduction

Given the recent rapid growth of platforms and their proliferation in the media, one may think that platform is a modern business model. However, this is not true since the original idea of the platform is actually simple and dates back in time. The platform's origins came from the purpose to facilitate the connection and communication between economic agents. For instance, traditional fairs create opportunities for merchants and buyers to meet and trade directly. By constructing this connection, traditional platforms benefit agents by saving their cost of finding and matching with another group of agents; in return of their intermediation, platforms earn profits from fees that need to pay to access or to use. Differently from digital platforms, traditional platforms would have to incur a high fixed cost to set up their business, such as brick-and-mortar stalls or printing factories. This is why for a long period of time, the platform's presence remained limited within several markets and regions, and the platform model was not applied to many businesses. The advances of communication and information technology in the internet era have solved these issues and led to the emergence of a new generation of platforms: digital platforms. Thanks to this new technology, digital platforms can operate the connection and communication between agents without the physical presence, and thus reduce a large amount of cost and improve significantly the efficiency. Merchants and buyers do not need to meet in some physical place to trade as they can do that online via virtual marketplaces.

Now, platforms have influenced and changed how we study, work, entertain, or even our habits and behaviour. Consumers enjoy many high-quality services offered by platforms at zero prices like search, messages, calls, or video watching, etc. Digital platforms not only bring great benefits to individuals but also create plenty of business opportunities. The European Commission emphasizes the crucial role of online platforms:

"Online platforms are strong drivers of innovation and play an important role in Europe's digital society and economy. They cover a wide range of activities including online marketplaces, social media, creative content outlets, app stores, price comparison websites, platforms for the collaborative economy as well as search engines. They increase consumer choice, improve the efficiency and competitiveness of the industry and can enhance civil participation in society." [1]

With their growing importance in the economy, digital platforms have attracted large bodies of research over the last twenty years, especially among industrial organisation (IO) and competition economists. Nevertheless, there are still many aspects of digital platform economics, which either lack consensus among IO researchers or are not well understood or are still unexplored. The main reason is that competition in platform markets is more complex because of its unique features, compared to conventional one-sided markets. Besides, although they generate great benefits, platform markets have a tendency of tipping towards monopoly, which can eventually harm competition and consumers. The aforementioned factors all together bring many challenges to competition authorities and regulators to make sure that competition law and regulation can cope with the rapid changes and complexity of platform markets. In this chapter, instead of an exhaustive and generalized literature review[2], we focus on providing a brief literature review of concepts and definitions, main features of digital platforms, the degree of competition, and competition policy in platform markets.[3]

The structure of the chapter as follows: The next section introduces the origins of the economic literature on multi-sided platforms. Then, the third section will summarize the key drivers and discuss four dimensions of competition in platform markets; before discussing competition policy and antitrust issue. The final section identifies key topics worth future research.

2.2 Digital platforms: definitions and features

2.2.1 Definition of digital platforms

Until now, an official definition of digital platforms is not yet confirmed. Broadly speaking, platforms are similar to networks: they connect groups of agents to create additional value through their interaction, which is otherwise not possible in the absence of platforms. For example, social networks like Facebook or Twitter facilitate connections between people in different locations, enables them to interact by posting status, commenting on each other posts, sharing photos, video, etc. Without social networking platforms, people certainly would not receive the value of such types of connections. When we have only one group of agents interacting via a platform, these platforms are called one-sided; instead, when the interaction is between different groups of agents, we have two-sidedness or multi-sidedness. A majority of digital platforms are either two-sided or partly two-sided.[4] Therefore, for some economists,

[1] https://ec.europa.eu/digital-single-market/en/online-platforms-digital-single-market.

[2] For more detailed and generalized literature survey on platforms and digital markets, see Robson (2005), Rysman (2009) , Sanchez-Cartas & Leon (2018), and Goldfarb & Tucker (2019).

[3] For a narrow and specialized literature survey on platforms, see Parker & Alstyne (2016) (Platform strategy), Calvano & Polo (2020) (market power, competition and innovation), Jullien & Sand-Zantman (2020) (competition and competition policy).

[4] Amazon is a one-sided platform for some products but two-sided platform for some other products. See Rysman (2009).

this feature is very crucial to define a platform, and they often refer platforms as two-sided platforms or multi-sided platforms or sometimes two-sided/multi-sided markets: *"many if not most markets externalities are two-sided"* (Rochet & Tirole 2003), *"Platform businesses compete in multi-sided markets"* (Evans 2003), etc.

The earliest works in economics studying two-sided platforms are seminal papers by Parker & Alstyne (2000, 2005), Rochet & Tirole (2003, 2006), Caillaud & Jullien (2003), Evans (2003), Armstrong (2006), Parker & Alstyne (2000) and Caillaud & Jullien (2003), although the two latter works do not mention the term two-sided platform.[5] These authors have attempted to give some useful insights in defining multi-sided platforms/markets, which is complemented later by Rysman (2009) and Hagiu & Wright (2015). Table 2.1 summarizes the several widely used definitions of two-sided/multi-sided platforms/markets. As can be seen, there is no consensus among the authors in terms of concept/definition. Each definition has its own flaws and has been criticised later by other authors.

While several authors usually refer to two-sided or multi-sided markets, others only use the concepts of two-sided platforms or businesses. The latter group argues that it is hard to find a pure two-sided market with only two-sided platforms competing. In most cases, it is typically the competition between one-sided pipeline firms and two-sided firms. Most authors define two-sided markets/platforms based on indirect network externalities. We will discuss this in more detail in the next section but roughly speaking, indirect network externalities occur when the value of participation in a platform of one group of users depends on the participation of users in the other group.

Although indirect network externality is an important feature in forming a two-sided platform, the definition based on this has some problems as argued by Rysman (2009) and Hagiu & Wright (2015). First, indirect network externality is not unique to two-sided platforms/markets. For example, traditional consulting firms are one-sided but there is possibly an indirect network effect as customer's willingness to choose a consulting firm depends on the number of qualified consultants they have, and a qualified consultant is more likely to choose a firm that has more customers. Therefore, the approach of defining a multi-sided platform based on the indirect network effect may lead to a very broad or over-inclusive definition. Second, indirect network externalities may not exist or only come from one group to the other but not vice versa. In the case of editorial platforms where academics, editors, and referees interact through the publication process, there is no indirect network effect since the adoption decision depends solely on the editors. Additionally, for newspaper platforms, the cross-network effect only has one direction from advertisers to readers, since readers may do not value advertisers, but advertisers have a high valuation for readers. Hence, the indirect network externality is not sufficient to define multi-sided platforms. Hagiu & Wright (2015) suggest that the more important condition is the direct interaction between two groups of users, which means they should control the essential terms of their transaction like prices, payment types instead of the platform. This is crucial to distinguish multi-sided platforms from one-sided firms like traditional consulting firms, which control the transaction terms of the two groups. According to this condition, supermarkets

[5]Parker & Alstyne (2000) study the operating system such as Linux, and Caillaud & Jullien (2003) study the matchmaking market.

are not a two-sided platform as they decide the prices, marketing, etc, but some economists would disagree with that. The other criteria are that each group needs to be 'affiliated' with the platform, which implies that the users in either group join platform intentionally to interact with the other group. This view is shared by Jullien & Sand-Zantman (2020)s' definition. This is to distinguish multi-sided platforms from input/contractor firms. Input firms provide services to multi-parties like raw material suppliers, producers, distributors, vendors, and these parties also interact directly. However, their purpose of affiliating to the input firm is to receive needed inputs rather than interacting with other parties. Although these authors do not have the same way of defining multi-sided platforms, there is still a common feature in their definition: platforms play a central role to enable and facilitate two or more distinct groups of agents interacting via them.

2.2.2 Features of digital platforms

Strong network effects

There are two types of network effects: direct and indirect. Users benefit more from joining a platform when there are more users in that platform because they can have more interaction with other users. This is called direct network effects. Direct network effects in digital platforms can be very strong as users rarely bear any cost to join, thus platforms can attract a large number of users in a short period, and the larger the number of users, the stronger the network effects are. However, the ability to multi-home/switch to another platform can mitigate network effects. For example, if many people use several texting platforms such as Skype, Whatsapp, Viber, etc., the benefits of joining a platform do not depend much on the number of users on that platform. When a digital platform is multi-sided, the network effects can be indirect as they can occur between different groups of users. Consumers receive indirect network effects (externalities) from buying on Amazon when there are more vendors selling products since they can choose from a wide range of varieties and qualities. On some occasions, indirect network effects are generated from consuming complement products, such as hardware and software. For instance, smartphone users enjoy more benefits from the app store if there are more and higher quality developers. The more users join the app store, the more incentive developers have to sell their apps in that store, which improves the varieties and quality of apps, and subsequently increases the number of users. Filistrucchi & Klein (2013) describe this process as the positive feedback loop, which can exaggerate the size of indirect network effects, and scale up rapidly the user base of the platform in a short time.

However, network effects are not always positive. For instance, consumers may find advertising annoying, thus, the more advertisers on the other side of newspaper platforms, the more negative indirect externalities they receive. Another example is the matchmaking market. Dating site users have more opportunities to match if there are more of opposite sex users joining but have less if there are more same-sex users. In this case, while the indirect network effect is positive, the direct network effect can be negative due to congestion effect. Congestion is often the result of the platform facing a capacity constraint, as too many users connecting at the same time can deteriorate the platform service quality. According to Evans (2012), these negative externalities can be mitigated by setting a limit to how many results and advertisements can be displayed to users. Finally, in the market where users consume complementary products offered by the other group of agents, indirect network effects can turn from positive to negative when the number of agents in the other group becomes excessive. In the beginning, smartphone users enjoy more benefits when there are more mobile applications in the store. However, when the number of mobile applications becomes too large, for example, in Google Play Store the number of apps rose dramatically from 100,000 in 2010 to over 2 million in 2016. This increases the search cost of users to find the app they need, which, at its turn, generates a negative indirect network externality. Recognizing this, Google recategorized the apps in its store in March 2014 to make it easier for users to search (Ershov 2018).

Low marginal cost and economies of scale

In contrast to many traditional industries, online platforms with digital products can serve a large number of users with very low or almost zero marginal cost (Varian et al. 2004, Scott-Morton et al. 2019, Parker et al. 2020). For example, Google may have spent some cost to set up its email service but then could serve extra millions of Gmail users with a minimal expense. Hence, the cost of running platform services does not increase proportionally with the number of consumers as in traditional businesses. Furthermore, there are economies of scale when a large number of consumers effectively decreases the average cost that digital platforms spend. This is a huge advantage of digital platforms and it enables us to explain why digital platforms can grow to a very large scale in few years, in contrast to decades of traditional firms to gradually invest, develop and expand.

Table 2.1: Summary of multi-sided platforms/markets definitions in economics literature

Paper	Definition of Multi-sided Platforms/Markets
Rochet & Tirole (2003)	A market with network externalities is a two-sided market if platforms can effectively cross-subsidize between different categories of end users that are parties to a transaction.
Evans (2003)	Multi-sided platforms coordinate the demands of distinct groups of customers who need each other in some way.
Wright (2004)	Two-sided markets involve two distinct types of users, each of whom obtains value from interacting with users of the opposite type over a common platform. In these markets, platforms cater to both types of users in a way that allows them to influence the extent to which cross-user externalities are internalized.
Jullien (2005)	At the intuitive level, the concept of two-sided market refers to situations where one or several competing "platforms" provide services that are used by two types of trading partners to interact and operate an exchange.
Armstrong (2006)	Many markets involve two groups of agents who interact via "platforms," where one group's benefit from joining a platform depends on the size of the other group that joins the platform.
Rochet & Tirole (2006)	Two-sided (or, more generally, multi-sided) markets are roughly defined as markets in which one or several platforms enable interactions between end-users and try to get the two (or multiple) sides "on board" by appropriately charging each side.
Evans & Schmalensee (2008)	These businesses serve distinct groups of customers who need each other in some way, and the core business of the two-sided platform is to provide a common (real or virtual) meeting place and to facilitate interactions between members of the two distinct customer groups.
Rysman (2009)	Broadly speaking, a two-sided market is one in which 1) two sets of agents interact through an intermediary or platform, and 2) the decisions of each set of agents affects the outcomes of the other set of agents, typically through an externality.
Evans (2012)	Multi-sided platforms create value by bringing two or more different types of economic agents together and facilitating interactions between them that make both agents better off.
Hagiu & Wright (2015)	MSPs have two key features beyond any other requirements (such as indirect network effects or non-neutrality of fees): 1) They enable direct interactions between two or more distinct sides. 2) Each side is affiliated with the platform.
Jullien & Sand-Zantman (2020)	Platforms, just like classical intermediaries, act as matching devices, allowing each side of the market, or at least one side of the market, to find the best agent on the other side—that is, the one that generates the highest surplus.

Zero monetary price

While zero monetary pricing is very rare in traditional markets, many services offered by digital platforms are free, e.g. search, map, social network, which give consumers a lot of benefits. This peculiarity allows big tech giants to defend their market power: how can they harm consumers when everything is free? However, this zero-price strategy does come from profit maximization rather than good intentions. According to OECD (2018), a firm's motivation of offering free products/services includes acquiring user's data, attracting user's attention to monetize via advertising, developing the consumer base, altruism, and other long term's objective. Scott-Morton et al. (2019) suggest that platform may have an incentive to subsidize users on one side if their participation attracts paying parties on the other side. For instance, as advertisers value users much higher than users value advertisers, there is a strong indirect network effect from users to advertisers, which makes additional users more valuable than additional advertisers. Therefore, a platform can maximize its profit by charging zero price to attract a large number of users first and extract profit from advertisers later. The special feature of low marginal and distribution costs discussed above, also allows platforms to maintain a zero price for consumers before reaching a critical user base and monetize via advertising.

Besides, providing free services does not mean that digital platforms obtain no benefit from consumers. Consumers do not pay the monetary price but need to provide their personal information to gain platform access, and their usage of platform services is also monitored by platforms. Platforms can extract data and either sell to advertising firms or use this to improve their service quality and attract more users. Shapiro & Aneja (2019) estimate that the value of Americans' personal information gathered and used by major online platforms, data brokers, credit card, and healthcare data companies from 2016-2018 is around $76 billion. To some extent, these personal data benefit platforms more than free services benefit users. In this case, the equilibrium prices must be negative, meaning that platforms would, in principle, be willing to pay users for their data. For instance, Microsoft rewards users each time they use its search engine, Bing. But these micro-payments are typically not applicable, and platforms normally set the price to zero (Scott-Morton et al. 2019).

2.3 Digital platforms competition

2.3.1 What drive digital platforms competition

Network effects

As discussed above, the network effect is a pillar to the success of digital platforms. Platforms with a significant amount of user base can exert strong network effects and grow exponentially, as a large number of users would keep attracting other users to join, and so on. This suggests that strong network externalities in platform markets can lead to a winner-take-all situation or market tipping towards a monopoly, at least when there are no congestion effects. Several digital platform markets have a dominant platform: on the online search, we have Google, on the social networking, we have Facebook, on the online marketplace, it is Amazon, etc.

However, the story of success is not so simple. Platforms can only attract additional users if there are enough users of the same type or different types on the platform for them to interact (critical mass), but the problem is how to get enough of these users in the first place. This is well-known as the chicken-and-egg problem that the platform must solve to launch successfully. This problem is mentioned in early multi-sided platform literature by Caillaud & Jullien (2003), Rochet & Tirole (2003, 2006), Armstrong (2006). While Rochet & Tirole (2003) mention that platforms must "get both sides on board", Rysman (2009) claims that to survive, platforms need to reach a critical mass of users. Jullien (2011) suggests that platforms can subsidy one side of the market to get this side onboard first (divide), and then use this side to attract the other side (conquer). For instance, Google first offered its search service for free to attract a large number of users, then advertisers became willing to pay for displaying their ads on the platform. Parker & Alstyne (2016) summarise different strategies that platforms have used to overcome this issue: subsidy, seeding, and marquee users, micro-market launch, and piggy packing.

For the above reason, network effects create a high barrier to entry as a potential entrant would find it difficult to compete with an incumbent, who already has a large consumer installed base. In the presence of strong network effects, consumers have little incentive to switch to a new entrant, unless the entrant can provide superior quality products or services, which is also very difficult when the incumbent has a large consumer database to improve their service quality to the highest level as possible. Even when the entrant can offer such high quality, consumers still hesitate to join the new platform if there are some switching costs, or do not expect other users to do so. Given the difficulty of gaining enough market share to cover the cost, the potential entrant has no incentive to enter the market. This illustrates why in several markets, such as search or social media, there are always very few entrants, even when the incumbents make a lot of profits (Scott-Morton et al. 2019). Thus, all platforms know that once they become a monopoly in the market, it will be very hard to challenge their market position (Parker et al. 2020). This leads to the competition "for" the market instead of "in" the market, which means platforms even accept tons of profit loss to compete intensely at the beginning and extract larger rewards after winning the market. For instance, Scott-Morton et al. (2019) provide an example that Uber and Lyft have suffered year-after-year losses to compete fiercely and try to win the market. To conclude, network effects can generate anti-competitive effects by creating high-barrier to entry but also can be pro-competitive as they stimulate fierce competition between platforms.

Economies of Scale

As mentioned, digital platforms enjoy economies of scale when serving a large number of customers, and thus also have increasing returns to scale. According to Parker et al. (2020), this feature amplifies the first-mover advantage of the incumbent and reduces the potential profit of the new entrant. This is another barrier to entry as the incumbent has a huge advantage over the new entrant: it is less costly for them to offer higher quality products. As a result, the incumbent can even charge a high-quality product/service at a lower price than the entrant.

Whereas, the entrant, who has not reached the large scale of customers as the incumbent, will undertake high costs to produce such high-quality products/services but does not have enough return to cover these costs. Foreseeing this situation, potential entrants would opt for not entering the market to challenge the incumbent firm.

Product differentiation

Given it is unprofitable to step in the market and compete with a strong incumbent in the same kind of products/services, the potential entrant can avoid this by differentiating from the incumbent (Crémer et al. 2019). This can be done by offering superior quality products or services (vertical differentiation) or targeting a niche market by providing products with specialized prices/features to a certain group of consumers (horizontal differentiation). In the former case, Zhu & Iansiti (2012) suggest that if the entrant enters the market successfully, it can keep gaining more market shares and eventually take the lead from the incumbent despite the strong network effect. Google and Facebook both offered higher quality service and leapfrogged the incumbent after stepping in the online search and social media market. In the latter case, this strategy can help the entrant to secure a sufficient user base to survive in the market, before stepping up and challenging the market leader (Crémer et al. 2019). For instance, to compete with the strong market leader, Youtube, in the video sharing platform, Tiktok offered users a unique feature to make short videos and share immediately on the app, with focus on dance, music, comedy or entertaining. The effect of product differentiation on digital platform competition is perhaps similar to traditional markets and, in this respect, it may have both negative and positive impacts on the degree of competition in the market. On the one hand, platforms differentiate themselves from others to soften competition and protect their market power, as well as profits. On the other hand, product differentiation can be pro-competitive by neutralizing the network effects, facilitating market entry, and preventing the market from tipping towards a monopoly. Rysman (2009) explains that it is the reason while in many digital platforms market, we have several firms coexist even when strong network externalities are present.

Multihoming and compatibility/interoperability

When digital platforms are horizontally differentiated by (providing different features/services or having a different customer base, etc.), users have more incentive to join several platforms instead of one, to either enjoy larger network effects or larger benefits from different services. This is called "multi-homing", which has been studied extensively in the multi-sided platform literature: Rochet & Tirole (2003, 2006), Armstrong (2006), Doganoglu & Wright (2006), Armstrong & Wright (2007), Belleflamme & Peitz (2019). Multi-homing can be seen in many digital platform markets, for example, consumers can use several social networks, and advertisers typically can display their ads on different platforms. When agents on one side multi-home, agents on the other side may find it not necessary to do so, because they only need to join one platform (single-home) to interact with all users on the other side. The case of platforms where one side multi-home and one side single-home is called: "Competitive Bottleneck" (Armstrong 2006).

Armstrong (2006) and Armstrong & Wright (2007) study the competitive bottleneck model, and claim that the ability to multi-home soften the platform competition on the multi-homing side of the market and make platforms compete aggressively for single-homed users.

On the other hand, multi-homing can mitigate network effects and avoid market tipping in favour of one firm. This allows more rooms for firms with smaller users base competing with the market leader, thus lower the entry barrier created by network effects. According to Doganoglu & Wright (2006) and Farrell & Simcoe (2012), multi-homing is one way to achieve partial compatibility/interoperability. Compatibility/interoperability allows users to use the same products/services or interact with the same group of users on the other side across different platforms without any restriction. Consumers benefit compatibility/interoperability from enjoying larger network effects and varieties of complements. Compatibility facilitates the entry to digital platform markets as potential platform entrants can avoid the high cost of achieving user installed base and developer entrants can avoid the cost of entry.

Data

As discussed in the previous section, consumers typically provide their data to access free services offered by platforms; this enables platforms to extract ”big” data on user information. Platforms now can use machine learning techniques to analyse this big data and learn more about consumer preferences or behaviours. Scott-Morton et al. (2019) explain that with such knowledge, digital firms first can attract more advertisers as the data helps advertisers to target their ads to the right group of users. They can also use this data to improve their products/services to attract more users and obtain more data. This process of data feedback loop can amplify the network effects and drive the market towards a monopoly, as was done for example by Google in the search market or Facebook in the social media market. Also, platforms can capitalize their learning of user data and existing user base to envelope their business to a new market, as observed by Eisenmann et al. (2011) and Condorelli & Padilla (2020). For example, Google started its business as a search engine platform, but now it operates in multiple markets such as maps, flight search, price comparison, smart devices, cloud computing, etc. This is indicated by economists as “economies of scope”, which means that large firms with data received from their existing services can enter adjacent markets more efficiently than smaller potential entrants (Scott-Morton et al. 2019).

As data play a very important role in driving innovation, targeted marketing, improving product and service quality, an incumbent owning most of the data will create a “chicken and egg” problem for the entrant to solve. To compete with the incumbent and gain enough user base, the entrant must offer at least as high quality as the incumbent’s services, but they would need enough user information from a similar consumer base as the incumbent to improve their services to such quality. Katz (2019) suggests that if user data have significant commercial value and can not be substituted or shared across platforms, this can forms a ”data barrier to entry” and thus, contributing to the high concentration in digital platform markets.

2.3.2 Competition among digital platforms

Competition among digital platforms can be intense in markets where several platforms coexist, or soft when there is a dominant platform. Platforms can compete in several dimensions, and in this section, we provide a brief survey of four important aspects of platform competition: pricing, quality, governance strategies, and asymmetric competition.

Pricing Competition

The literature on multi-sided markets has largely been devoted to studying price competition between platforms. Prices in multi-sided platforms do not only depend on the marginal cost and elasticity of demand on one side but also the decision of participation of the other side. Moreover, a price cut on side (A) leads to a higher demand of that side, which results in higher demand on the other side, and again attracts more side (A) users. In other words, this implies the effect of a price cut in the presence of indirect network effects is more pronounced than in traditional markets. Generally speaking, platforms can choose between several price schemes: registration/membership fee, transaction fee, usage fee or combination of these (two-part tariff). While the transaction fee is mostly used in the credit card industry, registration/membership fee is widely used by digital platforms, for example, Amazon Prime, Youtube Premium, etc. These pricing strategies are discussed in depth by early seminal papers: Rochet & Tirole (2003, 2006), Armstrong (2006) and Caillaud & Jullien (2003).

Although these works study two-sided markets under different settings and pricing schemes, they all agree that the price structure depends largely on how the two groups of agents value each other, and this also applies widely to other digital platforms. If group A values group B more than group B values group A, then group B should be subsidized, and group A should be charged high prices. This is because one additional user in group B would generate greater network externality than one additional user in group A.[6] Since group B users are more valuable to platforms, they would compete aggressively for this group, while ignoring the other group. Intense competition leads to lower prices on group B users, which is very similar to what happens in traditional markets. However, in platforms markets, the strong network externality can dampen the prices below marginal costs for one side, which is not possible in traditional ones. This helps to explain in the many instances, when network effects are at the extreme, prices charged by platforms even go to zero or become negative.

These above seminal works are extended and complemented by Hagiu (2006, 2009), Weyl (2010), and Tan & Zhou (2020). Hagiu (2006) argues that the previous works may not suit the two-sided platform markets where there is one side accessing the platform first instead of two sides joining the platforms simultaneously. For example, in video game consoles, developers have to adopt one platform and write the games for it before consumers buy the console, because no users would buy a console without any game. Hagiu (2006) considers the a sequential game, where sellers arrive first to the platform, followed by the adoption of buyers,

[6]The context that one side single-homes and one side multi-homes implies implicitly this: the side that multi-home should value the other side more, as they join more than one platform to interact with more users of the other side.

and shows that in the equilibrium, a monopoly platform has an incentive not to commit to the buyer prices, whereas, competing platforms may commit when multi-homing is possible. Hagiu (2009) extends the Armstrong (2006) competitive bottleneck model by adding intra-platform competition and allowing network effects to be endogenous as they are determined by consumer preferences for the variety of complementary products. The paper concludes that consumer preferences for product variety are important in determining the optimal price structure as, if it is strong enough, a price cut to attract more users will be not effective. Although addressing the multi-homing case, none of these previous work studies the case when both sides of platforms multi-home, for instance, users normally use several social networks, and advertisers also put their apps on these platforms. Bakos & Halaburda (2020) make a rare attempt to tackle this gap as they study the price competition when both sides are multi-homers. The authors prove that when this is the case, the common strategic choice of subsidizing the price charged to one side is no longer valid.

One of the most cited papers in the literature on platform pricing is Weyl (2010). Based on the same context as Rochet & Tirole (2006), the paper models how the platform opts for the participation of both sides by introducing an "insulating tariff": To ensure the participation on both sides, the platform can charge the price to group A taking into account the participation rates chosen by the platforms. The "insulating tariff" is practically often used in digital platforms, for instance, when the platform sells advertising spaces for advertisers (whose price depends on the participation rates of advertisers), and also charges advertisers per user's click on the ad (whose price depends on the participation rates of users). The main contribution of Weyl (2010) is to provide new insights into why platform prices can be very high or very low. Since the monopoly platform has an excessive incentive to internalize the network externalities of marginal users rather than average users, Weyl (2010) argues that profit maximization would lead to not only classical price distortion (market power), but also Spence's price distortion (network effects). He proves that the Spence's distortion can lead to a very high/low price for group A users compared to the social optimum if the interaction value of average users in group B is greater/smaller than that of marginal users. This result confirms that the user's heterogeneity matters in determining optimal price structures in platform markets. Tan & Zhou (2020) generalise the Armstrong (2006) model by studying platform competitions among $n \geq 2$ platforms, and analyse the impacts of competition measured by the number of competing platforms on price, which have been largely ignored in the literature on multi-sided platforms. Their results show that the conventional negative relationship between competition and price may not hold in the multi-sided platform market in the presence of cross-network effects. They find that in this case, there would be a U-shape relationship between competition and consumer surplus, whereas the competition and profit relationship is inverted U-shape.

While there are the extensive theoretical works on price competition in platform markets, there are limited empirical studies testing these price theories. Most of the empirical works on pricing in platform markets studies newspaper industries: Kaiser & Wright (2006), Argentesi & Filistrucchi (2007), Filistrucchi & Klein (2013). These papers all confirm the pricing theories, that readers (single-homers) are subsidized and pay the prices below the marginal costs as advertisers (multi-homers) have a high valuation for them. Jin & Rysman (2015) provide useful insights into platform pricing in the context of sports cards conventions: when consumers are charged positive prices, dealers' prices are not sensitive to competition. However, if the price charged to consumers is zero, the prices charged to dealers drop significantly with the competition.

Quality Competition

As pointed by Rysman (2009), another important dimension of platform competition is the investment in quality. Despite the importance of quality aspects in platform competition, there has been little attention in the literature on how platforms compete in quality. Viecens (2006) studies the two-sided markets with both sellers and buyers having preferences for service quality, and confirms that there is an equilibrium where asymmetric platform coexists. A similar conclusion is reached by Gabszewicz & Wauthy (2014) in a setting where platforms are vertically differentiated and there exists inter-group externalities. Tellis et al. (2009) is the earliest paper to emphasize the importance of quality in driving the demand for software platforms. By estimating a reduced-form model in which market shares depend both on software quality (review score) and network size (number of software users), they conclude that quality is more important than network effects in attracting users to join software platforms. Zhu & Iansiti (2012) study both theoretically and empirically whether platform quality or user-installed base impact on the success of entry of a new entrant. They show that when the indirect network effect is weak/strong, the success of the new entrant to the markets is quality-driven/installed base-driven. Based on the survey data on 2553 firms in seven European countries, Dutch-Brown (2017) estimates the impacts of platform quality on demands for both sellers and buyers, and on the efficient quality level by social planners. His findings emphasize that while higher quality platforms attract more buyers and sellers, platform service quality for sellers is likely under-invested, especially when sellers multi-home. While other works normally employ user ratings or reviews as the measure for quality, Liu (2017) has constructed a structural model to estimate the application quality in two stores: iTunes and Google Play. The estimation results show that Apple's app quality distribution is more concentrated, while Google Play app quality is wider spread. In other words, Google Play platform has a larger share of low-quality apps. This difference in quality distribution influences the entry decision of application developers. Low-quality apps existing in Google Play store induce more low-quality developers to enter, whereas, high-quality apps in Apple store have negative impacts on the entry of both developer types. This explains why the number of applications in Google Play store has increased more rapidly than in the iTunes store. In summary, quality competition among digital platforms is very important as platforms with superior quality can dominate the market, like Google or Facebook, which leads to higher concentration and market power. Therefore, further works along this line of research is necessary.

Governance strategy competition

Platforms can use "governance" rules as observed by Boudreau & Hagiu (2009) to regulate competition among affiliated users and maximize their profit. The governance rules can take place in various forms: the degree of openness, quality control, ranking and recommendation system, search filters, access to API, rules of payment and dispute resolution, information disclosure, rules of how users of different groups can interact, etc. Although these instruments have played a very important role in platform competition, there has been surprisingly little attention to this area of research, with only a few studies addressing the platform's strategies of controlling quality, openness, and information management. When users in one group value not only variety but also the quality of users in the other group, to maximize its profit, the platform may have an incentive to set quality control or reduce platform variety (Hagiu 2011, Casadesus-Masanell & Hałaburda 2014, Liu 2017).[7]

One of the important platform governance strategies is the degree of openness as discussed in the previous section. According to Boudreau (2010), platform openness is to ease any restriction on the use, development, and commercialization of the platform and system. Greater openness can promote more competition on the user's side, which leads to higher quality and innovation. Eisenmann et al. (2009) categorizes openness strategies into horizontal and vertical strategies. Horizontal strategies include licensing, joint standard-setting, and technical interoperability with rival platforms. Whereas, vertical openness control involves backward compatibility to previous platform versions, platform and category exclusivity, and absorption of complements. Boudreau (2010) studies the relationship between platform openness strategies and innovation captured by the rate of hardware product development. Interestingly, he finds that the innovation rates increase initially when platforms change from closed technology to granting access to hardware developers, then decrease when platforms open further and grant control to developers, thus forming an inverted U-shape relationship. Parker & Alstyne (2018) propose a model to determine the optimal levels of platform openness: the amount of intellectual property that can be exposed to developers and the amount of external innovation by developers being taken over by platform for other developers to build on. Their results show that the optimal level of platform openness decreases in the intrinsic value of the platform but increases in the value, the size of developers, and the reused resource.

The role of platform information management has been discussed in seminal papers by Hagiu & Halaburda (2014) and Jullien & Pavan (2019). While the former examines whether platforms have an incentive to disclose the price information to users, the latter focuses on the impacts of pre-launch and post-launch information policies on profits, welfare, and consumer surplus. Hagiu & Halaburda (2014)s' main finding is that the platform with more market power will be more profitable when users are informed rather than uninformed, whereas the opposite is true when the platform has less market power. The intuition here is that disclosing price information to consumers can exaggerate consumer responsiveness to price reduction, which amplifies the demand increase. This only benefits a platform with high market power (monopoly) as they can fully capture this increase in the demand, while platforms in an intense competition can not. Jullien & Pavan (2019) distinguish between the information strategy before and after the launch of platforms. Pre-launch information via advertising, blogs, forums, etc. helps users form their expectation of the participation on the opposite side and decide whether to join.

[7] See more detailed discussion of these papers in Chapter 5.

The post-launch strategy is to disclose the information of previous participation on the other side. The authors prove that the impacts of the pre-launch information strategy depend on whether the expectation of users on each side about the participation on the other side is aligned or misaligned. In the former case, the effects on profit and total welfare are positive, and the effect on consumer surplus is negative. Whereas, the opposite is true in the latter case. Finally, they show that such disclosure about earlier adoption of users on the opposite side has a positive impact on total welfare, but the effect on profits is ambiguous. To sum up, since most previous works dedicated to study the price competition and largely ignore non-price dimensions, platform governance strategies and non-price instruments have a huge potential for future research.

Asymmetric platform competition

The mainstream of literature on multi-sided platforms has largely studied monopoly platforms and competing platforms, all with the same groups of participating agents (symmetric competition). However, in the real world, platforms can decide whether to grant or limit access to a specific group of user, which leads to the setting of asymmetric competitions as platforms may not compete for the same group of agents (Eisenmann et al. 2009). For example, while iOS (Apple) is a closed platform and does not lend the license to any other smart device producers, Android (Google) is an open platform that licenses the operating system free to other hardware manufacturers. Hence, Apple only manages two sides of the market: developers and users, whereas, Google Android controls the participation of three sides: producers, developers, and users. These strategies have opposite implications on the competition: the open strategy (Google Android) leads to more intense competition, whereas, the close strategy (Apple iOS) softens competition and preserves market power. According to Evans & Schmalensee (2012), asymmetric competition happens when a multi-sided platform competing with a one-sided firm on any side, or multi-sided platforms competing on several but not all sides.

The coexistence of platforms with different business models leads to the emergence of a branch of theoretical studies on competition between closed (proprietary) versus open platforms, with seminal papers: Economides & Katsamakas (2006), Casadesus-Masanell & Ghemawat (2006), Casadesus-Masanell & Llanes (2011), Llanes & de Elejalde (2013), Casadesus-Masanell & Llanes (2015).[8] Another aspect of the asymmetric competition is that platforms may compete in the same market for one group of users but in different markets for the other groups. For example, Youtube and Facebook both compete for online advertisers but on the user side, while Youtube competes in the online video sharing/streaming market, Facebook competes in the social media market. This makes digital platforms' competition even more complex and difficult to analyse.

[8]See detail discussion of these papers in Chapter 5.

2.4 Competition policy in platform market

In this section, we will outline the main issues and debates of competition policy in digital platform markets with three aspects: market definition, market power, and merger control.

2.4.1 Market definition

Market definition or defining the relevant market is a "cornerstone", the first step of any antitrust analysis, which helps to identify whether competitors either in product scope or geographical scope have enough constraints on the dominant or merging firms, so that they are less profitable from raising the price or lowering quality (Evans & Schmalensee 2012).[9] Market definition is a useful tool to set up the context for assessing market power or evaluating the competitive effects of antitrust conduct. Hence, how the relevant market is defined will have critical impacts on the outcome of the antitrust case. For example, if the market is defined too narrow, we may easily condemn that the conduct is anti-competitive, while it is not. This is called type I error-false positive. On the other hand, the too widely defined market may lead to a clear of anti-competitive conduct, which is type II error-false negative.

Identifying the relevant market for digital platforms is a much more difficult job than traditional business because of its multi-sidedness and network externalities. Since a platform can internalize the indirect network externalities, it can raise the prices on one side and lower the prices on the other side at the same time. This makes the conventional small but significant non-transitory increase in price test (SSNIP)[10], which is normally used to identify the relevant market, inapplicable. Economic researchers have realized this and propose alternatives to the one-sided traditional SSNIP test. Emch & Thompson (2006) design a modified version of SSNIP in the context of the credit card market, which uses the total price charged to both sides for the test, assuming the relative prices to adjust accordingly. However, this approach is problematic when applied to platform markets where not only the price level matter but also the price structure, as criticised by Filistrucchi (2008). Evans & Noel (2008) propose using two-sided Critical Loss Analysis (CLA), which take into account the indirect network effects, to define the relevant market instead of SSNIP. They find that failing to consider the role of indirect network externalities leads to the underestimation of merger effects, and the biases are bigger when the size of network effects is larger. The approach of Evans & Noel (2008) is criticised by Filistrucchi (2008) as it does not allow the hypothetical monopolist to adjust the price on the other side, which would lead to a too widely defined market. Therefore, Filistrucchi (2008) suggests that the test should be performed by allowing the hypothetical monopolist to raise the price first on each side, and each time the monopolist also optimally adjusts the price of the other side. Besides, the difficulty of defining the platform market also comes from the fact there is no consensus way to define multi-sided platforms or interpret the definition of

[9]Within the scope of this chapter, we only focus on the product market since the main issues and debates about platform market definition is about how to define the product market.

[10]This test is implemented by keep adding products to the set of products owned by a profit-maximizing hypothetical monopolist until the profits are not estimated to decline following a small but significant increase in the price. The set of products owned by the monopolist in the last simulation constitutes the relevant market. See more details in Werden (2003).

multi-sided platforms. Therefore, it would be hard to identify whether the market definition tools should be applied in the traditional way or the adjusted way to fit the multi-sided context. For this reason, the gap here that needs further work by economists is to refine and develop a consensus definition of multi-sided platforms for antitrust analysis.

There have been several debates about market definition when the monetary prices charged to consumers by digital platforms are zero. Since the profit on the consumer side is zero, the one-sided approach may mistakenly conclude that this does not constitute a market (Evans 2003). However, ignoring one side of platform markets will leave out half of the story, since zero monetary price is normally the result of intense competition on the user side in the presence of strong indirect network effects from users to advertisers/developers/etc. If this is the case, the zero-price side should be considered as a part of the market instead of a separate market. On the other hand, we can still witness the case when free of charge services does not constitute the market, for example, Wikipedia (Crémer et al. 2019).

The most important debate recently about defining the relevant market in digital platform cases is whether one should consider all sides of platforms as one market or multiple interrelated markets. As Wismer & Rasek (2018), Katz (2018) and Wright & Yun (2019) observe, there are two schools of thought: the "single market approach" which claims that all sides must be taken into account as one integrated market[11] and the "multiple markets approach" which proposes that platform market can still be defined as the similar way as in one-sided market with the additional consideration of indirect network effects.[12] The main reasoning of the first school of thought is the interdependence between different sides of the market via indirect externalities, thus the product market must include all the sides of the platform.

Additionally, this approach is also consistent with the economic theory of multi-sided platforms that platforms maximizing profits by internalizing cross-network externalities, as pointed out by Ratliff & Rubinfeld (2014). The second school of thought criticised this approach and argues that the services offered by platforms to different sides are different and the interests of each side are not aligned, thus each side should be considered as a separate market. Katz (2018) also points out another problem with the single market approach as this approach does not account for the different competition condition between different sides. For instance, while platforms have monopoly power over the multi-homing sides, they have to compete intensely for single-homed users.

Despite the opposite arguments, the two schools of thoughts still share the broad consensus in the case of "non-transaction" platforms[13], like media platforms, which both agree that there should be defined as multiple interrelated markets. Wismer & Rasek (2018) and Wright & Yun (2019) analyse both of these approaches and reach the same conclusion that each approach has both pros and cons, and none of the schools of thoughts is fully right or wrong. The main advantages of the single market approach are the consistency with the multi-sided platform

[11] See Evans (2003), Emch & Thompson (2006), Filistrucchi & Klein (2013), Ratliff & Rubinfeld (2014), and Ward (2017).

[12] See Katz (2018), and Katz (2019).

[13] Filistrucchi & Klein (2013) divide platforms into transaction platforms (credit card type), which two sides interact directly via the platform and make a transaction, and non-transaction platforms (media type), which two sides do not interact directly via platforms.

theory and platform profit maximization reality, and the ability to capture explicitly the indirect network effects among different sides of the market. However, this approach depends on identifying multi-sided markets in the first place, in which there is still a lack of consensus in the way researchers/practitioners defining multi-sided platform or even interpreting the same definition (Katz 2019). Additionally, the single-market approach tends to analyse a single 'net' price like in Emch & Thompson (2006), which is very abstract and difficult for the court to interpret and apply (Wright & Yun 2019). Another shortcoming of this school of thought is the difficulty of incorporating the market shares of platforms on two sides since these can be asymmetric. On the other hand, the multiple market approach can avoid these shortcomings by a very straightforward market delineation, which does not depend on whether a platform is multi-sided or not. Moreover, this approach can account for all the heterogeneity of competition on all sides of the platform. Nevertheless, defining all sides of platforms as separate markets can easily lead to the omission of the interdependent relationship between different sides, the damages of this omission can be critical from the consumer welfare perspective when the analysis discounts the cross-network effects. Finally, most previous studies only focus on platforms with the participation of two groups and offer one type of product/service. However, several platforms can have more than two sides, for instance, application stores with users, developers, and advertisers. Additionally, there are platforms covering a wide range of different products/services (multi-purposes platforms), which competing with different competitors in different markets. Hence, how to define the market in these cases requires further analysis to fill this gap.

2.4.2 Market power

The natural tendency towards the winner-take-all market and the rising of big tech platforms like Amazon or Google has raised a lot of concerns about the issue of market power in digital platform markets. Market power is generally interpreted as the firm's ability to set the price above the competitive level, which is commonly the marginal cost in the conventional market (Evans & Schmalensee 2012).

Because of its special features, measuring the market power of a digital platform becomes more challenging and complex than conventional markets. It is not that we cannot use traditional market tools to measure platform market power, but we need to adapt these tools in the digital platform context with cautious consideration of all the factors that may impact the degree of market power. Market share is a very simple but common tool to assess market power in the traditional market. However, this tool may become misleading if the market is not well defined. Since there is still no consensus in the market definition approach, market share may be not a reliable measurement for market power. Moreover, as pointed out by Evans & Schmalensee (2012), measuring market shares in digital platform markets can be challenging as it is not clear how to compute market shares with all sides of the market taken into account. Additionally, the market share of platforms on each side may not be symmetric, which will be hard to interpret the degree of market power. One can think of weighting the market share of each side by sale units or profitability of that side when measuring the market power. For instance, Tremblay (2018) suggests that although Nintendo has a smaller market share for the game console, it still has great market power as it has the largest shares in games, the side generating 8-10 times of sale units than the console side. Finally, computing market share becomes more difficult when there is the competition between platforms and customers, for example, in Amazon Market Place platform, there are products by Amazon competing with products by other vendors participating in the platforms. Therefore, in this case, identifying market shares needs special care to account for this competition as the common measurement of market shares using the customer base is no longer valid.

The most widely used approach to measure the market powers of platforms in both empirical and theoretical literature is margins and profitability. In the non-merger context where one focuses on the level rather than the change in market power, Rochet & Tirole (2006), Weyl (2010), and Tremblay (2018) have provided theoretical rationale of measuring margins by alternative multi-sided versions of Lerner index[14], which account for the price-cost markup in all sides of the platform. Argentesi & Filistrucchi (2007) and Song (2012) develop a structural model of the two-sided market in the context of newspaper and magazine respectively and estimate the price-cost margins with a modified formula, in which indirect network effects are taken into account. Although economists have developed useful and advanced tools to measure price markup as a proxy for market power, this measurement still raised questions about its interpretation. As Evans & Schmalensee (2012) observe, digital platforms usually incur fixed costs and very small marginal costs, thus, to cover the fixed costs, firms must have positive margins. Therefore, what level of margins indicating high market power would depend on the level of fixed costs, which is unfortunately not observed or difficult to estimate in most cases. In the merger cases, a useful back-of-envelope tool to predict the changes in platform market power is upward pricing pressure (UPP), developed by Farrell & Shapiro (2010). The idea of UPP comes from two possible effects of the merger on merger entity pricing behavior: 1) the upward pressure as the results of the reduced competition after the merger, and 2) the downward pressure caused by any synergies generated by the merger (lower marginal costs, etc.). Then, we can predict whether the price would go up by estimating the difference between the two effects. Based on this approach, Affeldt et al. (2013) extend the UPP measure to apply in a merger case between two two-sided platforms, this uses six diversion ratios to account for the indirect effects between two sides of the market. The advantage of the UPP measure is its calculation does not depend on the assumption of competition in the market or market characteristics, which makes this a useful screening tool to evaluate the unilateral effect of a merger. Hence, this measure can be computed even when the marginal costs or price elasticities are not available by using consumer survey data on all sides. Besides these above tools, when data is particularly not available for estimating markups or Lerner index, Collyer et al. (2018) suggest that preliminary analysis can use other standard tools to assess market power, such as looking at the competition on the multi-homing vs single-homing side or switching costs or barrier to entry and expansion. Although previous works have provided useful tools for

[14]The Generalised Lerner Index (GLI) proposed by Tremblay (2018) can be easily implemented in practice as a quick tool to assess market power level when administrative data on firm's profits, fixed costs, and revenues are available.

assessing market power, the question remaining is how firms exercise their market power, as recognised by Jullien & Sand-Zantman (2020). Previous literature typically finds evidence that firms exploit their market power by setting a high mark-up. However, in the platform market, there is the case of zero-monetary prices and firms have many other instruments to practice their market power, for instance, Amazon uses its dominant position to exploit consumer data from third party sellers. Therefore, it requires further both theoretical and empirical works on firms exercising market power via different strategies. To sum up, measuring market power in digital platform markets is more challenging, and requires more comprehensive tools and data than the traditional market. Competition authorities need to take cautious steps when assessing market powers of platforms with care for platform special features like the interdependence between two sides, multi-homing vs single homing, etc.

2.4.3 Merger

Whether merger policy needs to be reviewed and reinforced to adapt to the fast-changing platform market has been a hot question in recent years.[15] The reason for this is a rapidly increasing number of mergers and acquisitions by a dominant platform without any scrutiny from competition authorities. It is mainly because these M&A cases were taken place at the time the young start-up had not yet generate the revenue over the notification threshold in the European Union Merger Regulation ("EUMR"). Even when several mergers were scrutinised[16], competition authorities often opt to avoid the risk of incorrect intervention (false positive-type I error) rather than the risk of incorrect clearance (false negative-type II error) and approve all these mergers (Argentesi et al. 2019). This raises a lot of concerns about the costs of some false-negative cases that might have been approved and many other cases have not been investigated. These concerns have drawn special attention from researchers and policymakers recently about merger control in the digital era.

Prat & Valletti (2019) propose a stylized model of oligopoly competition in the social media platform market, where platforms compete for user's attention and sell target ads to advertisers. The study highlights that the merger between two platforms would damage consumer welfare more when there is less overlapping user base between the two. Cabral (2018) studies the relationship between merger policy and innovation in the context of digital markets where a dominant firm (giant) is competing with fringe firms (dwarfs). The paper explains the distinction between radical innovation, which is the innovation rewarding firms the dominant of the market, and incremental innovation, which is the innovation leading to higher-level technology in the market. Cabral (2018) finds the theoretical evidence that a stricter merger policy to restrict big tech from buying small firms would encourage more radical innovation and discourage incremental innovation. The rationale here is when the merger is allowed, the start-up has more incentive to invest in incremental innovation to be bought by the dominant firm, whereas it has less incentive to invest in radical innovation and replace the dominant. This view is shared by both Bryan & Hovenkamp (2020) and Bourreau & de Streel (2020), which also claim the

[15]See Gilbert (2020) for a detailed discussion about this question.
[16]For example, Facebook/Instagram, Google/Waze, Microsoft/Skype, Apple/Shazam, etc.

incentive of a start-up to distort innovation to favor the dominant firm and thus increases the price of the buyout. In the context of oligopoly competition between a leading dominant and a lagging firm, Bryan & Hovenkamp (2020) claim that the dominant firm has the incentive to buy a startup and obtain the exclusive right to the invention, which strengthens its dominant position and widens the gap with a lagging firm. To avoid this and promote competition in the market, Bryan & Hovenkamp (2020) suggest two possible antitrust interventions: blocking the acquisition or allowing it under the condition that the dominant firm must resell the invention license at a reasonable price to the lagging firm. Bryan & Hovenkamp (2020) finally conclude that while the former intervention would lead to a decrease in the innovation since the start-up has less reward for its invention, the latter would mitigate the damage of the merger on both competition and innovation level in the market.

There is a debate recently about whether big tech platform mergers facilitate entry and innovation.[17] One claims that potential entrants have more incentive to innovate and enter the market if they expect to be bought by a big tech firm, thus merger would promote new entries and innovation level.[18] Other claims that this is not always the case, as big tech mergers can undermine the participation of users in the new platform if users expect the new platform to be bought. This decrease the reward of new entrant if entering the market, hence, results in less entry and innovation or a "kill zone".[19]

Another significant paper studying the impact of big tech merger on innovation is Motta & Peitz (2020). They propose a very simple model of a dominant incumbent and a potential entrant, with an innovative on-going project but may not have enough resources to develop it successfully with a probability. The dominant firm with no financial constraint decides whether to buy the entrant, and whether to develop its project after the acquisition. The authors show that the merger is anti-competitive in two cases: first, the incumbent does not develop the project (killer acquisition), and second, the potential entrant has sufficient funding to complete the project but still being bought, which will reduce the potential competition while has no difference in innovation. Although M&A of the five biggest digital platforms: Google, Amazon, Facebook, Apple, Microsoft (GAFAM) draw special interests from many researchers, only two papers so far have studied explicitly their merger activities: Argentesi et al. (2019) examining Google, Amazon, and Facebook acquisitions and Gautier & Lamesch (2020) investigating all five firms.[20]

These papers suggest that merger control enforcement so far has not been able to cope with challenges in the digital market, but the CAs need to review whether more can be improved within the existing framework before considering the change in regulation and legislation. This view is shared by most other researchers and practitioners. More detail of policy review and recommendation of merger control in the digital market can be found in the three influential reports about competition policy in the digital market: Crémer et al. (2019), Scott-Morton et al. (2019) and Furman et al. (2019). Finally, although all of these above papers provide

[17]See detailed discussion of this debate in Chapter 6.

[18]See Bryan & Hovenkamp (2020) and Bourreau & de Streel (2020).

[19]see Kamepalli et al. (2020).

[20]See discussion of these two papers in Chapter 6.

useful insights and policy recommendations of recent mergers by big digital platforms, there is still a lack of research that examine explicitly the impact of these mergers on the competition and innovation —which has important implications on the assessment and re-enforcement of competition policy.

2.5 Potential future research topics

Although the literature has been growing incredibly over the last two decades, there are still many gaps and rooms for future research to tackle. In this section, we will highlight several key areas that should be addressed by future research.

Measuring network effects and platform quality. Despite a large number of empirical works in the literature on indirect network effects, quantifying network effects remains challenging as previous literature only focused on a very limited number of markets such as online newspapers or video games. The measurement of network effects is crucial in antitrust analysis, especially assessing market power and evaluating the effects of mergers on prices. Therefore, more theoretical or empirical works to study measuring network effects in other digital platform markets will be good references and provide tools for competition authorities in antitrust cases. The remaining issue when quantifying indirect network effects in the platform market is the role of quality. Conventional works on network effects identify the variety (the number) of complementary products or the number of users in the other group as the only source of indirect network effects. However, several works such as Corts & Lederman (2009) or Kim et al. (2014) have pointed out that quality also matters since higher quality software can bring more benefits to hardware users and thus generate more demand on the user side. Therefore, it is necessary to take quality into account when measuring network externalities in the digital platform market. The next two chapters of my thesis will attempt to tackle this gap by focusing on the role of application quality of the competition in the tablet PC market. How to measure quality is also a remaining issue, since it is not directly observed, and users may have a different dimension for quality across digital platform markets. For example, in search platforms, users may view how quick and precise the search results are as the primary metrics for quality. However, in the food ordering platform, people may value the restaurant coverage and delivery time as the key measures for quality. Therefore, potential future research should develop a more novel approach to measure platform quality and analyze the role of quality in driving digital platform competition.

The role of data in driving digital platform competition. As discussed in previous sections, data has become increasingly important in the digital platform market, where consumer data can be a source of market power and create a barrier to entry. Whereas, whether data can be portable or interoperable also has a significant impact on the competition among digital platforms. Recently, a few remarkable theoretical papers have started drawing its attention to big data in digital platforms: de Corniere & Taylor (2020), Hagiu & Wright (2020), Lam & Liu (2017), Kerber (2019) and Prüfer & Schottmüller (2017). de Corniere & Taylor (2020) and Prüfer & Schottmüller (2017) are the only two papers that analyse the role of big data in driving competition. While the former uses the competition-in-utility framework to assess the different impacts of data on market structure, data-driven merger and privacy policy in two cases: data is pro/anti-competitive, the latter introduces a dynamic model of data-driven network effects and study whether this would lead to market tipping towards an incumbent with the first-mover advantage. Despite these theoretical works addressing the big data and competition in the digital platform market, there are many related issues needed to be tackled in future research. For example, what is the role of big data in driving innovation and quality competition in digital platform markets? Would the ability to purchase user's data from the incumbent facilitate entry and innovation? Is there any competitive advantage when big tech firms are operating in several markets and can combine user data in these markets? We just named a few interesting topics but there are still many more gaps needed to be filled in this literature.

Mergers in digital platform market While previous literature had always devoted its attention to horizontal mergers in platform markets, there is an increasing number of recent works that focus more on the acquisitions of young startups by big tech firms, which is more likely considered as vertical or conglomerate mergers. In contrast with horizontal mergers, these mergers are more easily to escape the scrutiny of competition authorities since the startup normally has not generated enough revenue or the startup does not compete directly with the acquirer at the time of the merger. However, as analysed in the previous sections, these mergers can have potential anti-competitive effects, which would raise the market power of big tech firms and foreclose potential entrants. This causes a strong demand for studying these types of mergers and how the competition authorities should deal with these merger cases. Although there are a significant number of ongoing researches on this topic, there are still many questions that needed to be answered in future research. For instance, recent papers have not provided any empirical evidence of startup acquisitions on the innovation in the market, and whether these acquisitions facilitate or prevent entry. The last chapter of my thesis will contribute to the literature by addressing the former in the context of the cloud computing platform market, the market which has not been well studied in IO literature. Acquisition strategies of big tech firms is another aspect of digital platform merger which should be studied further. Finally, future research should also seek more empirical evidence of data-driven mergers on innovation and competition in the digital platform market.

Chapter 3

The impacts of indirect quality effect in multi-sided platforms: closed versus open

3.1 Introduction

The proliferation of platform markets has attracted economic researchers and practitioners, resulting in the fast-growing literature on multi-sided markets and digital platforms. However, most of this literature has been devoted to studying the equilibrium pricing structure of different market conducts, like monopoly platform or competing platforms, with single homing/multihoming (Armstrong 2006, Rochet & Tirole 2003, 2006). Previous research often neglects that digital platforms can have different business models: they may be closed (proprietary) (Microsoft/Windows, Apple/iOS, video game console platforms, etc.), or open (Google/Android, Linux, etc.). In the tablet PC market, Apple iOS is a closed platform, as it controls both the production of hardware and the operating system used by users to download and install software provided by developers. In contrast, Google Play is an open platform, as it licenses its operating system (Android) free to any hardware producer and only plays a role in the software market. These competing platforms with asymmetric structures are growing rapidly with hundreds of million users worldwide. This has attracted many developers, resulting in exponential growth in the number of software/mobile applications.

Previous literature has highlighted the importance of indirect network effects, generated by the variety (number) of software on demand for hardware (Nair et al. 2004, Clements & Ohashi 2005, Park 2004). However, in the case of the tablet PC market, when the number of applications in the store becomes millions, it is reasonable to believe that consumers would rather care more about the quality than the variety. Thus, the indirect externalities generated by application quality become more important than the variety. Only a few works are addressing this issue, especially in the context of asymmetric platform competition. We tackle the gap in the literature as we study whether asymmetric platform business models lead to asymmetric impacts of the indirect quality effect generated by software on hardware.

We model the platform competition in the context of the hardware-software market where a closed platform competes with an open platform in the presence of indirect quality effects. We aim to derive hypotheses based on our theoretical results which can be tested empirically using tablet and application data in the next chapter of the thesis. Here, we focus on three main research objectives. The first one is about deriving the equilibrium outcomes in the hardware market. The second one focuses on determining from a theoretical perspective on how possible policy interventions that lead to a change in software quality can have impacts on hardware demand, prices, and profits. The last objective is to establish whether there is any difference in impacts between different platform structures.

We will develop a formal theoretical model for the hardware-software industry with the participation of platforms, hardware producers, software developers, and users. We model a specific setting in which there are two competing platforms with different business models: platform 1 is closed, and produces hardware and controls the software store; platform 2 is open and only controls the store, where $n \geq 2$ hardware producers can join for free. In our model, we assume that each hardware manufacturer produces only one tablet model, which is compatible with only one platform, and users only buy hardware compatible with a platform (single-homing). Instead, developers can sell software on both platforms (multi-homing).

We first find that the open platform (Google Android) can obtain more share in the hardware market than the closed platform (Apple iOS) if it's hardware and software quality are not too inferior compared to the closed platform's hardware and software, and vice versa. This may help to explain the fact that, while in the early period Apple dominated both smartphone and tablet PC markets, after several years this leading position disappeared. On the other hand, the closed platform could charge a higher equilibrium tablet price even when it produced a lower quality. This is unsurprising since the closed platform has more market power and does not face the fierce competition between tablet manufacturers producing for the open platform. We examine the impact of software quality on the hardware market by comparing the equilibrium demands, prices, and profits of hardware produced for the two platforms. We distinguish between two types of effects: own-platform effects and cross-platform effects. Our results suggest that the own effects are positive, the cross-effects are negative, and that the own-effects are always larger than the cross-effects.

Previous literature on platform mainly focus on the pricing structure, and often largely ignore the impacts of non-pricing strategies/policies/regulations, which are implemented by either platforms or policymakers. However, these strategies/policies/regulations are very important and have been widely used by digital platforms. For instance, Nintendo limits the number of games that developers can sell on the gaming platform, or Apple used strict quality control to avoid low-quality apps in the store. Hence we aim to fill in this gap in the previous literature by analysing a possible platform governance policy of excluding the lowest quality software and possible intervention of imposing full multihoming/compatibility/interoperability across platforms by policymakers. The analysis of the platform policy is motivated by the fact that platforms have been actively implementing this quality control to improve the average software quality. For example, Apple excludes a large number of low-quality apps (copycat, spam, or non-updated apps) from Apple App Store in 2016, and Google Play followed the same policy in 2017. Therefore, it is important to understand the reasoning behind this policy by platforms. Also, the previous literature has discussed the role of multihoming/compatibility/interoperability on platform competition, but all the previous works mainly focus on asymmetric platforms. We aim to complement previous studies by analysing the impacts of imposing full multihoming/compatibility/interoperability on the equilibrium outcome of asymmetric platform competition.

Our results suggest that the quality control policy by platforms generates an increase in market share and profits, as well as a larger price increase for the closed platform than for the hardware producers in the open platform. Whereas, the intervention that imposes full compatibility/interoperability by the policymaker has ambiguous impacts on hardware producers in the two platforms. The direction of the impact depends on whether the average software quality of the closed platform is higher or lower than that of the open platform. If higher, the intervention would increase the market share and profit of hardware in the open platform, while decreasing the market share and profit of hardware in the closed platform. If lower, the opposite is true.

We start by discussing a basic model on the developer side with the preliminary purpose of providing the intuition about platform choice adoption by developers and the formulation of their software quality. Then we introduce our main model, which focuses on the hardware market concerning the role of software quality. We consider a two-stage game for hardware producers and users. At stage one, users choose which platform to join given the hardware prices and software quality. In the second stage, if users chose the closed platform in the first stage, they would buy the hardware produced by that platform. If users chose the open platform in stage one, they need to decide which hardware to buy within the open platform. We solve this game by backward induction.

The structure of the chapter is straightforward: previous literature is discussed in section 2. The model is introduced with a detailed discussion in section 3. Section 4 discusses the possible quality control policy by platforms and interoperability intervention by the policy maker and sets up the hypotheses to be tested in the next chapter. Section 5 concludes.

3.2 Literature review

Indirect network effects have received attention in the economics literature since the early nineties. One of the first papers, Church & Gandal (1993), adopts a CES demand model to examine the software provision by developers. The authors find that the higher software variety (measured by the number-aggregate count of available software) drives higher hardware sale, thus there are indirect network effects from software to hardware. Since then, many empirical articles have provided evidence of indirect network effects in various industries. For example, Clements & Ohashi (2005) and Corts & Lederman (2009) focus on the video games industry, Park (2004) studies the VCR industry, Ackerberg & Gowrisankaran (2006) investigate the ACH banking industry. In more detail, Park (2004) quantifies the indirect network effects generated by the variety of complementary products but does not model explicitly the provision of complementary products. Whereas, Clements & Ohashi (2005) model both hardware demand

and software supply and investigate the effect of software variety on hardware price over the product life cycle. The literature on indirect network effects tends to traditionally concentrate on the indirect effects caused by the variety (the aggregate count) of complementary products and ignore the role of quality. Nevertheless, quality effects are relevant, especially in digital platforms. For example, Tellis et al. (2009) provides empirical evidence that software quality plays an important role in driving higher user demand for software. Additionally, Binken & Stremersch (2009) shows empirically that superstar software (exceptional high-quality software) has a positive significant impact on hardware sales. The conceptual difference between the indirect effects generated by variety and quality of complementary software on hardware sale is that in the former case, consumers have the same valuation for all software and only care about the total number of software (variety), whereas, in the latter case, consumers have a different valuation for each software, i.e. consumers receive higher utility from higher quality software (Kim et al. 2014). When quality matters, high-quality software would have a larger impact on hardware sales than low-quality software. Therefore, we need to account for the role of software quality in quantifying the indirect network effects. Corts & Lederman (2009) is among the earliest papers which take into account the indirect network effects from the game quality. By employing hit titles of video games as the measurement of quality, they find that the availability of hit titles of video games has a significant positive indirect network effect on the demand for game consoles. Interestingly, their results also suggest that and cross-platform positive effects from the user installed base of a platform on the software provision of the competing platform.

This chapter contributes to a thin branch of platform literature that looks at the role of product quality. Hagiu (2011) introduces a simple two-sided platforms model, taking into account the impact of average software quality on the indirect network externalities. His paper focuses on whether the platform has an incentive to exclude low-quality agents to increase the average quality on one side; so as to attract more agents on the other side. A similar study by Casadesus-Masanell & Hałaburda (2014) show the effect of restricting the number of software to increase average quality, which is seen as an attempt to reduce the competition on the developer's side. However, both studies only examine platform incentive to implement such policy, without analysing explicitly the impacts on the equilibrium outcome.

We aim to fill this gap by analysing what the equilibrium outcome would have been if a similar policy is imposed by platforms, with possible indirect externalities on a hardware market where two competing platforms adopting different business models. Differently from the above papers, Claussen et al. (2013) study the social media platform Facebook and provide empirical evidence of a different platform strategy to improve the software quality: Facebook rewards highly engaging apps (high-quality apps) in the platform. In terms of empirical research, to the best of our knowledge, Kim et al. (2014) is the first paper to quantify the indirect network externalities by capturing the variation in software quality explicitly. They estimate the effects of software quality on the hardware demand and use a quality-differentiated measure to compute the indirect network effects. Their main finding is that if the quality dimension is not captured, the indirect network effects can be under/over-estimated, depending on the variation in software availability for high/low-quality. Additionally, Nosko & Tadelis (2015) emphasize the role of quality externalities in the eBay platform. Using both empirical and field experiment analysis, they find that the user's belief in high-quality sellers can generate reputation externalities on the buyer side. Although the previous literature has supplied empirical evidence of the role of quality in driving indirect network effects, limited articles provide theoretical insight into the role of quality-induced network externalities. Dutch-Brown (2017) estimates the impacts of platform quality on demands for both sellers and buyers, and the quality-efficient level by social planners. His findings emphasize that while higher quality platforms attract more buyers and sellers, platforms offering quality for sellers are likely under-invested, especially when sellers multi-home.

This chapter contributes to the literature by developing a theoretical model to analyse the indirect network effects generated by software quality on the platform market. The main literature on platforms often assumes that platforms are symmetric and draws little attention to the case when platforms have an asymmetric structure. However, analysing the different platform paradigms is important, since asymmetry may lead to different equilibrium outcomes and implications than in the symmetric case. This stimulated a new stream of literature, studying the proprietary/vertical integrated platform versus open platform. Our paper also contributes to this small growing literature. Early papers by Casadesus-Masanell & Ghemawat (2006) and Economides & Katsamakas (2006) are based on the context of the PC software industry with the competition between Windows and Linux. Both papers assume that the open platform earns zero profit and the business model choice is exogenous and, instead, focuses on determining the market equilibrium, as well as profit and welfare analysis. The difference between these two studies is that the former only analyzes one-sided pricing, while the latter considers the two-sided pricing strategy imposed by Microsoft. Following those, later papers Casadesus-Masanell & Llanes (2011) and Haruvy et al. (2008) investigate the profit-seeking platform decision of whether to keep a software proprietary or let it be open, but do not study the direct competition between proprietary and open platform. On the other hand, Sacks (2015) and Llanes & de Elejalde (2013) examine the oligopoly competition between the proprietary and open platform and find that there exists an equilibrium where both platform structures coexist. Both papers study the investment levels chosen by firms but, differently, Llanes & de Elejalde (2013) concentrate on the endogenous platform business model, giving platforms the choice of whether to be proprietary or open. However, none of these above works examines the role of indirect quality effects as well as the impacts of policy interventions by platforms/policymakers in the competition between the proprietary/closed platform versus the open platform.

Similar, in the spirit, to previous work, our paper also studies the direct competition between a closed platform and an open platform. We contribute to the previous literature by analysing the impact of application quality as well as two possible policies by platforms/policymakers on the equilibrium market outcomes in the peculiar tablet PC market where there are two asymmetric competing platforms. Following Armstrong (2006), we model the competition in both sides of platforms by classic Hotelling horizontal product differentiation and show how the application quality affects the equilibrium tablet prices, market shares, and hardware profits, thus have implications for platform policy to the market outcome.

3.3 The model

For notation convenience, we will use superscript h for the tablet producer's side, superscript s for variables referred to the application. Subscript 1 will be used for the closed platform; subscript 2 for the open platform.

3.3.1 Developers and software quality

In this section, we develop a simple model to illustrate the developer's choice of entering the platform depending on their quality. Commonly, high-quality developers produce high-quality software. Thus, the adoption decision of developers would endogenously determine the level of average quality in the platform. Since in this chapter we focus on analysing the impacts of software quality on the hardware market, we do not solve for the full equilibrium outcome on the developer side. The scope of this chapter is to illustrate the developer's platform adoption choice, which depends on the quality of the software produced by the developer as well as the horizontal differentiation between the two platforms. The developer's platform adoption rule, allows us to formulate the average software quality in the two platforms and identify the factors that can affect that average quality. Then, we can study the impacts of policy interventions aimed at changing the software quality on the hardware market.

The developer d chooses to publish their software of quality z_d^s in the platforms that give them positive profits. In this setting, we assume that z_d^s is uniformly distributed with support $(\underline{z}^s, \overline{z}^s)$. Denote with p_i^s ($i \in \{1, 2\}$) the lump sum access fee charged by the platforms (stores) to each developer. Developers willingness to publish in the platform is affected both by the expected number of users joining that platform (the network size), determined by Q_i^{he} , and by the revenue that the developer can extract from each user, which depends on the quality of the software z_d^s and the willingness to pay of users for the platform i, θ_i. The developers incur the cost f_i of developing software and are charged the lump sum access fee p_i^s to join the platform i. Unlike for the user side, we allow the developer side to be both horizontally and vertically differentiated. The vertical differentiation comes from the different quality levels of their software, ranging from $\underline{z}^s$ to $\overline{z}^s$. At each level of quality z_d^s, the developers are uniformly distributed alongside the Hotelling line, and the two platforms are located at the two extreme points zero and one (horizontal differentiation). The pay-off for a developer d located at $x^s \in (0, 1)$ when selling their software in each platform and are:

$$
\begin{aligned}
V_1^s &= z_d^s \theta_1 Q_1^{he} - p_1^s - f_1 - x^s t_2 \\
V_2^s &= z_d^s \theta_2 Q_2^{he} - p_2^s - f_2 - (1 - x^s) t_2
\end{aligned}
$$

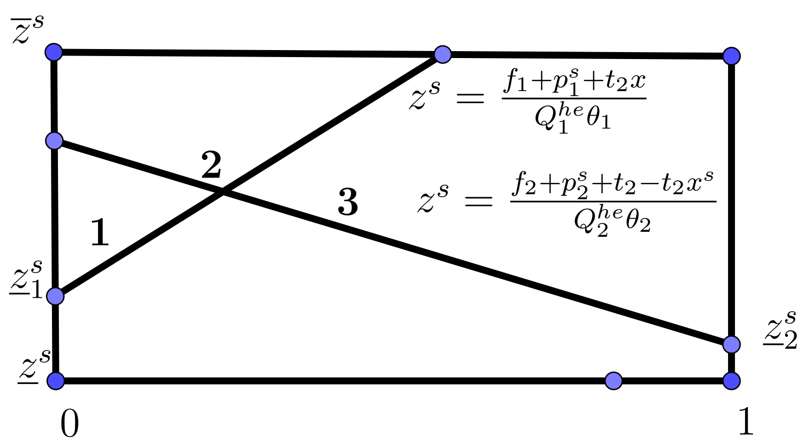
The parameter t_2 is the degree of platform differentiation on the developer side, which means that $x^s t_2$ and $(1 - x^s) t_2$ are costs due to the differentiated platforms . Each developer faces the decision to join the platform that gives him positive payoff or choose not to join any platform if accessing either platform give him negative profit. The developer receives positive payoff from two platforms if:

$$\begin{aligned} (a) \quad V_1^s &> 0 \Leftrightarrow z_d^s > \frac{f_1 + p_1^s + t_2 x^s}{\theta_1 Q_1^{he}} \\ (b) \quad V_2^s &> 0 \Leftrightarrow z_d^s > \frac{f_2 + p_2^s + t_2 - t_2 x^s}{\theta_2 Q_2^{he}} \end{aligned} \tag{3.1}$$

Instead of calculating explicitly the equilibrium, we present one of the possible equilibrium outcomes in Figure 3.1. In this figure, the area above the line $z^s = \frac{f_1 + t_2 x^s}{Q_1^{he}\theta_1}$ (area 1+2, where condition (a) is satisfied) highlights the developers choosing platform 1, whereas the area above the line $z^s = \frac{f_2 + p_2^s + t_2 - t_2 x^s}{\theta_2 Q_2^{he}}$ (area 2+3, where condition (b) is satisfied) depicts the developers choosing platform 2. The overlapping area (area 2) captures multi-homed developers, and the area below the two lines is the share of developers, who do not join any platform because both platforms give them negative profits.

As can be seen in the figure, low-quality developers ($z^s < min\{\frac{f_1 + p_1^s}{Q_1^{he}\theta_1}, \frac{f_2 + p_2^s}{Q_2^{he}\theta_2}\}$) choose not to join any platform since the low-quality software generates low revenues, which cannot cover the cost. By contrast, high-quality developers can publish their software on both platforms. The quality level of developers entering a platform also depends on the distance of developers from that platform. For instance, the developer far away from a platform needs to have quality high enough to enter that platform.

Figure 3.1: Developer shares for two platforms (two platforms are located at zero and one)



Denote the lowest quality level of developers joining two platforms as $\underline{z}_i^s$, with $\underline{z}_i^s = \frac{f_i + p_i^s}{Q_i^{he}\theta_i}$. From the developer adoption equilibrium depicted in Figure 3.1, we can derive the average quality of software in each platform as:

$$z_i^{s*} = \frac{\displaystyle\int_{\underline{z}_i^s}^{\overline{z}^s} z\frac{Q_i^{he}\theta_i z - f_i}{t_2}dz}{\displaystyle\int_{\underline{z}_i^s}^{\overline{z}^s} \frac{Q_i^{he}\theta_i z - f_i}{t_2}dz} = \frac{2Q_i^{he}\theta_i(\overline{z}^s)^2 - 3f_i\overline{z}^s}{3Q_i^{he}\theta_i\overline{z}^s - f_i} - \frac{2-3f_i}{3Q_i^{he}} \tag{3.2}$$

The average quality of software in each platform depends on the number of expected hardware users, their willingness to pay θ_i, and the cost of developing software for the platform. There are several policy interventions by platforms/policymakers that affect average software quality. First, if platforms have a stricter quality check before approving the software, then developers will need to produce higher quality apps, incurring the higher cost f_i. This leads to a higher quality entry threshold z_i^s, which will increase the average software quality. Second, if two platforms become compatible/interoperable, which means developers do not incur additional costs of porting the software to the other platform, then all developers can multi-home (full multi-homing). In this case, the two platforms would have the same average software quality.

3.3.2 The model of hardware market

Users

We assume that the hardware market is horizontally differentiated. Consumers choose the hardware in two stages. In stage one, users decide between which platform to join or not joining any platform (choosing the outside option). In stage two, those that have chosen platform 2 will buy their most preferred hardware among all products produced for platform 2.

Stage 1-Interplatform competition. Denote the quality of hardware compatible with platform 1 and 2 as z_1^h and z_2^h respectively, which assumes all hardware manufacturers selling via platform 2 produce the same quality. After buying hardware, users can download software available in the store (platform) with the average quality z_i^{s*} and the total number of software N_i^s ($i \in \{1,2\}$). As we do not solve for the full equilibrium on both sides of the platform market, in our model, both the number of software and the average quality are exogenous and taken as given. Suppose the expected utility that the consumer receives from consuming software is $\phi(N_i^s) + \gamma_2 z_i^{s*}$, where $\phi(N_i^s)$ has a functional form satisfying the following assumption:

$$\phi'(N_i^s) > 0 \quad \phi''(N_i^s) < 0 \quad \forall N_i^s \tag{3.3}$$

Therefore, for any positive number ϵ close to 0, there exists $\overline{N}_i^s$ such that for any $N_i^s > \overline{N}_i^s$, $\phi'(N_i^s) < \epsilon$. As of our research interest, N_i^s is large that $\phi'(N_i^s) \to 0$. Thus, for a sufficiently large number of varieties, the utility that the consumer receives from software variety is independent of variety. This is a reasonable assumption because when the number of varieties of software is large, the consumer begins to care more about quality than variety. For this reason, we omit the software variety in our analysis to simplify the model without affecting the equilibrium outcomes. The hardware producers set the hardware price at p_1^h and p_{2j}^h ($j = \overline{1,n}$).

Under symmetry, all the hardware produced for the open platform (platform 2) will have the same price p_2^h in the equilibrium. Consumers are assumed to be uniformly located along the Salop circle with the outside option and the two platforms located equidistant from each other at 0, 1/3, and 2/3 respectively. We assume that the net utility of the outside option is normalized to a constant u_0. Note that software is not compatible across platforms. The utilities of users located at $x^h \in [0, 1/3]$ when choosing between the outside options and platform 1, at $x^h \in [1/3, 2/3]$ when choosing between platform 1 and 2, and at $x^h \in [2/3, 1]$ when selecting between platform 2 and the outside option are given by:

$$\begin{aligned} u_{01} &= u_0 - t_1 x^h, \quad u_{10} = \gamma_1 z_1^h + \gamma_2 z_1^{s*} - \alpha p_1^h - t_1(1/3 - x^h) \\ u_{12} &= \gamma_1 z_1^h + \gamma_2 z_1^{s*} - \alpha p_1^h - t_1(x^h - 1/3), \quad u_{21} = \gamma_1 z_2^h + \gamma_2 z_2^{s*} - \alpha p_2^h - t_1(2/3 - x^h) \\ u_{20} &= \gamma_1 z_2^h + \gamma_2 z_2^{s*} - \alpha p_1^h - t_1(x^h - 2/3), \quad u_{02} = u_0 - t_1(1 - x^h). \end{aligned} \tag{3.4}$$

where t_1 is the transportation cost (or product differentiation) parameters that measures the competitiveness in the market. Indifferent consumers of each local competition are given by:

$$\begin{aligned} x_{01}^h &= \frac{1}{6} - \frac{\gamma_1 z_1^h + \gamma_2 z_1^{s*} - \alpha p_1^h - u_0}{2t_1} \\ x_{12}^h &= \frac{1}{2} + \frac{\gamma_1(z_1^h - z_2^h) + \gamma_2(z_1^{s*} - z_2^{s*}) - \alpha(p_1^h - p_2^h)}{2t_1} \\ x_{20}^h &= \frac{5}{6} + \frac{\gamma_1 z_2^h + \gamma_2 z_2^{s*} - \alpha p_2^h - u_0}{2t_1}. \end{aligned} \tag{3.5}$$

We can derive the total user's demand for each platform as:

$$\begin{aligned} Q_1^h &= q_{10}^h + q_{12}^h = \frac{1}{3} + \frac{\gamma_1(2z_1^h - z_2^h) + \gamma_2(2z_1^{s*} - z_2^{s*}) - \alpha(2p_1^h - p_2^h) - u_0}{2t_1} \\ Q_2^h &= q_{20}^h + q_{21}^h = \frac{1}{3} + \frac{\gamma_1(2z_2^h - z_1^h) + \gamma_2(2z_2^{s*} - z_1^{s*}) - \alpha(2p_2^h - p_1^h) - u_0}{2t_1} \\ q_2^h &= \frac{Q_2^h}{n}. \end{aligned} \tag{3.6}$$

Where Q_{h1} is the user's demand for platform 1 (hardware 1), Q_{h2} is the total user's demand for platform 2 and q_{2j}^h ($j = \overline{1, n}$) is the user's demand for each tablet model in platform 2.

Stage 2-Intra-platform competition In this stage, users choose to buy one hardware in platform 2. Assume that in this step, $n \geq 2$ hardware producers in platform 2 are located equidistantly in a Salop circular city with the length Q_2^h, on which users are uniformly distributed on. Firm j ($j = \overline{1, n}$) located at jQ_2^h/n has two competitors located to the left and right, which charging the same price p_{h2} and produce at same quality z_2^h. Suppose that firm j charges the price p_{2j}^h, a user located at a distance x^h between firm j and firm $j+1$ is indifferent between two firms if:

$$\begin{aligned}\gamma_1 z_2^h + \gamma_2 z_2^{s*} - \alpha p_{2j}^h - t_1(x^h - \frac{jQ_2^h}{n}) &= \gamma_1 z_2^h + \gamma_2 z_2^{s*} - \alpha p_2^h - t_1(\frac{(j+1)Q_2^h}{n} - x^h) \\ \Leftrightarrow x^h &= \frac{-\alpha(p_{2j}^h - p_2^h) + t_1 Q_2^h/n}{2t_1}.\end{aligned}$$

Then the demand for each hardware in platform 2 is:

$$q_{2j}^h = 2x^h = \frac{-\alpha(p_{2j}^h - p_2^h) + t_1 Q_2^h/n}{t_1}. \tag{3.7}$$

3.3.3 Profit maximization of hardware producers

The closed platform and the hardware producers in platform 2 will maximize their profits with respect to tablet prices:

$$\begin{aligned}\pi_1^h &= (p_1^h - c)Q_1^h \\ \pi_2^h &= (p_2^h - c)q_2^h.\end{aligned} \tag{3.8}$$

where c is the marginal cost, which is common to all hardware producers. We will solve this by backward induction. First, we solve for the profit maximization of tablet producers in the open platform. As we assume all the tablet produced for the open platform are of the same quality, hardware firm j in platform 2 maximizes:

$$\pi_{2j}^h = (p_{2j}^h - c)\frac{\alpha(p_2^h - p_{2j}^h) + t_1 Q_1^h/n}{t_1}. \tag{3.9}$$

In the symmetric equilibrium, we have the same price, which is a function of the quantity set by all firms producing for platform 2:

$$\begin{aligned}p_2^h &= c + \frac{t_1 Q_2^h}{\alpha n} = c + \frac{2t_1 + 3[\gamma_1(2z_2^h - z_1^h) + \gamma_2(2z_2^{s*} - z_1^{s*}) - \alpha(2p_2^h - p_1^h) - u_0]}{6\alpha n} \\ \Leftrightarrow p_2^h &= \frac{cn}{n+1} + \frac{2t_1 + 3[\gamma_1(2z_2^h - z_1^h) + \gamma_2(2z_2^{s*} - z_1^{s*}) + \alpha p_1^h - u_0]}{6\alpha(n+1)}.\end{aligned} \tag{3.10}$$

Substituting Equation 3.10 into Equation 3.6 we have:

$$Q_1^h = \frac{(2n+3)(2t_1 - 3u_0) + 6c\alpha n + 3(4n+3)(\gamma_1 z_1^h + \gamma_2 z_1^{s*}) - 6n(\gamma_1 z_2^h + \gamma_2 z_2^{s*}) - 3(4n+3)\alpha p_1^h}{12t_1(n+1)} \tag{3.11}$$

Then substituting Equation 3.11 into the profit function, and solving the first order of conditions with respect to p_1^h, yields the subgame perfect Nash equilibrium:

$$\begin{aligned}
p_1^{h*} &= c + \frac{(2n+3)(2t_1 - 3c\alpha - 3u_0) + 3(4n+3)(\gamma_1 z_1^h + \gamma_2 z_1^{s*}) - 6n(\gamma_1 z_2^h + \gamma_2 z_2^{s*})}{6\alpha(4n+3)} \\
p_2^{h*} &= c + \frac{(2n+3)(2t_1 - 3c\alpha - 3u_0) + 6(7n+6)(\gamma_1 z_2^h + \gamma_2 z_2^{s*}) - 3(4n+3)(\gamma_1 z_1^h + \gamma_2 z_1^{s*})}{12\alpha(4n+3)(n+1)} \\
Q_1^{h*} &= \frac{(2n+3)(2t_1 - 3c\alpha - 3u_0) + 3(4n+3)(\gamma_1 z_1^h + \gamma_2 z_1^{s*}) - 6n(\gamma_1 z_2^h + \gamma_2 z_2^{s*})}{24t_1(n+1)} \\
Q_2^{h*} &= \frac{(2n+3)n(2t_1 - 3c\alpha - 3u_0) + 6n(7n+6)(\gamma_1 z_2^h + \gamma_2 z_2^{s*}) - 3n(4n+3)(\gamma_1 z_1^h + \gamma_2 z_1^{s*})}{12t_1(4n+3)(n+1)} \\
q_2^{h*} &= \frac{Q_2^{h*}}{n}.
\end{aligned}$$

For notation simplification, we denote the quality values of hardware and software in the two platforms with: $\delta_1 = \gamma_1 z_1^h + \gamma_2 z_1^{s*}$ and $\delta_2 = \gamma_1 z_2^h + \gamma_2 z_2^{s*}$. The following lemmas characterize the equilibrium hardware prices and quantities:

Lemma 3.1. *If the quality of the open platform is not too inferior to the quality of the closed platform ($\delta_2 > \delta_1 - \dfrac{t_1}{3(2n+1)}$), the former occupies more user share in the hardware market than the closed platform.*

Proof. We have:

$$Q_2^{h*} - Q_1^{h*} = \frac{3(2n+1)(\delta_2 - \delta_1)}{8t_1(n+1)} + \frac{(4n^2-3)(2t_1 + 3\delta_2 - 3c\alpha - 3u_0)}{8t_1(n+1)(4n+3)}.$$

From Equation 3.5, we know that $x_{20}^h > 2/3$, which leads to $3\delta_2 + t_1 > 3\alpha p_2^h + 3u_0 > 3\alpha c + 3u_0$. Thus,

$$Q_2^{h*} - Q_1^{h*} > \frac{3(2n+1)(\delta_2 - \delta_1)}{8t_1(n+1)} + \frac{(4n^2-3)t_1}{8t_1(n+1)(4n+3)}.$$

For $n \geq 2$, we have: $4n^2 - 3 \geq 8n - 3 = 5n + 3n - 3 \geq 5n + 3 > 4n + 3$. Then combining this with $\delta_2 > \delta_1 - \dfrac{t_1}{3(2n+1)}$:

$$Q_2^{h*} - Q_1^{h*} > \frac{3(2n+1)(\delta_1 - \frac{t_1}{3(2n+1)} - \delta_1)}{8t_1(n+1)} + \frac{(4n+3)t_1}{8t_1(n+1)(4n+3)} = 0.$$

The total user share of the open platform is greater than that of the closed platform. □

Lemma 3.2. *If the quality of the open platform is too inferior to the quality of the closed platform ($\delta_2 < \delta_1 - \dfrac{t_1(4n^2-3)}{(2n+1)(4n+3)}$), the latter gains more user share and profit than the hardware producers in the open platform.*

Proof. We have:

$$Q_1^{h*} - Q_2^{h*} = \frac{3(2n+1)(\delta_1 - \delta_2)}{8t_1(n+1)} + \frac{(4n^2-3)(-2t_1 - 3\delta_2 + 3c\alpha + 3u_0)}{8t_1(n+1)(4n+3)}.$$

From Equation 3.5, we know that $x_{20}^h < 1$, which leads to $3c\alpha + 3u_0 + t_1 > 3\delta_2$. Hence:

$$Q_1^{h*} - Q_2^{h*} > \frac{3(2n+1)(\delta_1 - \delta_2)}{8t_1(n+1)} - \frac{3t_1(4n^2-3)}{8t_1(n+1)(4n+3)}.$$

Since $\delta_2 < \delta_1 - \dfrac{t_1(4n^2-3)}{(2n+1)(4n+3)}$, this above inequality leads to:

$$Q_1^{h*} - Q_2^{h*} > \frac{3(2n+1)(\delta_1 - (\delta_1 - \dfrac{t_1(4n^2-3)}{(2n+1)(4n+3)})}{8t_1(n+1)} - \frac{3t_1(4n^2-3)}{8t_1(n+1)(4n+3)} = 0.$$

Therefore, the closed platform occupies more user share than the open platform. On the other hand, from the results of the equilibrium, we know that:

$$p_1^{h*} - c = \frac{4t_1(n+1)Q_1^{h*}}{\alpha(4n+3)} \quad p_2^{h*} - c = \frac{t_1 n q_2^{h*}}{\alpha n}.$$

Therefore, we can rewrite the profits of the two platforms in the hardware market as:

$$\pi_1^{h*} = \frac{4t_1(n+1)(Q_1^{h*})^2}{\alpha(4n+3)}, \quad \pi_2^{h*} = \frac{t_1(nq_2^{h*})^2}{\alpha n}. \tag{3.12}$$

With the condition a) and b) holding we have $Q_1^{h*} > nq_2^{h*} = Q_2^{h*}$. Moreover, for $n \geq 2$, $\dfrac{4(n+1)}{4n+3} > \dfrac{1}{n}$. Thus, the profit of selling hardware for the closed platform is larger than that of the open one. $\square$

The first two lemmas explain why a closed platform like Apple-iOS can dominate the market at the beginning, then lose its market share and profit when the market evolves. This is because both its hardware and software products are of the top quality relative to the Android products. At the early stage of development when n is small, the condition in Lemma (3.2) is likely to be met. However, as more hardware producers join the open platform (n increase), the threshold $\dfrac{t_1(4n^2-3)}{(2n+1)(4n+3)}$ becomes larger. Additionally, when the open platform's manufacturers start producing a higher quality product, the condition in Lemma (3.2) is more unlikely to hold. On the contrary, the condition in Lemma (3.1) is met when δ_2 is large enough. As a result, the closed platform no longer dominates the hardware market.[1] The intuition behind this is that the proliferation of Android products causes tougher competition among the Android hardware manufacturers. This leads to a greater variety of products and low prices, which attracts more demand, especially from low- and middle-income consumers. Apple maintains its high-quality product and the market power to charge a higher price than Android products as illustrated in the following lemma:

Lemma 3.3. *If the quality of hardware and software in the closed platform is not too inferior to the quality of hardware and software in the open platform* ($\delta_1 > \delta_2 - \dfrac{t_1(4n^2-3)}{6(2n^2+9n+6)}$, *then*

[1] While Apple dominated the tablet PC market in 2012 with 60%, Android overtook Apple in 2018 as a share of 62.1% tablet devices worldwide run on Android operating system (source: Statista).

its hardware price is higher than in the open platform.

Proof. The difference between the two equilibrium prices is:

$$p_1^{h*} - p_2^{h*} = \frac{(2n^2+9n+6)(\delta_1-\delta_2)}{2\alpha(n+1)(4n+3)} + \frac{(4n^2-3)(3\delta_1+2t_1-3u_0-3c\alpha)}{12\alpha(4n+3)(n+1)}. \tag{3.13}$$

From Equation 3.5, as $x_{01}^h < 0$, we have: $t_1 + 3\delta_1 - 3u_0 - 3\alpha p_1^h > 0$. Because $p_1^h > c$, it leads to: $3\delta_1 + t_1 - 3u_0 - 3c\alpha > 0$. Then, we only need to prove that:

$$\begin{aligned}\frac{(2n^2+9n+6)(\delta_1-\delta_2)}{2\alpha(n+1)(4n+3)} + \frac{(4n^2-3)t_1}{12\alpha(4n+3)(n+1)} > 0 \\ \Leftrightarrow \delta_1 > \delta_2 - \frac{t_1(4n^2-3)}{6(2n^2+9n+6)}.\end{aligned} \tag{3.14}$$

Hence, we can conclude that the closed platform charges a higher hardware price than the hardware producers in open platform: $p_1^{h*} > p_2^{h*}$. □

The intuition behind the result in lemma 3.3 is that the asymmetry in the business models leads to a more intense competition among producers in the open platform, which results in lower hardware prices in the open platform compared to the closed platform. This can be illustrated by using (3.14). Set $A = \frac{t_1(4n^2-3)}{6(2n^2+9n+6)}$, so $p_1^{h*} > p_2^{h*} \Leftrightarrow \delta_1 > \delta_2 - A$. We have $\frac{\partial A}{\partial n} = \frac{t_1(12n^2+12n+9)}{2(2n^2+9n+6)^2} > 0$. Therefore, the more intense the competition among producers in the open platform (larger n), the easier the condition $\delta_1 > \delta_2 - A$ is satisfied and the more likely that the hardware price in the open platform is lower than in the closed platform.

3.3.4 The role of indirect quality effects

With the above assumptions we differentiate Q_1^{h*}, Q_2^{h*}, p_1^{h*} and p_2^{h*} with respect to z_1^{s*} and z_2^{s*}, so to have the partial effects of software quality on hardware demand and price:

$$\begin{aligned}
\frac{\partial Q_1^{h*}}{\partial z_1^{s*}} &= \frac{\gamma_2(4n+3)}{8t_1(n+1)} & \frac{\partial Q_2^{h*}}{\partial z_1^{s*}} &= -\frac{\gamma_2 n}{4t_1(n+1)} \\
\frac{\partial Q_2^{h*}}{\partial z_2^{s*}} &= \frac{\gamma_2 n(7n+6)}{2t_1(n+1)(4n+3)} & \frac{\partial Q_1^{h*}}{\partial z_2^{s*}} &= -\frac{\gamma_2 n}{4t_1(n+1)} \\
\frac{\partial p_1^{h*}}{\partial z_1^{s*}} &= \frac{\gamma_2}{2\alpha} & \frac{\partial p_2^{h*}}{\partial z_1^{s*}} &= -\frac{\gamma_2}{4\alpha(n+1)} \\
\frac{\partial p_2^{h*}}{\partial z_2^{s*}} &= \frac{\gamma_2(7n+6)}{2\alpha(4n+3)(n+1)} & \frac{\partial p_1^{h*}}{\partial z_2^{s*}} &= -\frac{\gamma_2}{\alpha(4n+3)}.
\end{aligned} \tag{3.15}$$

On the one hand, the signs of the software quality on hardware demand are as we expected. The higher the software quality in any platform, the more utility the users receive from buying hardware, leading to hardware demand expansion for that platform. With the assumption of no switching costs, the demand expansion is generated both by users consuming outside options and hardware produced for the rival platform. As a result, this reduces the demand for hardware in the competing platform. Unsurprisingly, the cross-effect is smaller than the own-effect as a decrease in the demand for the competing platform only accounts for part of the demand expansion for hardware produced for the own platform. Interestingly, the own-effect is larger for the open platform. It is because the open platform has far more products than the closed platform, causing a stronger demand shift from the outside options:

Lemma 3.4. *An increase in the average software quality leads to a higher demand shift from outside options towards the open platform:* $\left|\frac{\partial q_0^{h*}}{\partial z_2^{s*}}\right| > \left|\frac{\partial q_0^{h*}}{\partial z_1^{s*}}\right|$.

Proof. We have:

$$\left|\frac{\partial q_0^{h*}}{\partial z_2^{s*}}\right| = \frac{3\gamma_2(20n^2 + 18n)}{24t_1(4n+3)(n+1)} > \frac{3\gamma_2(8n^2 + 18n + 9)}{24t_1(4n+3)(n+1)} = \left|\frac{\partial q_0^{h*}}{\partial z_1^{s*}}\right| (\forall n \geq 2).$$

□

On the other hand, the effect of software quality on the hardware equilibrium prices carries the same sign of the impact on hardware demand. To be specific, an increase in software quality will raise the willingness to pay of consumers for hardware produced for that platform. Therefore, the platform has an incentive to charge higher hardware prices to users. The closed platform can increase its hardware price more than hardware producers in the open platform, given the same increase in the software quality. The intuition is that hardware producers in the open platform face intense competition and strong business stealing within the platform. The role of competition in driving the asymmetric effects of software quality on hardware prices in the two platforms can be interpreted via the term n in equations 3.15. From equations 3.15, we can see that the effect of software quality on hardware prices in both platforms depends on the consumer valuation of software quality γ_2 and consumer's sensitivity to prices α. However this effect on hardware prices in open platform $\partial p_2^{h*}/\partial z_2^{s*}$ depends on n, while this effect in the closed platform $\partial p_1^{h*}/\partial z_1^{s*}$ does not. The term $\frac{7n+6}{(4n+3)(n+1)}$ in $\partial p_2^{h*}/\partial z_2^{s*}$ is smaller than 1 with $n > 2$, hence the same increase in software quality would lead to a smaller rise in hardware prices of the open platform than the closed platform. Additionally, we have $\frac{\partial p_2^{h*}}{\partial z_2^{s*}}/\partial n = \frac{\gamma_2}{2\alpha}\frac{-28n^2 - 48n - 21}{[(4n+3)(n+1)]^2} < 0$. Thus, the larger the number of hardware producers in the open platform (more intense competition) is the smaller effect of software quality on prices charged by these producers. On the other hand, when software quality in a platform is higher, to prevent consumers from switching, hardware producers in the competing platform have an incentive to lower their prices to protect their market shares, and this results in the negative cross effect of software quality on hardware prices. The impacts of software quality externalities on the hardware market are summarised in the following proposition.

Proposition 3.1. *The impacts of software quality on hardware demand, prices and profits are the followings:*

a) The software quality generates a higher own-effect for the open platform hardware demand: $\frac{\partial Q_2^{h*}}{\partial z_2^{s*}} > \frac{\partial Q_1^{h*}}{\partial z_1^{s*}}$ *and the cross platform effects generated from software quality to the* *hardware demand are always smaller than the own platform effects:* $\left|\frac{\partial Q_1^{h*}}{\partial z_1^{s*}}\right| > \left|\frac{\partial Q_2^{h*}}{\partial z_1^{s*}}\right|$ *and* $\left|\frac{\partial Q_2^{h*}}{\partial z_2^{s*}}\right| > \left|\frac{\partial Q_1^{h*}}{\partial z_2^{s*}}\right|$.

b) The software quality has a higher own-effect on the hardware price charged by the closed platform: $\frac{\partial p_1^{h*}}{\partial z_1^{s*}} > \frac{\partial p_2^{h*}}{\partial z_2^{s*}}$. *The cross-effect of the software quality in a platform on the other platform hardware price is smaller than the effect on the own platform:* $\left|\frac{\partial p_1^{h*}}{\partial z_1^{s*}}\right| > \left|\frac{\partial p_2^{h*}}{\partial z_1^{s*}}\right|$ *and* $\left|\frac{\partial p_2^{h*}}{\partial z_2^{s*}}\right| > \left|\frac{\partial p_1^{h*}}{\partial z_2^{s*}}\right|$.

c) If the quality value of hardware and software in the closed platform is superior to the quality of hardware and software in the open platform ($\delta_1 > \delta_2$)(c), then an increase in the software quality of the own platform leads to a higher increase in the profit of the closed platform in the hardware market:

$$\frac{\partial \pi_1^{h*}}{\partial z_1^{s*}} > \frac{\partial \pi_2^{h*}}{\partial z_2^{s*}}. \tag{3.16}$$

where $\pi_1^{h*} = (p_1^{h*} - c)Q_1^{h*}$ *and* $\pi_2^{h*} = (p_2^{h*} - c)Q_2^{h*}$.

Proof. The first two parts of the proposition can be easily derived from Equation 3.15. Now we will prove the third part of the proposition. Use Equation 3.12 to derive the partial effects of software quality on hardware profit:

$$\frac{\partial \pi_1^{h*}}{\partial z_1^{s*}} = \frac{8t_1(n+1)Q_1^{h*}}{\alpha(4n+3)}\frac{\partial Q_1^{h*}}{\partial z_1^{s*}}, \quad \frac{\partial \pi_2^{h*}}{\partial z_2^{s*}} = \frac{2t_1 Q_2^{h*}}{\alpha n}\frac{\partial Q_2^{h*}}{\partial z_2^{s*}}. \tag{3.17}$$

Substitute the partial effects of software quality on hardware demand as in Equation 3.15 into Equation 3.17 and simplify, so to have:

$$\frac{\partial \pi_1^{h*}}{\partial z_1^{s*}} = \frac{Q_1^{h*}}{\alpha}, \quad \frac{\partial \pi_2^{h*}}{\partial z_2^{s*}} = \frac{(7n+6)Q_2^{h*}}{\alpha(4n+3)(n+1)}. \tag{3.18}$$

- With $n = 2$, the latter partial effect becomes: $\frac{\partial \pi_2^{h*}}{\partial z_2^{s*}} = \frac{40q_2^{h*}}{33\alpha} < \frac{9q_2^{h*}}{7\alpha}$. Moreover:

$$Q_1^{h*} - \frac{9q_2^{h*}}{7} = \frac{257(\delta_1 - \delta_2)}{66t_1} + \frac{17(3\delta_1 + 2t_1 - 3u_0 - 3c\alpha)}{792t_1}.$$

The first term in Equation 3.19 is positive as $\delta_1 > \delta_2$. Moreover, in the proof for Lemma (3.2), we already showed that $3\delta_1 + 2t_1 - 3u_0 - 3c\alpha > 0$. Hence, the second term in Equation 3.19 is also positive, which means $Q_1^{h*} > \frac{9q_2^{h*}}{7}$. We can conclude that Equation 3.16 holds given condition (c) when $n = 2$.

- With $n = 3$, the partial effect of the software quality on the total profits of hardware produced for the open platform is: $\frac{\partial \pi_2^{h*}}{\partial z_2^{s*}} = \frac{81q_2^{h*}}{60\alpha} < \frac{3q_2^{h*}}{2\alpha}$. In addition, we have:

$$Q_1^{h*} - \frac{3q_2^{h*}}{2} = \frac{21(\delta_1 - \delta_2)}{40t_1} + \frac{3\delta_1 + 2t_1 - 3u_0 - 3c\alpha}{80t_1} > 0.$$

Therefore, (3.16) is true given the quality condition when $n = 3$.

- With $n \geq 4$, we always have: $(7n+6)n = 7n^2 + 6n < 8n^2 + 14n + 6 = 2(4n+3)(n+1)$. Thus, $\dfrac{\partial \pi_2^{h*}}{\partial z_2^s} < \dfrac{2Q_2^{h*}}{n\alpha} = \dfrac{2q_2^{h*}}{\alpha}$.Then, part c) of Proposition (3.1) would be proved if we can show that $Q_1^{h*} > 2q_2^{h*}$ when $\delta_1 > \delta_2$ and $n \geq 4$. Indeed,

$$Q_1^{h*} - 2q_2^{h*} = \frac{(24n^2 + 186n + 144)(\delta_1 - \delta_2)}{24t_1(4n+3)(n+1)} + \frac{(8n^2 - 22n - 27)(3\delta_1 + 2t_1 - 3u_0 - 3c\alpha)}{24t_1(4n+3)(n+1)}.$$

With $n \geq 4$, $8n^2 - 22n - 27 \geq 32n - 22n - 27 = 10n - 27 > 0$, which means $Q_1^{h*} > 2q_2^{h*}$. Under condition (c), (3.16) hold for all $n \geq 2$. $\square$

This proposition explains why a closed platform like Apple-iOS has a greater incentive than an open platform like Android to improve their software quality, as the same increase in software quality will lead to a greater increase in the closed platform profit. The mechanism of this result can be explained as follows: although an increase in software quality will expand the demand for hardware in the open platform more, the closed platform can charge a significantly higher price. We have $\dfrac{\partial p_1^{h*}/\partial z_1^{s*}}{\partial p_2^{h*}/\partial z_2^{s*}} - \dfrac{\partial Q_1^{h*}/\partial z_1^{s*}}{\partial Q_2^{h*}/\partial z_2^{s*}} = \dfrac{4(12n^2 - 21) + 3n(4n^2 - 3) + 27}{(7n+6)(4n+3)^2} > 0$ with $n \geq 2$. Thus, as the effect of software quality on prices dominate the effect on demand, the profit of closed platform hardware profit will eventually rise more than the open platform hardware profit.

3.4 Quality control policy by platforms and intervention by the policy maker

The above lemmas and proposition describe how the equilibrium quantities, prices, and profits change in absolute value when there is a change in the average software quality. The question is what can cause a change in the average software quality. In this section, we will analyze the impacts of possible policy by platform and intervention by the policymaker that can affect the average software quality in the two platforms: the exclusion of the lowest quality software, and the imposition of full multi-homing/interoperability on the developer side. The policy and intervention have different implications on the average software quality in the two platforms. While the policy by platforms to exclude the lowest quality software would certainly increase the average software quality in both platforms, imposing interoperability would only improve the average software quality of platforms with lower software quality and lower the average software quality of the platform with higher software quality.

3.4.1 Exclusion of lowest quality software

As discussed in the previous literature (Hagiu 2009, Casadesus-Masanell & Hałaburda 2014), platforms might opt for excluding the lowest quality software to improve the overall software quality in the store, to attract more users and generate profits.

We will examine whether this policy has heterogeneous impacts on the hardware in different platforms in terms of price, market shares, and profits. We focus on these effects in terms of the proportional change for each hardware product instead of the absolute change, since this measure is comparable across products in different platforms. Suppose that by excluding the lowest quality apps, the closed platform and the open platform can improve their average software quality by Δz_1^{s*}, and Δz_2^{s*} respectively. Liu (2017) provided evidence that when Apple and Google exclude the same amount of lowest quality apps, the average quality of Apple apps goes up more than Google apps. In the next chapter, we also confirm this result empirically. Therefore, it is reasonable to assume that $\Delta z_1^{s*} > \Delta z_2^{s*}$. The impacts of this policy are summarised in the below proposition.

Proposition 3.2. *If the quality of hardware and software produced for the closed platform does not overwhelm the quality of hardware and software in the open platform:* $\delta_1 < \delta_2 + \dfrac{(4n^2-3)t_1}{3(6n+5)(4n+3)}$ *(2a), an increase in software quality leads to a more significant percentage change in hardware demand, price and profit of the closed platform:*

$$\frac{\partial Q_1^{h*}}{\partial z_1^{s*}}\frac{\Delta z_1^{s*}}{Q_1^{h*}} > \frac{\partial q_2^{h*}}{\partial z_2^{s*}}\frac{\Delta z_2^{s*}}{q_2^{h*}} \tag{3.19}$$

$$\frac{\partial p_1^{h*}}{\partial z_1^{s*}}\frac{\Delta z_1^{s*}}{p_1^{h*}} > \frac{\partial p_2^{h*}}{\partial z_2^{s*}}\frac{\Delta z_2^{s*}}{p_2^{h*}} \tag{3.20}$$

$$\frac{\partial \pi_1^{h*}}{\partial z_1^{s*}}\frac{\Delta z_1^{s*}}{\pi_1^{h*}} > \frac{\partial \pi_2^{h*}}{\partial z_2^{s*}}\frac{\Delta z_2^{s*}}{\pi_2^{h*}}. \tag{3.21}$$

Proof. From (3.15), we have:

$$\frac{q_2^{h*}}{\partial q_2^{h*}/\partial z_2^{s}} - \frac{Q_1^{h*}}{\partial Q_1^{h*}/\partial z_1^{s}} = \frac{3(6n+5)(\delta_2-\delta_1)}{2(7n+6)} + \frac{(4n^2-3)(3\delta_2+2t_1-3c\alpha-3u_0)}{2(7n+6)(4n+3)}.$$

Because $q_{20} > 0$, we can claim: $3\delta_2 + t_1 - 3c\alpha - 3u_0 > 0$, which leads to:

$$\frac{q_2^{h*}}{\partial q_2^{h*}/\partial z_2^{s*}} - \frac{Q_1^{h*}}{\partial Q_1^{h*}/\partial z_1^{s*}} > \frac{3(6n+5)(\delta_2-\delta_1)}{2\gamma_2(7n+6)} + \frac{(4n^2-3)t_1}{2\gamma_2(7n+6)(4n+3)}. \tag{3.22}$$

When the condition (2a) is satisfied, the right hand side of (3.22) is greater than 0, thus:

$$\frac{q_2^{h*}}{\partial q_2^{h*}/\partial z_2^{s*}} > \frac{Q_1^{h*}}{\partial Q_1^{h*}/\partial z_1^{s*}} \Rightarrow \frac{\partial Q_1^{h*}}{\partial z_1^{s*}}\frac{\Delta z_1^{s*}}{Q_1^{h*}} > \frac{\partial q_2^{h*}}{\partial z_2^{s*}}\frac{\Delta z_2^{s*}}{q_2^{h*}}.$$

On the other hand, we can write:

$$\begin{aligned} \frac{p_2^{h*}}{\partial p_2^{h*}/\partial z_2^{s*}} \quad &- \quad \frac{p_1^{h*}}{\partial p_1^{h*}/\partial z_1^{s*}} = \frac{q_2^{h*}}{\partial q_2^{h*}/\partial z_2^{s*}} - \frac{Q_1^{h*}}{\partial Q_1^{h*}/\partial z_1^{s*}} + \frac{c\alpha(64n^3+48n^2-48n-36)}{2\gamma_2(4n+3)(7n+6)} > \\ &> \frac{2c\alpha(4n^2-3)}{\gamma_2(7n+6)} > 0 \\ \frac{\partial p_2^{h*}}{\partial z_2^{s*}}\frac{\Delta z_2^{s*}}{p_2^{h*}} \quad &< \quad \frac{\partial p_1^{h*}}{\partial z_1^{s*}}\frac{\Delta z_1^{s*}}{p_1^{h*}}. \end{aligned} \tag{3.23}$$

Hence, the inequality (3.20) is proved. We can substitute Equation 3.12 and (3.17) into the last inequality and rearrange:

$$
\begin{aligned}
\frac{\pi_2^{h*}}{\partial \pi_2^{h*}/\partial z_2^{s*}} - \frac{\pi_1^{h*}}{\partial \pi_1^{h*}/\partial z_1^{s*}} &= \frac{4n+3}{4t_1 Q_1^{h*}(n+1)} - \frac{n(7n+6)}{t_1 q_2^{h*}(4n+3)(n+1)} \\
&= \frac{\gamma_2}{2}\left(\frac{q_2^{h*}}{\partial q_2^{h*}/\partial z_2^{s*}} - \frac{Q_1^{h*}}{\partial Q_1^{h*}/\partial z_1^{s*}}\right) > 0 \\
\Rightarrow \frac{\partial \pi_2^{h*}}{\partial z_2^{s*}}\frac{\Delta z_2^{s*}}{\pi_2^{h*}} &< \frac{\partial \pi_1^{h*}}{\partial z_1^{s*}}\frac{\Delta z_1^{s*}}{\pi_1^{h*}}. \qquad (3.24)
\end{aligned}
$$

Thus the last inequality is always true under the condition (2a). □

Proposition (3.2) shows that the positive effect of removing the lowest quality software on market share, price, and profit of hardware in the closed platform could be potentially larger than in the open platform in terms of proportional change. When the quality of hardware and software produced for the closed platform is not too relatively high compared to the quality of the open platform, the closed platform is likely to obtain a smaller user share (Lemma 3.1). Therefore, the effect on hardware demand in terms of percentage change should be larger for the hardware in the closed platform. The intuition for the impacts on the price changes is the same as in the last section: the closed platform does not face severe competition as hardware producers in the open platform. Unsurprisingly, the larger effects of this policy on both market shares and prices lead to a larger effect on the profit of hardware produced for the closed platform. From this proposition, we can form the first hypothesis to be tested in the next chapter of the thesis.

Hypothesis 3.1. *The exclusion of the lowest quality software will lead to a greater proportional increase in the market share, price, and profit of hardware produced for the closed platform than that produced for the open platform.*

3.4.2 Full multi-homing/compatibility/interoperability on the developers side

Previous literature (Katz & Shapiro 1985, 1986, Economides 1989, Farrell & Simcoe 2012) has proved that platforms may have an incentive to produce compatible and complementary components/products to attract more consumers, as consumers would enjoy larger network effects. Moreover, works on multi-homing of the multi-sided platform (Malueg & Schwartz 2006, Adner et al. 2019, Belleflamme & Peitz 2019) have suggested that platforms might be profitable when developers multi-home as they would expand the network effects that platforms can internalise. Besides, users also gain more benefits from a larger number of developers, and thus there is an increase in consumer welfare. Therefore, the policymaker may have an incentive to impose full multi-homing/compatibility/interoperability on the developer side, which means that the software will be available on both platforms. To impose this, the platform can make it compatible with each other, so that developers can develop the software once and port it to different platforms without incurring additional cost. This policy intervention would lead to the new average software quality in both platforms to be the same: $z_1^{s*\prime} = z_2^{s*\prime} = z^{s*}$. Suppose Δz^{s*} is the difference between the average software quality between the closed platform and the open platform, $\Delta z^{s*} > 0$ if the former is greater than the latter (and vice versa). We can derive the changes in hardware prices, and market shares as follows:

$$\Delta p_1^{h*} = -\frac{(2n+3)\Delta z^{s*}}{2\alpha(4n+3)} \quad , \quad \Delta p_2^{h*} = \frac{(10n+9)\Delta z^{s*}}{4\alpha(4n+3)(n+1)}$$
$$\Delta Q_1^{h*} = -\frac{(2n+3)\Delta z^{s*}}{8t_1(n+1)} \quad , \quad \Delta q_2^{h*} = \frac{(10n+9)\Delta z^{s*}}{4t_1(4n+3)(n+1)}. \tag{3.25}$$

Therefore, the signs of changes in the hardware prices and market shares after imposing the full multi-homing/compatibility/interoperability policy depend on which platform has lower average software quality. This is because that platform with lower average software quality will improve its average software quality after the implementation of multi-homing. It makes this platform becoming more attractive to users and shifts the demand towards hardware produced for the platform. As users are more willing to join the platform, the hardware producers in that platform can charge higher prices and enjoy more profits. In contrast, hardware producers in the platform with higher average software quality will suffer the loss in both market shares and profits. This result has different implications for platforms and the policymaker. While the platform with lower average software quality would favor compulsory interoperability, the platform with higher average software quality would likely oppose this policy. On the other hand, the policymaker has an incentive to impose this policy since this would increase the surplus of consumers joining the open platform, while do not likely harm consumers joining the closed platform. We can form the second hypothesis, which can be empirically tested in the third chapter:

Hypothesis 3.2. *The implementation of full multi-homing/compatibility/interoperability on the developer's side would lead to an increase in the market shares, prices, and profits of hardware in the platform with lower average software quality. This policy would have opposite effects on the market shares, prices, and profits of hardware in the platform with higher average software quality*

3.5 Conclusions

We developed a theoretical model that exploited the strategic asymmetry between a closed and open platform to study the role of the indirect externality-induced by software quality on the hardware market. We found that either of the platforms can gain hardware market shares at the expense of the other platform if they improve the quality of hardware and software products. All else equal, if the quality of the closed platform is sufficiently superior to the quality of the open platform, the former would gain a larger user's share as well as profit. By contrast, if the quality of the open platform is not too inferior to the quality of the closed platform, then the hardware producers in the open platform would access a greater market share. This is consistent with the case of Apple iOS (closed platform) and Google Android (open platform).

In the beginning, Apple dominated the market with superior quality, as Android producers only offered low-end products at lower prices to attract low-income users, which is the majority of the population. In terms of application quality, Google also did not control for the application quality, so to attract a large number of developers. Hence both tablet and application quality of Android products were inferior to Apple. However, after obtaining a critical number of users, Android manufacturers started to target high-end tablets and Google began to control more strictly for application quality, which resulted in the higher quality of both Android-based tablets and applications.

In terms of pricing, the closed platform is more likely to set a higher hardware price. This because competition in the hardware market is affected by the asymmetry between the two platforms. While the hardware producer in the open platform faces fiercer competition from many manufacturers joining this platform and producing similar products, the closed platform confronts less competition because of its differentiated product. This helps to explain why Apple's overturned leadership in the market by Android did not affect its decision to maintain high-quality and high-priced products.

The main focus of this chapter is to study the role of software quality on the equilibrium outcomes in the hardware market and show how the policy intervention by platforms can change these outcomes. Interestingly, the comparison of the effects on two asymmetric platforms is ambiguous. For instance, an increase in the software quality would lead to a higher market share expansion for hardware produced for the open platform but a greater price increase for the closed platform. Moreover, if the quality of both hardware and software in the closed platform is larger than that in the open platform, then the software quality will have a stronger impact on the closed platform profits. This is why Apple has more to gain than Android from being stricter on the selection of mobile application quality.

We study the changes in the hardware equilibrium outcome when first, platforms exclude the lowest quality software, and second, platforms impose full multi-homing/compatibility on the developer side. The former policy is likely to have larger positive impacts on the market shares, prices, and profits of hardware produced for the closed platform. This again supports the fact that Apple was more eager to remove bad apps from the store in 2016, while Google only started this policy one year later. The effects of the latter policy will be positive on the market shares, prices, and profits of hardware produced for the platform with lower average software quality, and be negative on the hardware in the other platform. These results will be tested and confirmed in the next chapter of the thesis.

Future research in this area can study the endogenous choice of quality by the platforms and provide insight into whether the closed or the open platform has more incentive to choose the high-quality level. Another direction that could be interesting is to investigate the effects of hardware quality on the software market and understand the incentive to produce high-quality software when the hardware manufacturers sell higher quality products.

Chapter 4

Platform competition in the tablet PC market: the role of application quality

4.1 Introduction

Before the launch of the new version of the operating system platform iOS, together with the application distribution store Apple App Store in 2008, no one could imagine that the mobile application market would grow exponentially to reach millions of apps within only several years. This launch turned two separate markets, smartphone, and mobile applications, into a multi-sided market, where users and developers interact directly via the application store. This created significant network externalities, which led to the booming of the smartphone and mobile application industry. Based on the growing app industry, a new generation of smart device tablet PCs —based on two operating systems, Google Android and Apple iOS, was introduced respectively in 2009 and 2010. This new generation of tablet PC has quickly become one of the devices used most by users all over the world. Statista.com estimates that the total number of tablet users would reach 1.41 billion at the end of 2020.

According to Statista[1], the tablet PC market is dominated by two operating system platforms, Apple iOS and Google Android, with a total share of more than 90%. The market is peculiar as the two platforms follow different business strategies. While the former is a closed platform —Apple controls both device production and the app store, the latter is an open platform —Android can be licensed free to other competitive manufacturers producing tablet PC devices. The app store compatible with Android —Google Play —is managed by Google. This chapter contributes to the literature on indirect externalities in high-tech markets. Early works by Katz & Shapiro (1986) and Church & Gandal (1993) have shown that high-tech firms can gain more market share and entrench their market position by attracting more hardware users and software developers. In this work, we focus on the tablet PC market. We examine empirically the impacts of app quality on the market outcome. This is different from the classic literature on indirect network externalities, which is typically related to the availability/variety of complementary products.

We analyse the impacts of indirect effects induced by application quality rather than ap-

[1]https://www.statista.com/statistics/273840/global-market-share-of-tablet-operating-systems-since-2010/

plication variety. This is because the number of applications already exceeds 1 million in both Apple Store and Google Play at the time of our dataset. Thus, consumers are likely to care more about application quality than variety. It would not be interesting to quantify the effect of the number of applications available in the store, as this would have a very minimal impact on consumer decision to buy a tablet. Therefore, it is sensible in the econometric model to assume that the number of applications does not impact consumer's utility when buying tablets. As we expect that the number of applications does not have a significant impact on the tablet demand, our findings will not likely change if this assumption is allowed to relax. Since consumers value application quality, it is also reasonable to assume that the higher the quality of applications developed within a platform, the higher the utility received from buying a tablet associated with that platform, and the greater the demand.

Based on the discrete choice literature for product differentiation (Berry 1994, Berry et al. 1995, Nevo 2001), we construct an econometric model for both tablet demand and supply to examine the role of application quality in the tablet PC market. Following the previous literature (Binken & Stremersch 2009, Kim et al. 2014), we employ the average user rating to measure the application quality. For each store in each period, we consider the average rating of the top 1000 apps, weighted by the total downloads. This measure allows us to capture the heterogeneity in the popularity or attractiveness of apps to users and, hence, to account for the well-known "superstar" effect in the hardware-software market, according to which the availability of top software applications is one of the main drivers in hardware demand (Binken & Stremersch 2009). We employ the random coefficients nested logit function to model tablet demand as in Grigolon & Verboven (2014). The nest structure captures the consumer heterogeneity within operating systems (Apple iOS and Google Android). This is because users are likely to make their tablet purchase decision in two stages. In line with our theoretical model in the previous chapter, we assume that they first choose the operating system, and then one of the tablets compatible with that operating system. In addition to the nested logit structure, we also incorporate random coefficients for the tablet price following Nevo (2001). The advantage of including these coefficients is that it allows consumers to have heterogeneous preferences towards prices depending on demographic characteristics. Besides, it also solves the problem of unrealistic price elasticities in the simple nested logit model. We estimate the econometric model based on a sample, which combines product-level data for tablets and apps distributed in five European countries (Germany, France, Italy, Spain, and the UK) over three quarters, from the 2013 third quarter to the 2014 first quarter.

To estimate tablet demand and supply simultaneously, we also model the cost side of producing tablets and derive the pricing equation. Incorporating the cost side in our estimation would address the potential simultaneity bias of the demand-supply system and improve greatly the efficiency of the estimates. Additionally, the advantage of estimating a system of simultaneous equations is to back out the primitives on the tablet market and, most importantly, to perform counterfactual experiments. The first counterfactual experiment is the exclusion of the lowest quality apps by application stores. The second one, the implementation of full multi-homing/interoperability by the policy maker on the developer side. The motivation for studying the first counterfactual analysis is that both Apple and Google had removed a sizeable number of low-quality apps in each store in 2016 and 2017, respectively. Therefore, it would be interesting to test whether this policy impacted the tablet PC market. On the other hand, previous literature has discussed platforms' incentives to be compatible/interoperable. The fringe firms have more incentive to be compatible as they would enjoy much larger network effects than the dominant firm. Furthermore, on the consumer side, previous works have shown that they would prefer compatibility across platforms to incompatibility since they can enjoy larger network effects by joining one platform. Thus, the regulator may want to force firms to be compatible/interoperable. However, there is still a lack of empirical evidence of the benefits of compatibility/interoperability in the literature. We aim to fill in this gap by studying the second counterfactual. We compute the new market equilibrium after implementing platform policy/policymaker intervention and test the two hypotheses proposed in Chapter 3 of the thesis.

We find evidence that there are positive and significant indirect quality externalities from applications to tablet demand. The results of the first counterfactual experiment confirm the first hypothesis in the previous chapter. Market shares and profits of both platforms shall increase if they remove the low-quality apps from their stores. Therefore, this policy will increase the market shares, prices, and profits of Apple iPads more than Android tablets. Interestingly, this helps explain why Apple Store has a much stricter quality check for new apps than Google Play since Apple has more incentive to keep apps at high quality.[2] The results of the second policy experiment show a gain in market shares and profits for Android tablets. By contrast, Apple would suffer a loss in both. This is because Android has lower average application quality, and the policy will improve the Android apps' average quality which shifts more user demand towards Android tablet producers. Meanwhile, this policy will enhance total consumer welfare, which implies that the social planner may have an incentive to force full multi-homing/compatibility on the developer side across platforms.

The outline of this chapter is the following. We review the relevant literature in the next section. In the third section, we will propose the econometric model of tablet hardware demand-supply to be estimated. The description of the data and summary statistics is discussed in section 4. We then present the estimation strategy and the empirical estimation, along with a discussion of the main results in section 5. The conclusions are in section 6.

4.2 Literature review

This chapter contributes to the literature on network externalities in the context of complementary products. An early paper by Church & Gandal (1993) develops a CES utility model, which they use to study the indirect network externalities in the hardware-software market. In their model, consumer preferences for software variety are assumed to be identical, which means that the benefits from software variety are the same for all consumers after buying hardware and joining the platform. Under this assumption and free entry condition for software developers, they derive the equilibrium outcomes and find that software variety has a positive

[2]See Comino et al. (2019) for further discussions of different approaches towards quality control between Apple App Store and Google Play.

indirect network effect on hardware demand.

Following that, several papers, including Gandal (1995), and Park (2004), provide indirect evidence of cross-network effects in the technology market and quantify how the value of hardware increases with software variety. These papers model the extent of consumer adoption and ignore software provision. The first empirical work to estimate hardware demand and software supply simultaneously is Gandal et al. (2000), which does that for the CD market. By examining the diffusion of compact disc players, they find that the indirect network effect of an increase in the variety of CD titles has a significant effect on the adoption of CD players. They formulate a rudimentary dynamic model, where both consumers and developers are infinite-lived and simultaneously choose to purchase and supply. The CD players' price in their model is assumed to be exogenous and hardware heterogeneity is neglected.

Similar to Church & Gandal (1993), Nair et al. (2004) adopt the CES utility function and model consumer preferences over Personal Digital Assistant technologies. Their model presents not only software demand and supply but also hardware demand. This enables them to fit the model into an econometric framework and, subsequently, quantify the indirect network effect empirically. In their framework, network externalities enter both hardware demand through the number of available software and software provision through the hardware installed base (the number of hardware users). Their results show a significant indirect network effect generated by software variety on hardware demand, and then from the hardware installed base on the software supply. Their findings also suggest that the cross-network effect can be enhanced by improving the hardware product's quality. This raises consumer demand directly through the utility and indirectly through the positive feedback from software variety. Clements & Ohashi (2005) investigate how the effects of hardware price and software variety evolve throughout the video game console cycle. They find that in the introductory phase, the hardware demand is more elastic for the price than the software variety is. When the product becomes more mature, while software variety has a more significant impact on hardware demand, the price elasticity decreases substantially.

However, the above papers only quantify the indirect network externalities induced by software variety on hardware demand and ignore the software quality effects. It is natural that the higher the software quality, the more benefits the consumer enjoys. It will be problematic if software quality is not accounted for as a driver of hardware demand. Several works subsequently tried to incorporate the effects of software quality when quantifying the cross-network externalities in platform markets. Corts & Lederman (2009) identify both software variety and quality as sources of indirect network effects. They measure the software quality by calculating the average amounts of US dollars spent on a game title per person. Then, they determine the thresholds of the 50^{th}, 75^{th} and 95^{th} percentile of the distribution as three quality levels. Employing the nested logit demand structure, they estimate the effects of each game's quality level on hardware demand and find that a higher level of quality has larger impacts on the market shares of video game consoles. Song et al. (2017) find a similar result when they study the effects of game quality measured by Metascore.com ratings on game console demand, which is that high-quality software has a positive impact on the demand for game consoles.

Kim et al. (2014) argue that there are potentially biased estimates when measuring the indirect network effects if one ignores the role of software quality. Following ?, they propose a model to incorporate software quality heterogeneity into the indirect network effects, allowing in this way, consumers to have different marginal utilities from different game quality levels. Kim et al. (2014) is the closest paper to ours as the two works both quantify the effects induced by game/application quality rather than variety. Besides, we both measure quality by using review scores/ratings as a proxy. The main difference is that we do not analyse the software supply side as they do in their work. We, instead, focus on the tablet PC market and construct a structural model of tablet demand and supply, following Berry (1994), Berry et al. (1995), and Nevo (2001) with the quality of complementary applications being incorporated into the model. On the other hand, while Kim et al. (2014) only concentrate on quantifying the indirect network effects generated by the software quality, this chapter complements their work by providing further insight into the role of application quality, as we perform the counterfactual experiment to test the hypotheses proposed in the previous chapter.

Our first counterfactual analysis contributes to the small branch of the literature on platform regulation and policy. Boudreau & Hagiu (2009) suggest that platforms may have an incentive to remove low-quality agents. They refer to the mobile application "I Am Rich"—eliminated by Apple because of its poor function and unreasonable high price. Hagiu (2011) studies platform incentive to exclude low-quality sellers to attract more buyers. He develops a theoretical model of two-sided platform competition, and capture cross-network effects as the interaction between the seller quality and variety. The results show that platforms have more incentive to exclude low-quality sellers when the buyer valuation of seller quality is higher than that of variety. Furthermore, the results show that platforms have more incentive to exclude low-quality agents when agent valuation of quality is higher than variety. Furthermore, Casadesus-Masanell & Hałaburda (2014) show that platforms can profitably limit the number of software developers, as it reduces the competition on the developer side, with negative effects on network externalities. Claussen et al. (2013) provide empirical evidence of Facebook's policy of rewarding high-quality apps has positive impacts on the average app quality on Facebook in the subsequent period. Albeit the above papers have discussed how the exclusion of low-quality agents/software benefits platforms, it is still necessary to provide further empirical evidence from different platform markets, especially the effect of this policy on the other side of the market. Our first policy experiment aims to fill this gap. We estimate the effects of excluding low-quality applications on the prices, market shares, and profits of tablets in the two platforms and confirm the first hypothesis in the last chapter.

Our second counterfactual analysis provides additional empirical insight into the platform literature on multi-homing and interoperability. Interoperability means that an application can run on different operating systems/platforms without any restrictions. This means that users of one platform can download the apps of the other platform. Typically, platforms can benefit from interoperability as it enables users to enjoy larger network externalities that firms can internalize. The platform interoperability problem had been studied early in the literature by Katz & Shapiro (1985), Farrell & Saloner (1985), Matutes & Regibeau (1988), Economides (1989), and Katz & Shapiro (1994). They examine whether hardware firms have incentives to produce compatible components with other competing manufacturers. They confirm that homogeneous platforms have more incentive to be compatible, as this would mitigate the competition and amplify network externalities, which would attract more consumers to the platform. Doganoglu & Wright (2006) find that the user ability to multi-home mitigates the platform incentive to commit to interoperability. Whereas Malueg & Schwartz (2006), Chen et al. (2009) suggest that larger installed base platforms prefer to be incompatible to preserve their market dominance, while a policymaker has an incentive to force platforms' compatibility to boost consumer welfare. Interestingly, Adner et al. (2019) proves that it may be profitable for platforms to implement one-way compatibility if the asymmetry between the platform's standalone utilities is sufficiently large. Despite the extensive literature on multi-homing/interoperability, none of the previous works has addressed the incentive that platforms, and social planners, have in activating compatibility. Our second policy experiment aims to fill this gap in the literature. We find evidence that Android tablet producers would prefer all applications to multi-home/be compatible, as it would improve the average quality of applications available to Android users, thus, attract more users to buy Android tablets, leading to a gain in profits.

4.3 Econometric model

In this section, we will present an econometric model for tablet demand and supply. First, we model demand by employing the Random Coefficients Nested Logit Model. Then, we characterise the empirical cost function of a multi-product firm. This, to derive the first-order conditions for profit maximization. We then derive the pricing equation that is estimated simultaneously with the demand equation. Last, we discuss the steps to estimate a system of simultaneous demand and supply equations by nonlinear GMM.

4.3.1 Empirical demand function

In this section, we present the Random Coefficients Nested Logit model, built on Grigolon & Verboven (2014). This empirical model is fairly general, as it allows for: product-level utility, individual preferences on the price, unobserved tablet characteristics, individual unobserved heterogeneity for the operating system, and an idiosyncratic random variable. Importantly, this model is in line with our theoretical model in the last chapter since consumers continue choosing the tablet in two stages. First, they select the operating system (iOS, Android, or nothing) and then which tablet model to buy within the operating system. There are T country-period markets, each having I_t consumers. The products belong to one of three groups: $g = 0$ (outside option), $g = 1$ (iOS), $g = 2$ (Android). Consumer i from market t can choose between buying one of J_t new tablets, $j = 1, 2, \cdots, J_t$ or a composite outside good $j = 0$. The indirect utility associated with buying tablet j in group g in market t is given by:

$$u_{ijt} = x_{jt}\beta_i + \xi_{jt} + \zeta_{igt} + (1 - \rho)\epsilon_{ijt}, \tag{4.1}$$

where x_{jt} is a $1 \times K$ vector of observed tablet characteristics including the price, storage, screen size, screen resolution, connectivity, and the quality of mobile applications. While some of the tablet characteristics are market-invariant; prices tend to vary both over the market and by the product. Also, the application quality varies across (t) and groups (g). The unobserved product characteristics are captured by the term ξ_{jt}. The $K \times 1$ parameters β_i are random coefficients. The term ζ_{igt} is consumer valuation, which is common to all the products that use the same operating system in the market, and is random with probability distribution function that depends on the within-group correlation parameter ρ, with $0 \leq \rho < 1$. The idiosyncratic error term ϵ_{ijt} is assumed to be identically and independently distributed extreme value, and so is the composite term $\zeta_{igt} + (1-\rho)\epsilon_{ijt}$ (see Cardell 1997). When ρ gets closer to 1, users perceive tablets in various operating systems as nearly perfect substitutes, prompting a strong business stealing effect, in which case, a small difference in the utility between two tablet models can result in a large difference in market shares. By contrast, as ρ approaches 0, ζ_{ig} converges to zero and the model reduces to a standard random coefficients logit. As in Nevo (2001), the random coefficients can be decomposed into of $M \times 1$ observable demographics d_i and $K \times 1$ unobservable variables of individual heterogeneity v_i, drawn from a multivariate standard normal:

$$\beta_i = \beta + \Pi d_i + \Sigma v_i. \tag{4.2}$$

The matrix of parameters Π has dimension $K \times M$, and Σ is $K \times 1$ diagonal matrix of standard deviations σ. Equations 4.1 and 4.2 characterise the Random Coefficients Nested Logit (RCNL) model as in Grigolon & Verboven (2014). If Π and Σ are both zero matrices, we have the Nested Logit (NL) model. In our empirical section, we will also estimate the Nested Logit demand model in addition to the Random Coefficients Nested Logit.

Consumer i in market t chooses the product j that gives the highest utility. In the case of the RCNL model, the conditional probability of that choice is

$$\phi_{ijt}(x_t, \xi_t, d_i, v_i, \theta) = \frac{exp\left(\left(x_{jt}\beta_i + \xi_{jt}\right)/\left(1-\rho\right)\right)}{exp\left(I_{ig}/\left(1-\rho\right)\right)} \frac{exp\left(I_{ig}\right)}{exp\left(I_i\right)}, \tag{4.3}$$

where $\theta = \{\beta, \Pi, \sigma, \rho\}$ is a vector of parameters to be estimated and McFadden's (1978) I_{igt} and I_{it} are McFadden's (1978) inclusive value, which is defined by:

$$I_{igt} = (1-\rho)\ln \sum_{l=1}^{J_{gt}} exp\left(\left(x_{lt}\beta_i + \xi_{lt}\right)/\left(1-\rho\right)\right),$$

$$I_{it} = \ln\left(1 + \sum_{g=1}^{G_t} exp\left(I_{igt}\right)\right). \tag{4.4}$$

The upper limit J_{gt} in the summation of I_{igt} is the total number of products in group g in market t, and the 1 entering I_{it} is the effect of the outside group $g = 0$, since this contains only the outside good, for which $u_{i0t} = \zeta_{i0t} + (1-\rho)\epsilon_{i0t}$.

A_{jt} is the multidimensional support of individual characteristics associated with product j in market t. The market share of product j in market t, s_{jt}, can be obtained by integrating

Equation 4.3 for the distribution of d_i and v_i,

$$s_{jt} = \int_{A_{jt}} dP_\varepsilon dP_v dP_D \tag{4.5}$$

where P denotes the population distribution function of three different multivariate distribution functions. The solution can be approximated by Monte Carlo simulations (see Nevo 2001, Berry et al. 1995):

$$s_{jt} = \frac{1}{ns}\sum_{i=1}^{ns} \phi_{ijt} = \frac{1}{ns}\sum_{i=1}^{ns} \frac{exp((\delta_{jgt} + [-p_{jt}]'(\Pi D_i + \Sigma v_i))/(1-\rho))}{exp(I_{igt}/(1-\rho))} \frac{exp(I_{igt})}{exp(I_{it})} \tag{4.6}$$

where ns is a number of draws from the probability distributions that characterise the random coefficients.

4.3.2 Empirical pricing equation

The reason for fully specifying and adding the supply side is that jointly estimating the demand and supply can address the simultaneity bias in the demand-supply system and improve the efficiency of the estimates (Nevo 2001). According to Berry (1994), joint demand and supply estimation would also account for the cross-equation restrictions on nonlinear parameters impacting both demand and supply: price coefficient α and within-nest coefficient ρ. Multi-product tablet producers observe the demand for tablets and choose the prices that maximize their profit given the prices and characteristics of other products in the market. The marginal cost of producing tablets is assumed to be constant in output and linear in product characteristics (some observed w and some unobserved ω):

$$c_{jt} = w_{jt}\gamma + \omega_{jt}. \tag{4.7}$$

Tablet manufacturer m produces a set $\mathcal{J}_{mt}$ of J_t tablets. Given the demand (share) function in Equation 4.5, the profit of tablet manufacturer m is:

$$\pi_{mt} = \sum_{j \in \mathcal{J}_{mt}} (p_{jt} - c_{jt}) s_{jt} I \tag{4.8}$$

where I is the market size. For any $j \in \mathcal{J}_{mt}$, the price p_{jt} satisfies the first-order condition:

$$s_{jt} + \sum_{r \in \mathcal{J}_{mt}} (p_{rt} - c_{rt}) \frac{\partial s_{rt}}{\partial p_{jt}} = 0. \tag{4.9}$$

Upon defining Δ_t a $J \times J$ matrix whose (j, r) element is:

$$\Delta_{jr} = \begin{cases} -\dfrac{\partial s_{rt}^T}{\partial p_{jt}^T}, & \text{if } r, j \in \mathcal{J}_{mt}, \\ 0, & \text{otherwise,} \end{cases} \tag{4.10}$$

The system of the first order conditions of all products can be written in matrix notation as:

$$s_t - \Delta(p_t - c_t) = 0. \tag{4.11}$$

Hence, the equilibrium prices and markups (b) are:

$$\begin{aligned} p_t &= c_t + (\Delta_t)^{-1} s_t, \\ b_t &= (\Delta_t)^{-1} s_t. \end{aligned} \tag{4.12}$$

Thus, the first order condition in 4.9 can be read as price equals marginal cost plus a mark-up, and given the primitives from estimating the demand, one can use the pricing equation 4.12 to back out marginal costs for each product. Then, substituting in the expression for the marginal cost in the equation 4.7, we obtain a pricing equation to estimate:

$$p_t - b_t = w_t \gamma + \omega_t. \tag{4.13}$$

4.3.3 Estimation procedure

In our empirical estimation, we assume that the variables entering the exogenous demand vector $\tilde{x}$ are: a constant, storage capacity, screen resolution, screen size and type of connection, and dummies for time, firm, and country.[3] The same set of variables enter the marginal cost function, i.e. $w = \tilde{x}$. Only the price has random coefficients and we only use individual income as an observable demographic characteristic. Thus, the price and the application quality are the last variables entering the vector of all observable characteristics x on the demand side. In terms of the notation above, Π is a vector of zeros apart from the second last element and this is also the case for the vector σ. Thus, we have the set of all parameters to be estimated $\theta = \{\beta, \gamma, \pi_{\mathrm{P}}, \sigma_{\mathrm{P}}, \rho\}$. There are only two groups ($G = 2$ operating systems) in addition to the outside option group, and these are iOS and Android.

Both the unobserved heterogeneity from the demand side, ξ_{jt}, and the unobserved heterogeneity from the pricing equation, ω_{jt}, are random variables. The exogenous product characteristics entering the demand are the vector x_{jt} without the price and app quality variables, which we relabel as $\tilde{x}_{jt}$. The exogenous variables entering the pricing equation are the observed product characteristics w_{jt} (some of these are also included in $\tilde{x}_{jt}$). Denoting the vector of exogenous variables in market t with $z_t = [\tilde{x}_{1t}, w_{1t}, \cdots, \tilde{x}_{J_t,t}, w_{J_t,t}]$, and that for all markets as $z = [z_1, \cdots, z_T]$. The price and the average quality of mobile applications are treated as endogenous variables. We work with the assumption of conditional independence of the type, $E(\xi_{jt}|z_t) = E(\omega_{jt}|z_t) = 0$, which implies that both demand and supply unobservable characteristics are mean independent of the observables. In the estimation procedure, we account for correlation between the demand and pricing equations by using Cholesky factorization T_t of the inverse of the covariance matrix $\Omega(z_t) = E\left((\xi_{jt}, w_{jt})' (\xi_{jt}, w_{jt}) | z_t\right)$. Defining with $H_{jt}(z_t)$

[3] Firms that sell less than three products are part of a residual category to avoid the problem of too many firms dummies, which can cause the matrix singularity.

the $L \times 2$ matrix of instruments, it is possible to write the set of moment conditions as

$$G_t = E_j \left(H_{jt}(z_t) T(z_t) \left[\begin{array}{c} \xi_{jt} \\ \omega_{jt} \end{array} \right] \right). \tag{4.14}$$

Upon generalising the moment conditions G_t to all markets $G = [G_1, \cdots, G_T]$, the function to be minimised is

$$\min_{\theta} E_t (G'G). \tag{4.15}$$

The first-order conditions of Equation 4.15 are linear in the β parameters (excluding the price coefficient, β_{P}, and application quality coefficient as these enter nonlinearly in the pricing equations) and the γ parameters, and are nonlinear for all other parameters entering θ. This will simplify the estimation procedure by allowing us to partition out the linear parameters and concentrate the nonlinear search on the other parameters: $\beta_{\mathrm{P}}, \pi_{\mathrm{P}}, \sigma_{\mathrm{P}}, \rho$. For a given initial value of parameters in π_{P}, σ_{P}, and ρ, we solve for the mean utility levels δ_t that equate the predicted market shares to the observed market shares by using contraction mapping as in Grigolon & Verboven (2014):

$$\delta_t^{r+1} \equiv \delta_t^r + (1 - \rho) \left[\ln(s_t) - \ln(s_t(\delta_t^r)) \right]. \tag{4.16}$$

Convergence is reached when for each market t, $\delta_t^{r+1} \approx \delta_t^r$. Upon convergence, it is possible to recover the unobserved heterogeneity entering the mean utility term, ξ_{jt} and ω_{jt}:

$$\begin{aligned} \xi_{jt} &= \delta_{jt} - x_{jt}\beta \\ \omega_{jt} &= mc_{jt} - w_{jt}\gamma. \end{aligned} \tag{4.17}$$

The interaction of this variable with a set of instruments gives the moment conditions that enter the GMM function.

An issue in demand estimation is that the price is potentially endogenous since it is possibly correlated with the unobserved product characteristics (to the researcher) because of the omitted tablet quality. Since the correlation between price and tablet quality is likely to be positive, the OLS estimated price coefficients might be upwardly biased. The consequence is that the markup recovered from the pricing equation will be overestimated and cause many negative marginal costs, making no economic sense. The empirical IO literature has advanced instruments that can cope with this endogeneity (see Hausman & Taylor 1981, Berry 1994, Berry et al. 1995). Besides the price endogeneity, the indirect effect of application quality also raises concerns of endogeneity. The unobserved tablet quality can drive tablet sales, and consequently the user installed base, which induces the developers to produce higher quality applications.

4.3.4 Instruments

We deal with the endogeneity issue of price and application quality by employing a set of instruments. The tablet characteristics (except price) entering $\tilde{x} = w$ are assumed to be exogenous. Following previous related literature, we generate two sets of instruments for the price: BLP-type and Hausman & Taylor (1981)-type. The BLP-type instruments are the sum of observed product characteristics except for the price of other tablets produced by the same producer. The Hausman & Taylor's 1981-type instruments are based on the assumption that multi-product firms have a common cost structure, and once we control for the firm fixed effect, the average price of other products by the same firm can be used as an instrument. Following the previous literature (see Nair et al. 2004, Corts & Lederman 2009), we employ the average tablet characteristics of products within the same group as instruments for application quality.

We also employ the regression tree approach (Breiman et al. 1984) to capture any non-linear effects of tablet characteristics on prices and within market shares. This process enables us to generate a set of instruments for both prices and within market shares as follows. The list of instruments in addition to $\tilde{x}$ are: h_1 (sum of the screen size of other products by the same firm), h_2 (average price of other products in other markets by the same firm), h_3 (sum of screen resolution (log) of other products by the same firm), h_4 (average of the screen resolution (log) of products within the same segment), h_5, (average of the screen size of products within the same segment), h_6, (average of the storage of products within the same segment) and three instruments constructed using a regression tree approach: h_7 (a dummy taking value one if Storage>12 and zero otherwise), h_8, (a dummy taking value one if Storage>48 and Screen size>7.9 and zero otherwise), and h_9, (a dummy taking value one if Storage≥24 and zero otherwise).

The instruments listed above form the H_{jt} matrix that enter the moment conditions of Equation 4.14.

4.4 Data description

This section describes the two datasets used in this work, which are the tablet and application data. In the first place, we present the main features of the two datasets. We then discuss the variables that are relevant to the empirical analysis.

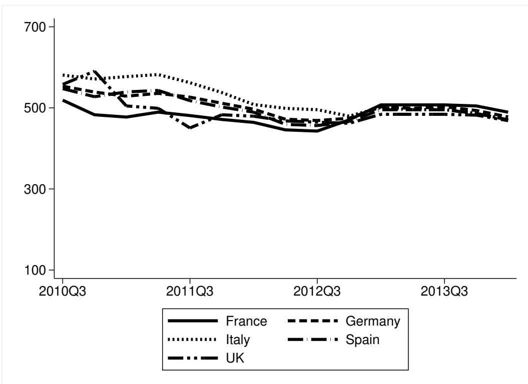
4.4.1 Tablet data

We obtain our tablet data from IDC CEMA. This data contains product-level information on tablet characteristics such as: model name, model ID, producer, operating system (OS), CPU type, connectivity, screen size, screen resolution, storage, prices, and sale units for five countries (the UK, France, Germany, Spain, and Italy). A total of 775 products are observed over 15 quarters from 2010Q3 to 2014Q1. Products are differentiated by specs, leading to 12,337 observations. These products are produced by 45 different vendors and are compatible with one of six operating systems: Android, iOS, Blackberry OS, Windows, Windows RT, webOS. For our analysis, a market is defined as a combination of country-time, which means that the number of markets is 75 (15×5). While tablet characteristics are market invariant, unit sales, prices, and the number of products vary by markets.

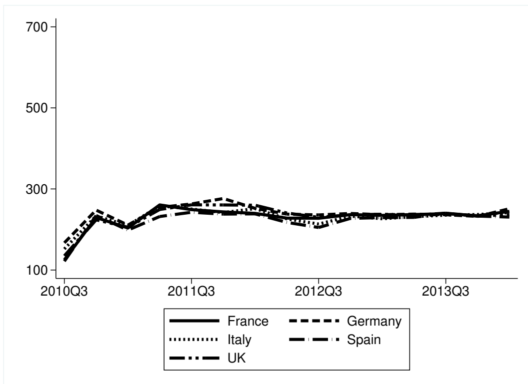
To illustrate how sales and (average) prices vary by time and country, we present their trend for the 5 European country markets in Figure 4.1. The unit sales of iPad exceed those of Android until 2012Q2 and, then the sales of Android-based tablets rise dramatically and surpass those of iOS. This can be explained by the different business models adopted by the two platforms. While Android is an open platform licensed to many producers, iOS is vertically integrated by Apple, and thus there is only one producer. The number of Android tablet models growing more significantly than the number of iPad models, hence resulting in higher unit sales. Seasonality also has a clear impact on unit sales, with noticeable Christmas period peaks. For average prices, the trend has opposite gradients for the two OSs at the early period—with iOS displaying a slight decrease in the average price and Android-based tablets showing a rise. The reason is that Apple originally launched very high-quality iPad models and then introduced smaller size iPads (iPad mini) at lower prices. By contrast, Android tablets targeted the low-quality segment first and then expanded to the middle and high-quality segment. Since 2012, the average price of both iPad and Android tablets became stable, with the former being significantly higher than the latter. Except for the last quarter of each year, the statistics are consistent with the law of demand. When the price falls/rises, sales surge/drop. In terms of the operating system, the data shows that iOS and Android-based tablets dominate the market, as the number of unit sales of other OS-based tablets is negligible. For instance, while unit sales of iOS and Android tablets in 2014Q4 are 1,035,642 and 709,961 respectively, there are only 15,040 units of other OS tablets. Therefore, when we concentrate our analysis on the two main OSs, we cover almost all markets.

Figure 4.1: Tablet unit sales and average prices in five countries between 2010Q3 and 2014Q1

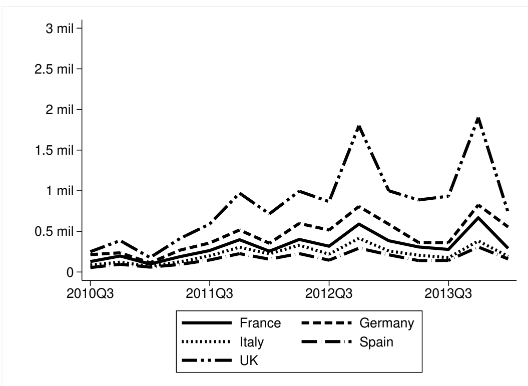
(a) Average iPad prices



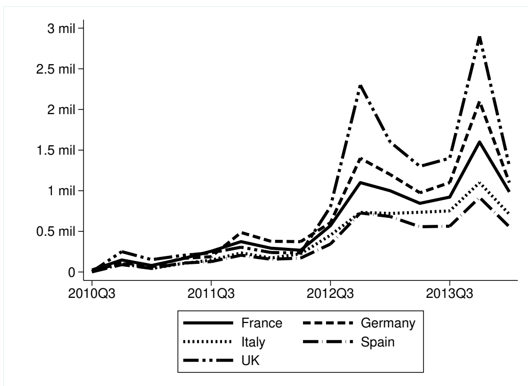
(b) Average Android tablet prices



(c) iPad sale units



(d) Android tablet sale units



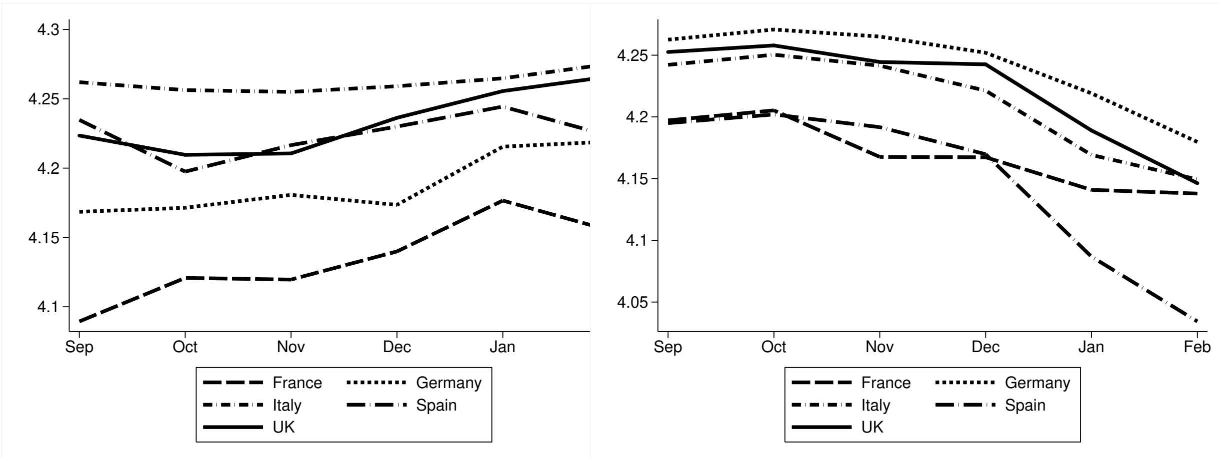
4.4.2 App data

The app data was bought from Priori Consulting Analytics. It contains six-monthly panels of top 1,000 ranked (most downloaded) apps in Google Play and Apple Store in each of five European countries (the UK, France, Germany, Spain, and Italy). The period covered by the data is September 2013-February 2014, which makes up to 30 country-time markets.

Our main interest in the application data is to extract a measure of app quality. As soon as tablet users download and use a mobile application, they are asked to write a review and rate that app on a scale of 1 to 5. We exploit the average user rating of each app in our dataset as a proxy of app quality. We believe it is a good indicator to reflect on how good and reliable an app is. For each market, we weigh the average app user rating with the number of all-time downloads. We weigh apps to capture the fact that popular apps contribute more to the average quality perceived by users than less popular ones. In the appendix, we show how results change if we use other metrics, such as the median of customer ratings, the weighted average rating of top apps, etc. We then calculate the weighted average rating of the top 1000 apps in each store in a country at a time period and use this measure as a proxy for average software quality and study its effect on tablet demand.

Figure 4.2 displays the weighted average app rating by period and country, i.e., by market. In most countries, the weighted average rating in Google Play store at the early period is slightly higher than that in Apple Store. However, it becomes lower at the later stages. The rating of any particular app is country invariant. Nevertheless, the average of top apps in each store still varies across time and countries (see the figure). Countries have a different portfolio of top 1000 apps because, first, an app does not need to be top in all countries in the same period (or in any period) and second, there are local apps that are distributed mainly in that country.

Figure 4.2: The average rating of the top 1000 ranked apps in the App Store and Google Play in 5 countries Sep 2013 - Feb 2014



(a) Apple Store (b) Google Play

Combining the app and tablet datasets

In this section, we will discuss how the two datasets (tablet and mobile application) are combined. As we aim to estimate the effect of cross externalities generated by application quality, the two datasets will have to be available in the same market. Therefore, we exclude non-overlapping periods. The periods of tablet data and application data do not coincide. The former is quarterly and spans a longer period (2010Q3-2014Q1), while the latter are monthly and are limited to the time sub-period 2013M9-2014M2. To achieve the maximum overlapping periods for quantifying the externality parameters, we select three months coinciding with three quarters. These are 2013M9, 2013M11, and 2014M2 and then match these to the quarters of tablet data 2013Q3, 2013Q4, and 2014Q1. Thus, tablet data are reduced to three quarters only, dropping the number of observations from 12,337 to 4,849. Besides that, as we only observe user ratings for applications distributed in Apple Store and Google Play, the tablet observations that are not compatible with these two stores will also be eliminated. Finally, we exclude 54 observations that have too tiny market shares, to avoid outliers. This leaves us with 3,753 observations of tablet and application data. Finally, we calculate each tablet market share as the ratio between that product unit sales and the market unit sales (assumed to be half of the country's population). We assume this because according to Statista, the number of tablet users in each of the five countries reached over 50% of the population in 2015.[4]

The summary statistics of the variables used in the estimation are presented in Table 4.1.

Table 4.1: Descriptive statistics main variables for estimation

	N	Mean	Std.dev	Min	Max
market share (s)	3753	2.3E-04	5.26E-04	2.53E-08	0.01
price (p)	3753	261.1	170.12	37.74	1050
screen size	3753	8.65	1.37	7	13.3
storage	3753	20.95	20.02	0.51	250
log screen resolution	3753	13.83	0.66	12.86	15.23
connectivity	3753	1.34	0.48	1	2
application quality	3753	4.13	0.07	4.03	4.28

Note: Connectivity takes the value 1 if the connectivity is WIFI and 2 if WIFI/3G or WIFI/4G. We multiply the two dimensions of the screen resolution and take the log as the value entering the estimation.

Eurostat Demographic Data

The last tranche of data used for estimation is given by demographics obtained from Eurostat, European Union Statistics on Income and Living Condition (EU-SILC) survey 2013. From the survey, we randomly draw 100 individuals for each country. To avoid issues that may arise by having too large income values (outliers) in the estimation, we restrict the income variable to its 5th and 95th percentile (5,000 and 100,000 EUR, respectively). We then rescale income by dividing it by 100,000. In the regressions, we interact income with the price and the variable

[4]See: https://www.statista.com/statistics/271001/penetration-rate-of-tablets/

app rating. Since we have no quarterly demographic data, and our timeline only lasts three quarters, we assume that individual income is time-invariant.

4.5 Results

In this section, first, we show the estimation results of joint demand and supply equations and then present the two counterfactual experiments. We are thus able to provide more insight into the role of indirect quality. We also test the hypotheses derived from the theoretical model described in Chapter 3.

4.5.1 Main results

Table 4.2: Joint estimation results

	OLS NL		NL		NL^e		RCNL		RCNL^e	
	Parameter (1)	SE (1)	Parameter (2)	SE (2)	Parameter (3)	SE (3)	Parameter (4)	SE (4)	Parameter (5)	SE (5)
Demand side										
Constant	-16.831**	0.499	-3.585**	0.028	-9.880**	0.032	-10.543**	3.349	-13.899**	0.032
Storage	-0.002	0.003	0.001	0.001	0.001	0.001	0.006	0.005	0.006**	0.001
Screen resolution	0.827**	0.047	0.186**	0.047	0.493 *	0.208	0.370**	0.096	0.546**	0.047
Screen size	0.015	0.022	0.013	0.015	0.084**	0.014	0.087	0.047	0.102**	0.016
Connection	0.098	0.069	0.054	0.040	0.057	0.040	0.258	0.151	0.288**	0.043
Application quality	-0.196	0.321	-0.536**	0.130	1.077**	0.135	0.376	0.205	0.700 *	0.306
Price (βp)	-0.008**	0.000	-0.002**	0.000	-0.018**	0.000	-0.006**	0.002	-0.009**	0.000
Price (σp)							0.006	0.044	0.006**	0.001
Price (πp)							0.011**	0.004	0.013**	0.001
Correlation ρ	0.264 *	0.104	0.859**	0.018	0.885**	0.001	0.740**	0.108	0.754**	0.016
Pricing equation										
Constant	-12.585**	0.037	-7.228**	0.157	0.023**	0.001	0.314	0.482	0.581**	0.058
Storage	0.016**	0.001	0.029**	0.001	0.473**	0.002	0.004	0.011	0.004	0.002
Screen resolution	0.762**	0.037	0.516**	0.037	0.237**	0.015	0.233**	0.072	0.237**	0.018
Screen size	0.384**	0.016	0.263**	0.015	0.628**	0.034	0.114	0.117	0.113**	0.024
Connection	0.882**	0.035	0.681**	0.034	0.061	0.117	0.269 *	0.137	0.265**	0.052
Model Statistics										
N	3753		3753		3753		3753		3753	
Pseudo R^2_D	0.684		0.987		0.989		0.697		0.715	
Pseudo R^2_S	0.769		0.678		0.702		0.681		0.662	
J-stat	5E-15		2.121		2.664		13.446		11.826	
N mc<0	1049		431		368		8		8	
Average PCM	0.513		0.460		0.429		0.272		0.252	

Notes: Significance level: $*p < 0.05$, $**\,p < 0.01$. e: Application quality is treated as endogenous. PCM: price-cost margin. Time, country and firm fixed effects are included both in the demand and pricing equations but not reported. Instruments: [Nested Logit: D=$h_2, h_3, h_4, h_8, h_9, h_{10}$], [Nested Logit^e: D=$h_1, h_2, h_4, h_6, h_7, h_8$], [RC Nested Logit: D=$h_2, h_5, h_8, h_9, h_{10}$],[RC Nested Logit^e: D=$h_1, h_2, h_4, h_6, h_7, h_8$]. We report the tests of strength and validity of the instruments in Table A.2 (Appendix A.2), where it is shown that the instruments that we have chosen are valid and strong.

The tablet demand and pricing estimation results are presented in Table 4.2. The first pair of columns show the results of a simple OLS estimation of nested logit tablet demand and supply without accounting for the endogeneity of price, within the market share, and application quality. Due to the endogeneity issue, most of the estimated coefficients on the demand side, especially the estimated coefficient for application quality, are not statistically significant. The consequence of ignoring this issue is that it leads to biased estimates, which causes a large number (about 28%) of negative marginal costs. Additionally, the price coefficient and within nest correlation ρ parameter are statistically significant and have the expected sign.

The next two pairs of columns present the results of nested logit joint demand and supply GMM estimate *without* (by *with*) controlling for the endogeneity of application quality. The advantage of using a GMM estimator is that it reduces the bias and improves the efficiency (of the estimates). This because the number of negative marginal costs has gone down significantly compared to the least-squares version. The estimated coefficients of the two specifications differ, especially that of application quality. Without controlling for the endogeneity, the coefficient of app quality is underestimated and turns out to be negative. After addressing the endogeneity issue, the coefficient of application quality becomes positive and significant. This finding confirms that the quality of available apps in the application store influences the demand for tablets associated with that store. Controlling for the endogeneity of within market shares has corrected the downward bias of the OLS estimates. The estimated within-segment coefficient, ρ, is above 0.85 in both specifications, which is considerably higher than in the benchmark OLS nested logit specification. The intuition here is that we have a strong business stealing effect within each platform. This means that a small increase in the price of a product can cause a large market share loss to other products within the same platform.

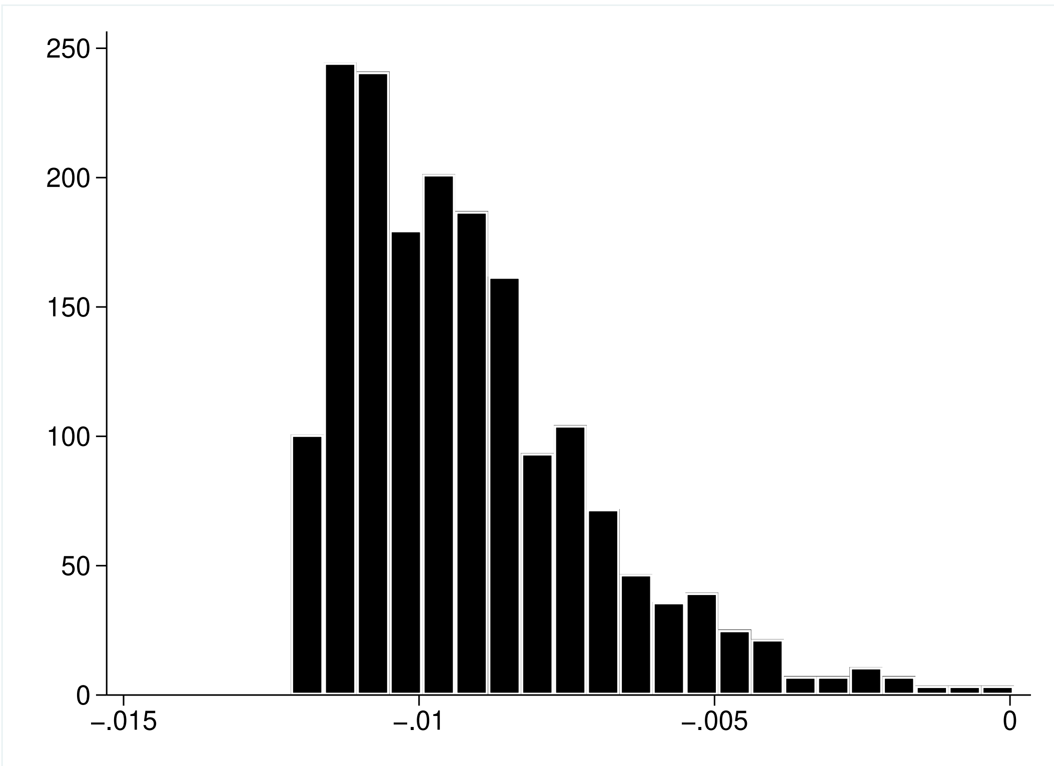
The joint estimation of demand and supply and the GMM approach tackles the issue of endogenous price. The coefficient is negative and significant. However, the price coefficient in all nested logit specifications is relatively small in absolute value, and the price elasticity of demand is not sufficiently picked by the within market share correlation coefficient, resulting in a great number of negative marginal costs also after correcting for the endogeneity (431 and 368, respectively).

In the last two columns, we show the RCNL model results when the application quality is treated first as exogenous, and, then as endogenous. As can be seen, the estimated coefficients in these two columns are statistically more significant than in the nested logit model. This suggests that the inclusion of the random coefficients has improved the efficiency of the estimator. As a result, the number of negative marginal costs has gone down substantially from NL to RCNL. Thus, we choose RCNL as our preferred model. For this one, we run an additional estimation where we control for the endogeneity of application quality. The first set of results are the mean marginal effect on the utilities (βs). Connection, screen resolution, screen size, and most importantly application quality, all have the expected positive significant effect on tablet demand. RCNL with application quality treated as endogenous generates slightly higher estimates in magnitude and smaller standard errors. When we do not treat application quality as endogenous, the estimated coefficient for application quality is not statistically significant. This implies that accounting for the endogeneity of the application quality has greatly improved the estimates' efficiency. Relative to the Nested Logit model, the nesting parameter in RCNL remains highly statistically significant from zero and one, but the magnitude is smaller. This suggests that the omission of random coefficients may lead to the overestimated within nest parameter ρ.

Besides the quality of mobile applications, our main focus is on the price parameters. The mean coefficient on the price (β_{p}) is negative and statistically significant from zero, suggesting that consumers receive disutility from higher prices. The magnitudes of the estimated mean price coefficients in the two RCNL specifications are significantly different from those in the two NL models. This because we have accounted for the heterogeneity in consumer preferences of the price in the RCNL models. The dispersion around the mean price effect induced by the unobserved and observed individual characteristics (income) are significant, apart from the effect of unobserved individual characteristics (σ_{p}) in the RCNL model with exogenous tablet quality. This implies that both unobserved and observed demographic would have significant impacts on consumer taste for prices. As one would expect, high-income individuals are less elastic to price changes. Figure (4.3) pictures the distribution of price sensitivity for all markets. There is sufficient heterogeneity of price sensitivity. Because of the skewed distribution of the price sensitivity, it does not surprise that there is a significant difference between the magnitude of the estimated mean price coefficient of RCNL and that of NL.

Finally, the bottom panel of Table 4.2 displays the results of the pricing equation side. Almost all the estimated coefficients are positive and statistically significant, which implies that the higher quality of tablet characteristics would induce higher marginal cost (of both production and distribution). For instance, to produce a tablet with an inch larger screen size, the marginal cost would increase by $exp(0.113) - 1 = 0.1196$ or 11.96%. Similar to the demand side, the estimated cost side parameters of the two RCNL specifications are similar to one another and different from those in the two NL specifications.

Figure 4.3: Frequency distribution of price sensitivity



We document the own and cross-price elasticities averaged over products and segments in Table 4.3. We separate the cross-price elasticities into cross-price elasticities of products in the same segment and products in other segments. The average own-price elasticities of Apple's products using iOS is, in absolute value, higher than that of Android-based tablets, but so is the average elasticity of products belonging to the same segment. These results have several implications for competition in the tablet market. As expected, competition between products within the same segment is more intense than that of products across segments. This is the result of a significant within-grouping parameter. This result tells us that products are differentiated across stores. Furthermore, the business stealing effect is stronger within the iOS than within the Android operating system; implying that iPads are more homogenous than Android-based tablets. This is not a surprise as many manufacturers produces Android tablets with various styles and designs. Finally, a price increase in price will lead to a larger loss of market shares of Apple products than Android-based tablets, due to the stronger business stealing effect in the iOS group.

Segment-level cross-price elasticities are reported in the last pair of columns. They show how much the market share of a product in the nest increases, on average, if the prices of all products in that nest (same group) or in other nests (different groups) increase by 1%. It is not surprising that cross-price elasticities are very small between different segments, as the market has not tipped towards either of the two platforms. This confirms again that there are soft competition and weak business stealing effects between tablet producers across platforms. Therefore, an increase in the price of a tablet in one platform only has a minimal impact on the demand for tablets in the competing platform, whereas it has larger impacts on the demand for tablets within that platform.

Table 4.3: Product-level and segment-level price elasticities in the UK 2014Q1

Store	Product-level (average)			Segment-level	
	Own-price elasticities	Cross-price elasticities		Cross-price elasticities	
		Same segment	Different segment	Same segment	Different segment
Nested logit					
Apple	-1.080	0.007	0.002	0.170	0.038
Android	-0.553	4E-04	1E-04	0.095	0.032
Nested Logit^e					
Apple	-0.959	0.005	0.014	0.131	0.035
Android	-0.491	3E-04	1E-04	0.075	0.029
RC nested logit					
Apple	-7.854	0.224	0.005	5.605	0.1238
Android	- 4.897	0.014	3E-04	3.384	0.0952
RC nested logit^e					
Apple	-8.487	0.242	0.006	6.044	0.148
Android	-5.394	0.015	5E-04	3.717	0.121

Notes: *e*: RCNL model with endogenous application quality. Product-level own-price elasticities, product-level and segment-level cross-price elasticities, based on estimates in Table 4.2. Product-level cross-price elasticities are averaged across products from the same segment and the different segment. Segment-level cross-price elasticities indicate how much the market share of a product in one segment would increase (in percentage) if all other products in the same or different segment increases by 1%.

4.5.2 Counterfactual analysis

We will perform two counterfactual experiments to test the two hypotheses stated in the previous chapter. In the first hypothesis, we examine what would have happened to the demands for tablets, prices, profits, and consumer surplus if each platform had chosen to exclude the lowest quality apps one at a time. In the second counterfactual, we show the effects on the demands for tablets, prices, profits, and consumer surplus if a regulator had imposed full multi-homing/compatibility of apps between the two platforms.

Counterfactual 1: Exclusion of low-quality apps

In the tablet results section, we have estimated the indirect quality parameter and found a positive indirect effect from mobile applications on the tablet demands. To gain a better insight into the impact, we conduct a counterfactual analysis in each of the five country-based tablet markets based on our estimates of the Random Coefficients Nested Logit model when application quality is treated as endogenous. We restrict the counterfactual to the last period, which is the first quarter of 2014. In this counterfactual, we aim to study the indirect effect of a policy by online stores to remove low-quality applications on the demands for tablets, prices, and profits of tablet manufacturers. Specifically, we investigate, for each online store, the exclusion, one at a time, of the 10% of the applications with the lowest quality. The intuition here is that the exclusion of low-quality apps can improve the average application quality, impacting the tablet market. The effects of this exclusion on the average application quality are shown in Table A.3 in Appendix A.2. As shown in the table, the policy is likely to improve the average quality of iOS applications more than for Android applications, which helps justify our first hypothesis in Chapter 3. From the tablet joint estimations, we backed out the marginal costs. We compute the new markups, calculate the new equilibrium prices, market shares while holding the marginal costs constant. The results of this counterfactual exercise are reported in Table 4.4.

The results confirm Hypothesis 3.1: the increase in the average application rating produced by excluding 10% of the applications with the lowest quality in the platform has positive spillovers on the demands of tablets and profits of manufacturers (and distributors) that work within that platform. The spillover is larger for Apple products, as confirmed by the K-Smirnov test. This may be why Apple was the first to raise the quality standard of the applications published in its store in 2016, by imposing stricter guidelines for approving applications written by developers. This strategy leads to an increase in tablet market shares worldwide for Apple as shown in Table A.4 in Appendix A.2. One year later, Google followed this strategy by imposing stricter control for applications, which lead to the removal of many low-quality applications. The exclusion of the lowest quality apps generated negative effects on the demands, and profits, of manufacturers selling via the other platform. The absolute values of the own-effects are much larger than those of the cross-effects. This because competition between tablet producers across platforms is soft, as shown by the limited substitution patterns of products across platforms highlighted in Table 4.3. Hence, an increase in the average application quality in one store leads to a larger market share gain from the outside option than from competitors in the competing

Table 4.4: Counterfactual 1 —Removing 10% of apps with the lowest rating

		France	Germany	Italy	Spain	UK
		Average own-effect				
Apple	Price changes (%)	0.097**(R)	-0.110** (R)	0.003 (F)	-0.323(F)	0.066(F)
		(0.001)	(0.023)	(0.002)	(0.233)	(0.077)
	Market share changes (%)	12.190**(R)	7.495**(R)	7.475**(R)	8.737**(R)	6.650**(R)
		(0.083)	(0.148)	(0.064)	(0.541)	(0.327)
	Profit changes (%)	12.539**(R)	7.225**(R)	7.483**(R)	7.941**(R)	6.808**(R)
		(0.074)	(0.128)	(0.065)	(0.041)	(0.378)
Android	Price changes (%)	-6.8E-04**	-0.023**	-0.009**	-3E-04	-0.016**
		(2.5E-04)	(0.002)	(0.001)	(0.005)	(0.005)
	Market share changes (%)	3.542**	3.462**	2.909**	2.010**	3.801**
		(0.008)	(0.015)	(0.009)	(0.019)	(0.031)
	Profit changes (%)	3.534**	3.363**	2.863**	1.992**	3.650**
		(0.008)	(0.016)	(0.012)	(0.009)	(0.042)
		Average cross-effect				
Apple	Price changes (%)	-0.022**(R)	-0.241** (R)	-0.061**(R)	-0.332(F)	-0.048(R)
		(4.8E-04)	(0.026)	(0.018)	(0.210)	(0.037)
	Market share changes (%)	-0.323**(F)	0.059(F)	-0.157**(R)	-0.157**(F)	-0.551 *(R)
		(0.019)	(0.163)	(0.009)	(0.016)	(0.245)
	Profit changes (%)	-0.397**(R)	-0.462** (F)	-0.325**(R)	0.104	-0.674**(R)
		(0.020)	(0.093)	(0.020)	(0.353)	(0.016)
Android	Price changes (%)	-0.015**	-0.126**	-0.031**	-0.018	-0.060**
		(7.4E-04)	(0.015)	(0.003)	(0.018)	(0.014)
	Market share changes (%)	-0.383**	-0.533**	-0.242**	-0.280**	-0.676**
		(0.015)	(0.063)	(0.018)	(0.061)	(0.083)
	Profit changes (%)	-0.466**	-1.016**	-0.386**	-0.380**	-0.901**
		(0.018)	(0.054)	(0.022)	(0.027)	(0.048)
		Consumer welfare effect (%)				
Apple		3.098	3.223	2.000	2.132	2.329
Android		2.673	1.840	2.094	1.441	0.925

Notes: Significance: $^{*}p < .05$, $^{**}p < .01$. Bootstrap standard errors are in parenthesis. We perform the K-Smirnov test, where the null hypothesis is that the changes for iOS and Android tablets are equally distributed. R=Reject at 5%; F=Fail to reject at 5%. The average own-effect is the (average) effect on the outcome variables of removing lowest quality applications in that store. Average cross-effect is the (average) effect on the outcome variables of removing lowest quality applications in the other store.

platform.

Counterfactual 2: Compulsory interoperability of apps

In this counterfactual, we aim to study the effects of a possible policy intervention by platforms/regulators, which consist of imposing all applications to be the same in both stores. This can be seen as a proxy for compatibility/interoperability. To implement this counterfactual we impose the average application ratings of both stores in a market (country-quarter) to be the highest application quality of both stores. The intuition is that users in the store with higher average app quality will not be affected. By contrast, users in the store with lower average quality can benefit from downloading higher-quality apps in the other store. Similar to the first counterfactual, we evaluate the effects of this counterfactual in the first quarter of 2014.

Table 4.5: Counterfactual 2 —All applications appear in both stores

		France	Germany	Italy	Spain	UK
Apple	Price changes (%)	-0.008**	-0.072**	-0.090**	-0.552 *	-0.085**
		(1E-04)	(0.009)	(0.006)	(0.272)	(0.045)
	Market share changes (%)	-0.613**	-1.199	-4.273**	-5.068**	-3.863**
		(6E-04)	(0.085)	(0.026)	(1.078)	(0.048)
	Profit changes (%)	-0.635**	-1.352**	-4.492**	-6.237**	-4.053**
		(3E-04)	(0.035)	(0.011)	(0.465)	(0.182)
Android	Price changes (%)	6E-04**	0.013**	0.004**	-0.006	0.020**
		(0.000)	(0.001)	(0.001)	(0.006)	(0.004)
	Market share changes (%)	0.582**	1.353**	4.306**	6.576**	4.162**
		(7E-04)	(0.007)	(0.007)	(0.019)	(0.047)
	Profit changes (%)	0.585**	1.399**	4.320**	6.551**	4.232**
		(0.002)	(0.010)	(0.004)	(0.010)	(0.010)
Consumer welfare effect (%)						
		0.283	0.147	1.922	2.830	-0.235

Notes: Significance: $^{*}p < .05$, $^{**}p < .01$. Bootstrap standard errors are in parenthesis.

The results support Hypothesis 3.2 of our theoretical model in Chapter 3: the market shares of Android products go up, while those of iPads go down. This simply because the average application quality in Apple Store is higher than Google Play[5], meaning that interoperability shall increase the average Android apps quality and decrease that of iOS apps. This leads to a shift in demand from Apple to Android tablet manufacturers. The profit results suggest that Android tablet producers gain from interoperability, while Apple loses and may want to fight to prevent this from happening. The effects on prices are asymmetric. Apple is willing to reduce its prices to protect its demand (and profits), whereas Android tablet producer prices do not increase much. In terms of consumer welfare, the counterfactual results suggest that on the tablet market, consumer welfare rises is likely to rise. The estimated consumer welfare is only a lower bound since we have not estimated the (positive) change in the consumer benefits in the application market.

[5] See Table A.3 in Appendix A.2

4.6 Conclusions

In this chapter, we study the role of cross-network externalities generated by applications on the tablet demand for the two dominant platforms: Apple iOS and Google Android. The chapter tackles a gap in the previous literature by allowing application quality to enter the tablet demand function, which accounts for the indirect externalities induced by app quality. We estimate a system of simultaneous demand and supply for tablets based on the combined tablet and application data from five European countries, followed for three quarters, 2013Q3-2014Q1. The estimates show a positive and significant indirect quality effect from applications to the tablet market. This suggests that an increase in application quality leads to an increase in the demand for tablets.

To study the importance of these effects on the tablet market and test the hypothesis from the theoretical model set up in the previous chapter, we conducted two counterfactual analysis. First, we separately let each application store exclude the 10 % of lowest quality applications and calculate the new equilibrium market shares, prices, and profits of the tablet producers. The results show that Apple gains more market share and profit from this policy than Android tablet manufacturers do. Therefore, Apple has an incentive to improve its application quality, for instance, by setting a strict quality control process to approve new apps. Our second counterfactual experiment examined whether platforms or policymakers have an incentive to make applications compatible/interoperable across platforms. This counterfactual is performed by setting all applications to appear in both stores and have the same functionalities. The implication is that the average app quality of each store would be the same. We find that Android tablet producers with lower perceived average application quality would gain more market shares and profits from this policy. By contrast, Apple would suffer a loss in terms of market share and profit. Interestingly, this policy has a significant negative impact on Apple product prices, but small and positive effects on Android tablet prices. On the other hand, the policymaker may have an incentive to force interoperability/full multi-homing across platforms since this would improve consumer welfare.

The chapter also has several limitations, and there is room for future research. First, we only focus on the tablet side of the market and do not analyse the application side due to data limitations. As the result, we can not fully capture the welfare effects of the quality control policy by platform and compulsory interoperability intervention by the policymaker. Hence, one possibility for future research is to exploit a richer dataset of both tablets and applications to quantify the indirect network externalities generated from users to developers and estimate, jointly, the market multi-sides to capture the full effect of cross-network externalities. Secondly, we employ a static empirical framework, which can not account for the dynamic long-term impacts of the quality control policy and interoperability intervention. For instance, the exclusion of low-quality apps will induce future developers to produce higher quality apps and improve further the average quality of apps in the store, which means the effect of this policy on the tablet demand may potentially become larger over time. Therefore, future research can employ a forward-looking dynamic model to address this limitation. Additionally, it would be interesting to study the role of indirect network effects from the user side on how developers choose to publish paid or free applications. Another point worth investigation is self-selection in app-rating by store by using the information on multi-homed apps. In this case, apps in different stores may identify users with different benchmark values for high and low quality. This has implications for the reviews for the same product.

Chapter 5

Quality versus variety in multi-sided markets: the case of closed and open platforms

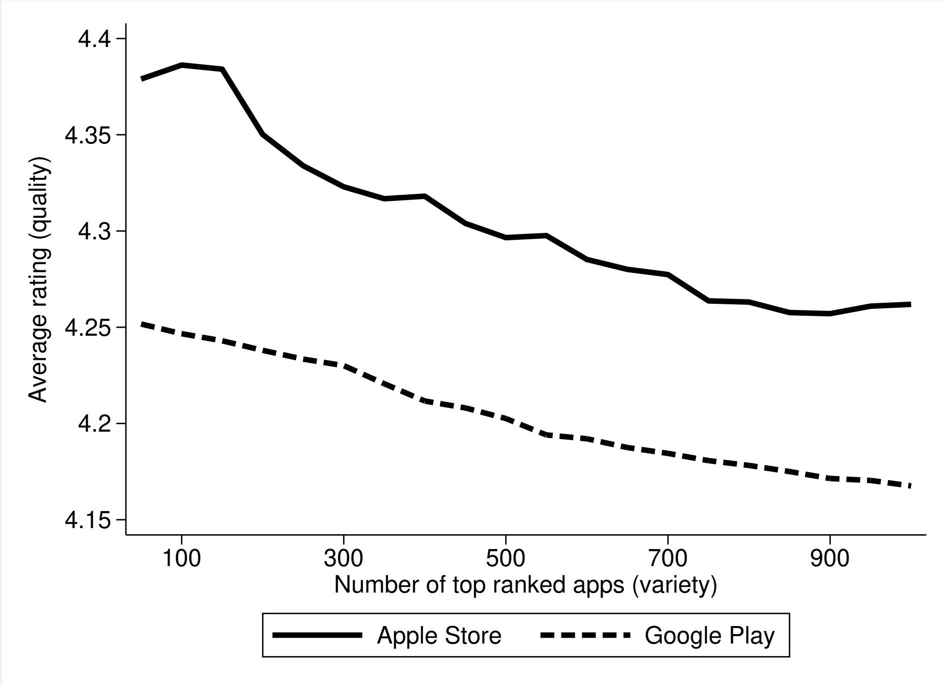
5.1 Introduction

Apart from competing in pricing, multi-sided platforms also can compete by using non-pricing strategies, such as "governance rules" as mentioned in (Boudreau & Hagiu 2009). They suggest that platforms may be profitable when restricting access to the network for a proportion of participants. In the late 1980s, Nintendo was among the first to adopt this strategy successfully, by capping the number of games a developer could sell, as well as the number of developers accessing their video game console, which rewarded them a leading position in the video games market in the following decade. This strategy came at the cost of a reduced variety of games available, which enabled Nintendo to indirectly control quality by avoiding the "lemons" market failure.[1] This example highlights a potential negative relationship between product variety and quality in a multi-sided market —with important implications for platform strategies. Another example of this negative relationship in another multi-sided market is displayed in Figure 5.1, where we analyse the mobile application market data. We employ data on top 1000 applications in Apple App Store and Google Play in February, 2014. These top applications are ranked by Apple and Google based on their attributes like number of downloads, number of reviews, average user's rating, etc. We measure the application quality by using the average user rating. To illustrate the relationship between application quality and variety, we compute average application quality for top 100, 200, ..., 1000 apps. As can be seen in Figure 5.1, the average applications quality is decreasing in both stores when we include higher number of applications. This provides descriptive evidence for the inverse relationship between quality and variety. Therefore, platforms might be faced with a trade-off problem: limiting variety to have higher average quality, or increasing variety with lower average quality.

The mainstream literature on two-sided markets (Armstrong 2006, Rochet & Tirole 2003, Hagiu 2011, Weyl 2010) mainly focuses on price competition between symmetric competing plat-

[1] Evans et al. (2006) point out this to be the main cause of a decline in the US video-game console industry.

Figure 5.1: Average mobile app rating (quality) against percentiles of ranking of top apps (variety) in Apple Store and Google Play in the UK (February 2014)



forms. However, there are many real-world situations where platforms operate with alternative business models. For instance, Apple has a closed-license operating system (iOS) —restricted to Apple products; whereas, Google has an open-license operating system (Android) —available for free to all hardware producers. Similarly, Windows is a closed-license operating system, compatible only with Microsoft products. Differently, Linux is an open-source operating system that can be ported to various hardware and modified by any software developer. On the other hand, platforms also employ variations of non-pricing strategy/governance rules, for instance: quality control, ranking and recommendation systems, search filters, access to API, rules of payment and dispute resolutions, information sharing, rules of how users of different groups can interact, etc. Because there is still a limited number of works on platform non-pricing strategies/rules and competition between asymmetric platforms, this chapter aims to fill in this gap in the literature on multi-sided platforms.

In this chapter, we build a model of competition between two platforms with different business models: a closed versus an open one, and study platform choice of the software quality standard. In practice, a platform can set the quality standard by checking the software before approving it. For instance, Apple has a strict review guideline, which may take a few days to check an app before accepting it in the store. This process ensures only apps with a certain quality standard can enter the platform. On the contrary, the app review process of Google Play store is not as strict as in Apple App Store and only takes a few hours. Therefore, one can argue that Apple App Store set a higher quality standard than Google Play store. Different from other theoretical works in the literature, we exploit the effect of consumer heterogeneity on platforms' strategic decisions by defining two groups of consumers based on their income. Consumers with different levels of income would have different preferences for prices, product quality, and variety. While low-income users are more price elastic and only value software variety but not quality, high-income users would value quality higher than variety. As high-income users are willing to pay more for higher quality, platforms might have an incentive to set a high quality standard to attract more users of this group. Similar to Hagiu (2011) and Zheng & Kaiser (2013), in our model, platforms also choose the level of software quality standard in addition to prices. The trade-off between software quality and software variety in our model is quite straightforward: the higher the software quality standard set by platforms, the fewer the number of developers joining, and implicitly the less software variety. The choice of high software quality standard will have positive direct effects on platform profits as the platform can extract more profits from higher income users. However, it also has a negative indirect impact on the platform's profit by reducing software variety. In this chapter, we aim to answer whether the asymmetric platform business model and user preference for software quality have impacts on platforms' decision to choose software quality over variety.

In our work, we exploit the asymmetry between two competing platforms and show that if the high-income hardware users have sufficiently strong preferences for software quality over variety, the closed platform will specialise in a high-quality standard by restricting access to developers and attracting a larger fraction of high-income users. This helps to explain why Apple, a closed platform, always has a much stricter quality control than Google Android, an open platform. By maintaining its high quality standard, Apple can keep attracting high-income users and protect its profit from the rapid expansion of Android apps. Additionally, we examine the impact of high-income user preference for software quality on the software quality standard set by platforms. We conclude that it is likely that if the user preference for software quality rises, both the closed platform and the open platform have an incentive for a higher quality standard. The remaining sections of this chapter are organised as follows: the next section summarising the related literature, section 3 presents the model and equilibrium analysis, section 4 concludes. All proofs and equilibrium derivations are included in Appendix B.

5.2 Literature review

The coexistence of asymmetric platforms with different business strategies leads to the emergence of a branch of literature on closed (proprietary) and open platforms. This chapter contributes to this literature. The earliest papers studying the role of strategic difference between proprietary and open-source platforms on competition in the market are Casadesus-Masanell & Ghemawat (2006) and Economides & Katsamakas (2006). The former examine the dynamic equilibrium outcomes of competition between Microsoft (proprietary platform) and Linux (open-source platform) on the user side, in which users can learn from past purchases and improve the open-source platform. Additionally, the equilibrium outcome is also influenced by the "decay rate", which is negatively correlated with the effect of past user purchase on the current value of the two platforms. The larger the decay rate, the smaller the impacts of past users joining on the value of platforms in the current period. They found that if the decay rate is small enough, the two platforms coexist in the long run. Otherwise, Microsoft would eventually leave the market as it's value would become lower after each period. Different from Casadesus-Masanell & Ghemawat (2006), Economides & Katsamakas (2006) provide a two-sided analysis of the competition between Microsoft and Linux, since they take into account platform profit maximization on the developer side. Their main finding is that the proprietary platform (Microsoft) is likely to earn a larger market share and profit than the open platform (Linux).

Similar to Casadesus-Masanell & Ghemawat (2006), Casadesus-Masanell & Llanes (2011) also model the competition between proprietary software platforms and open-source software platforms, and allow users to access and improve the quality and value of open source software. However, instead of taking the platform business models as given, they study the endogenous choice of platform to be a proprietary, an open, or a mixed model, which is the combination of both proprietary and open-source software. The idea of this decision comes from the trade-off when choosing open-source software. When the platform gives open access to software, users can freely modify the codes. The user innovation process can enhance the quality and value of the software, thus the platform can attract more users and obtain more profits. On the other hand, the competitors also get free access, and thus may create competitive pressure on the platform, which lowers the price and dampens the profit. Their results show that when the quality of the proprietary platform's software is higher than the software of open platform competitors, the former is less likely to open the software. Additionally, they also study the role of compatibility, in which the software is compatible across platforms. They find that the proprietary platform is more likely to open the software under an incompatibility regime than compatibility. In the same spirit as these papers, this chapter also studies the competition between open and closed (proprietary) platforms. However, these papers only analyse the software side, while this chapter complements these works by incorporating the hardware side into the model. We also take a different approach in terms of modelling, as we employ the branches of the horizontal product differentiation model like Hotelling and Salop circular city to analyse the platform competition.

On the other hand, several papers address the quality aspect of the competition between open and proprietary platforms as this work does. Casadesus-Masanell & Llanes (2015) investigate the incentive of a quality investment by open and proprietary platforms. While in the proprietary case, the quality investment can only be implemented by the platform itself, in the open platform, developers can get free access and invest in quality. They prove that in the equilibrium, open platforms may have a higher quality investment than the proprietary ones. The higher quality investment by the open platform has positive spillovers on closed platforms, which justifies why Microsoft is also keen on contributing to Linux development. In the same vein, August et al. (2020) examine the quality investment level endogenously determined in the competition between a proprietary software platform and an open-source software platform, which is managed by both the originator and contributor. Different from Casadesus-Masanell & Llanes (2015), they analyze the role of license restrictiveness in the platform incentive to invest in quality. They find an interesting result that increasing the level of license restrictiveness can raise the effort of open-source software contributors to invest more in quality. Therefore, this would improve the open-source software quality and consumer surplus. Relevant to this work, none of these above papers address the trade-off between quality and variety in a multi-sided market hosting closed and open platforms.

We address the gap in the literature by a theoretical model that accounts for both variety and quality in a multi-sided market with asymmetric platforms. Thus, we also contribute to the small stream of literature on platform governance rule and strategy, which focuses on platforms playing the role of a regulator in the market for groups of agents. Hagiu (2011) is the closest paper to ours, being one of the earliest works addressing the direct trade-off between quantity and quality in platform markets. He analyses competition between symmetric two-sided platforms with sellers and buyers, and studies whether platforms have the incentive to exclude low-quality sellers to improve the average seller quality. His main finding is when buyer valuation for software quality is sufficiently high, platforms will have an incentive to exclude low-quality sellers. Similar to our model, his model also allows buyers (users in our case) to value both seller (developers in our case) variety and quality. However, while he assumes that platforms do not compete for the seller, we still model platform competition on the developer's side. The other difference is that we study the asymmetric platforms and investigate whether this asymmetry leads to different decisions of platforms to choose quality over variety. Another paper that shares the same spirit with Hagiu (2011) is Zheng & Kaiser (2013). Zheng & Kaiser (2013) model farmers —consumers interdependence by using a two-sided market approach, where the market plays the role as a two-sided platform. They extend the Hagiu (2011) model to some extent, which is also similar to our approach. First, farmer's revenue is modeled explicitly, second consumers have a higher preference for quality over variety, and last, the quality standard is computed explicitly, which is not addressed by Hagiu (2011). Zheng & Kaiser (2013) reach the same conclusion as the higher the consumer valuation for quality, the higher the optimal quality threshold set by the platform. However, they only address the case of a specific market and do not study competition between platforms with different business models like us.

By the same token as this chapter, other papers in the literature on platform governance rules also examine whether platforms should limit variety. However, their intuition of this strategy is different from Hagiu (2011), Zheng & Kaiser (2013) and our work. Casadesus-Masanell & Hałaburda (2014) investigate the platform's strategy to limit the number of software. In their model, there exist the direct network effects generated by users using the same software. Thus, the reduction of the number of software would encourage more users to the same software. This will generate larger direct network effects and drive more profits to the platform. Similar to Casadesus-Masanell & Hałaburda (2014), Halaburda et al. (2018) study how matching platforms compete by limiting choice. In the matching platforms, both positive indirect network effects and negative direct network effects occur. A larger number of choices on one side can generate positive cross effects to the other side as it increases the probability to be matched, but also increase the competition/congestion effect on that side, thus, generating negative direct effects. Therefore, the paper suggests that platforms can solve this problem by restricting the number of choices and charging higher prices to users. They prove that there exists an equilibrium where different platforms with different sets of choices can coexist if users have different utilities from outside options. This is because users with high utility from outside options (staying alone) would prefer an unrestricted number of choices and the opposite is true for users with low utility from staying alone. Finally, Teh (2020) provides a general theoretical framework to study a wider range of governance rules set by platforms: control of seller entry, information provision and recommendation, quality control, and search design options. However, the paper only focuses on the implementation of these governance rules by using prices/fees as instruments.

5.3 Theoretical model and analysis

This section will develop the theoretical model to study the decision of platforms to choose quality versus variety. We consider an incomplete information game with four types of agents:

- Two competing **platforms**: Platform 1 (a closed platform —also producing hardware) —and platform 2 (an open platform hosting $J \geq 2$ hardware firms). Platform 1 sets hardware price, developer access fee, and software quality standard; platform 2 only sets developer access fee, and quality standard (hardware producers benefit from free access).

- **Hardware producers**: this group includes all producers in platform 2 and the producer in platform 1.

- **Users**: a proportion μ of users is high-income and $1-\mu$ is low-income, with μ expected to be low as the share of high-income people in the population is always small relative to the low-income of the population.

- **Developers**: Similarly to users, they are uniformly distributed alongside the Hotelling unit line and face a unit transportation cost.

In terms of notation, we denote with superscripts h and s hardware and software sides of the market. Superscript e is used for expected values. Similarly, we denote with H and L the high- and low-income users. Subscripts one and two are used to indicate platforms.

5.3.1 Users

The hardware market is horizontally differentiated, and consumers adopt hardware in two stages. First, they decide which platform to join, and if they happen to choose platform two, they will select among the hardware available in that platform.

Stage 1. For simplicity, we assume all hardware devices have the same standalone utility V^h. After buying the hardware, users can download software from the platform (store) that uses the operating system installed in the hardware. We denote with z_i^{se} the expected average quality of software in the platform i and with n_i^{se} ($i \in \{1,2\}$) the expected number of software (software variety). To ensure an equilibrium where two platforms coexist, we set the expected average software quality z_i^{se} and the expected number of software n_i^{se} to range between zero and one. We write the expected utility of a high-income user from using the software as $n_i^{se} + \gamma z_i^{se}$, and with $\gamma > 1$ we capture the situation that high-income users prefer quality over variety. For simplicity, we assume that high-income users are not sensitive to price changes and low-income users only care about software variety and not software quality. Thus, the expected utility that a low-income user receives from software can be written as: n_i^{se}.

Hardware producers set the hardware prices p_1^h and p_{2j}^h ($j = \overline{1, J}$). Under the assumption of symmetry, in equilibrium, platform 2 hardware producers set the same price p_2^h. Hence, the utilities for the hardware of the two types of users located at x_H^h and x_L^h in one of the platforms are:

$$\begin{aligned} u_{H1}^h &= V^h + n_1^{se} - x_H^h + \gamma z_1^{se} \qquad & u_{H2}^h = V^h + n_2^{se} - (1 - x_H^h) + \gamma z_2^{se} \\ u_{L1}^h &= V^h + n_1^{se} - x_L^h - \alpha p_1^h \qquad & u_{L2}^h = V^h + n_2^{se} - (1 - x_L^h) - \alpha p_2^h. \end{aligned}$$

We derive the demand for each group of users and total demand for each platform as:

$$\begin{aligned} Q_{H1}^h &= \mu \frac{1 + \gamma(z_1^{se} - z_2^{se}) + (n_1^{se} - n_2^{se})}{2} \qquad & Q_{H2}^h = \mu - Q_{H1}^h \\ Q_{L1}^h &= (1 - \mu)\frac{1 + n_1^{se} - n_2^{se} - \alpha(p_1^h - p_2^h)}{2} \qquad & Q_{L2}^h = 1 - \mu - Q_{L1}^h \\ Q_1^h &= Q_{H1}^h + Q_{L1}^h = \frac{1 + \mu\gamma(z_1^{se} - z_2^{se}) + (n_1^{se} - n_2^{se}) - (1 - \mu)\alpha(p_1^h - p_2^h)}{2} & \\ Q_2^h &= Q_{H2}^h + Q_{L2}^h = 1 - Q_1^h = \sum_{j=1}^{n} q_{2j}^h. & \end{aligned} \tag{5.1}$$

where Q_1^h is user demand for platform 1 (hardware 1) and Q_2^h is the user demand for platform 2, and q_{2j}^h ($j = \overline{1, J}$) is user demand for each hardware producer in platform 2.

Stage 2. Had users chosen platform 2 in stage one, they can access the hardware produced by one of the single-product firms available on this platform. Firm j charges price p_{2j}^h for hardware j. Since high-income users are not price-sensitive, the probability that they buy one of the J hardware available on platform 2 is simply $1/J$. On the other hand, low-income users are price-sensitive and this impacts competition. Platform 2 hardware producers competing for the low-income users in a Salop circular city of length Q_{L2}^h. Each producer is located equidistantly and users are uniformly distributed on the segment. Firm j located at j/J has two competitors located on its left and its right. A low-income user located at a distance x_{L2}^h between firm j and firm $j+1$ is indifferent between two firms if:

$$\begin{aligned} n_2^{se} - \alpha p_{2j}^h - (x_{L2}^h - \frac{j}{J} Q_{L2}^h) &= n_2^{se} - \alpha p_2^h - (\frac{j+1}{J} Q_{L2}^h - x_{L2}^h) \\ \Leftrightarrow x_{L2}^h &= -\alpha \frac{p_{2j}^h - p_2^h}{2} + \frac{Q_{L2}^h}{2J}. \end{aligned}$$

Then, the share of low-income users for each hardware in platform 2 is:

$$q_{L2j}^h = 2x_{L2}^h = -\alpha(p_{2j}^h - p_2^h) + \frac{Q_{L2}^h}{J}.$$

Thus, the demand of users for each hardware produced for platform 2 is:

$$q^h_{2j} = -\alpha(p^h_{2j} - p^h_2) + \frac{Q^h_{L2}}{J} + \frac{Q^h_{H2}}{J} = -\alpha(p^h_{2j} - p^h_2) + \frac{Q^h_2}{J}.$$

5.3.2 Developers

Developers choose the platform that offers the highest pay off. Denote with p^s_i the lump sum access fee charged by platform i to the developers. Developers' willingness to publish on the platform depends on the expected number of both types of users, Q^{he}_{Hi} and Q^{he}_{Li}. Each developer faces fixed cost $f^s_i = (z^s_i)^2$ to develop and produce a software meeting quality standard z^s_i set by platform i. The higher the quality standard set by the platform, the higher the cost faced by the developer. All this has negative implications on the number of developers joining the platform. Without loss of generality, we assume that the average revenue from each low-income user for each software is 1. The average revenue for each software from high-income users is $1+\theta\gamma z^s_i$ (because high-income users are willing to pay for quality). Since the expected marginal utility that high-income users receive from software quality is γ, it is reasonable to assume that $\theta < 1$. For computation simplicity, developers are assumed to produce only one software[2], implying that software variety is the same as the number of developers. Similar to the assumption set for hardware setting, We assume that developers are uniformly distributed along the Hotelling line, and the platforms are located at the two extreme points 0 and 1, with transportation cost normalized to 1. The pay-off of the developer located at x_s of the unit line when joining the two platforms are:

$$\begin{aligned} u^s_1 &= (1+\theta\gamma z^s_1)Q^{he}_{H1} + Q^{he}_{L1} - p^s_1 - (z^s_1)^2 - x^s \\ u^s_2 &= (1+\theta\gamma z^s_2)Q^{he}_{H2} + Q^{he}_{L2} - p^s_2 - (z^s_2)^2 - (1-x^s). \end{aligned}$$

yielding the demand for developers:

$$q^s_1 = \frac{1 + (1+\theta\gamma z^s_1)Q^{he}_{H1} - (1+\theta\gamma z^s_2)Q^{he}_{H2} + Q^{he}_{L1} - Q^{he}_{L2} - p^s_1 + p^s_2 - (z^s_1)^2 + (z^s_2)^2}{2} \quad q^s_2 = 1 - q^s_1. \tag{5.2}$$

Equation (5.2) shows that $q^{s\prime\prime}_1(z^s_1) < 0$. Hence, if the quality standard is sufficiently high, the number of developers (software variety) start to decrease and the platform faces the trade-off between quality and variety.

5.3.3 Equilibrium analysis: platforms and hardware producers

Platform 1, platform 2, and hardware producers in platform 2 maximise their profits for the access fees, quality standards, and hardware prices. For simplicity, the marginal costs of platforms are normalised to 0. The marginal cost of producing hardware is held constant at c.

$$\Pi_1 = (p^h_1 - c)Q^h_1 + p^s_1 q^s_1, \quad \pi^h_2 = (p^h_2 - c)Q^h_2, \quad \Pi_2 = p^s_2 q^s_2.$$

[2] In the real world, developers can develop more than one software/app. However this assumption will not have any impact on our results.

By backward induction, we maximize first the profits of platform 2's hardware producers. The profit function of hardware j on platform 2 is:

$$\pi_{2j}^h = (p_{2j}^h - c)\left(\alpha(p_2^h - p_{2j}^h) + \frac{Q_2^h}{J}\right).$$

Because of symmetry, all firms will set the same price in equilibrium, leading to:

$$\begin{aligned} p_2^h &= c + \frac{1}{\alpha}\frac{Q_2^h}{J} = c + \frac{1}{\alpha}\frac{1-Q_1^h}{J} \\ q_2^h &= \frac{Q_2^h}{J}. \end{aligned} \tag{5.3}$$

By substituting Equation 5.3 into equation 5.1 and solving for Q_1^h we have:

$$Q_1^h = \frac{(\alpha - \alpha(1-\mu)(p_1^h - c) + \gamma(z_1^{se} - z_2^{se}) + n_1^{se} - n_2^{se})J + 1 - \mu}{2J - \mu + 1}. \tag{5.4}$$

The profit functions of platforms 1 and 2 are given by:

$$\begin{aligned} \Pi_1 &= (p_1^h - c)\frac{(\alpha - \alpha(1-\mu)(p_1^h - c) + \gamma(z_1^{se} - z_2^{se}) + n_1^{se} - n_2^{se})J + 1 - \mu}{2J - \mu + 1} \\ &\quad + p_1^s q_1^s \\ \Pi_2 &= p_2^s q_2^s. \end{aligned}$$

We assume that ex-post expectations are fulfilled, i.e., that: $z_i^{se} = z_i^s$, $n_i^{se} = n_i^s = q_i^s$, $Q_{Hi}^{he} = Q_{Hi}^h$, $Q_{Li}^{he} = Q_{Li}^h$. Then, we can solve for the equilibrium outcomes.[3] From the equilibrium outcome, we can derive the condition to ensure the positive market shares for both platforms as in Lemma 5.1.

Lemma 5.1. *A necessary and sufficient condition for both platforms having positive shares of both high-income and low-income user group in equilibrium is that either high-income users have a sufficiently high preference for software quality, $\gamma > \overline{\gamma}$ or a sufficiently low one, $\gamma < \underline{\gamma}$.*

Proof. See Appendix B. □

The intuition of this lemma is that when γ is sufficiently high ($\gamma > \overline{\gamma}$) or low ($\gamma < \underline{\gamma}$), the gaps in the quality standard and the software variety between two platforms are not sufficiently large for market tipping towards one platform. In the former case, this ensures that the open platform would not set a too low quality standard, which results in a very large software variety in the open platform. In the latter case, this makes sure that the closed platform would not set a too high quality standard, which leads to a very small variety in the closed platform. In both cases, as the differentiation between the two platforms is not too extreme in terms of both software quality and variety, market tipping towards one platform is avoided in both segments: high-income users with a high preference for quality, and low-income users with an only preference for variety. In this work, we only focus on the equilibrium, with both platforms

[3] Please see details of the calculation in Appendix B

having positive shares for each group of users. To ensure this equilibrium, the preference of high-income users for software quality relative to variety is either sufficiently high or low, but with implications on which platform the two groups of users prefer:

Lemma 5.2. *The fraction of high- and low-income users adopting the two platforms depends on the user preference for software quality. We have that:*

(a) If user preference for software quality is sufficiently strong ($\gamma > \overline{\gamma}$), then more high-income users will join the closed platform and more low-income users will join the open platform.

(b) If user preference for software quality is sufficiently weak ($\gamma < \underline{\gamma}$), then more of both groups of users will join the open platform.

Proof. See Appendix B. □

Lemma 5.2 suggests that in the case of sufficiently high user preferences for software quality, the equilibrium market outcome is segmented. In this case, the closed platform becomes more attractive to high-income users, as they would set a higher software quality standard. As a result, a larger share of high-income users would prefer the closed platform over the open platform. On the other hand, in both cases, there is always a larger share of low-income users joining the open platform. This is due to the asymmetric competition across platforms in the hardware market. Many manufacturers produce hardware for the open platform and, thus, they face fierce competition. All this generates downward pressure on the prices of hardware in that platform. Whereas, the closed platform has only one manufacturer, which only faces the inter-platform competition but not the intra-platform competition like competing producers in the open platform. Therefore, in the equilibrium, hardware producers in the open platform will charge a much lower hardware price and attract more low-income users. By contrast, the closed platform can charge a high price and extract profits from more high-income users, since these are not price sensitive. This can lead to an equilibrium, where fewer hardware users adopt the closed platform than the open platform. The asymmetry of equilibrium hardware prices charged to users and user's shares is described in Corollary 5.1.

Corollary 5.1. *We derive two properties:*

(a) The price of hardware produced for the closed platform is higher than that for the open platform.

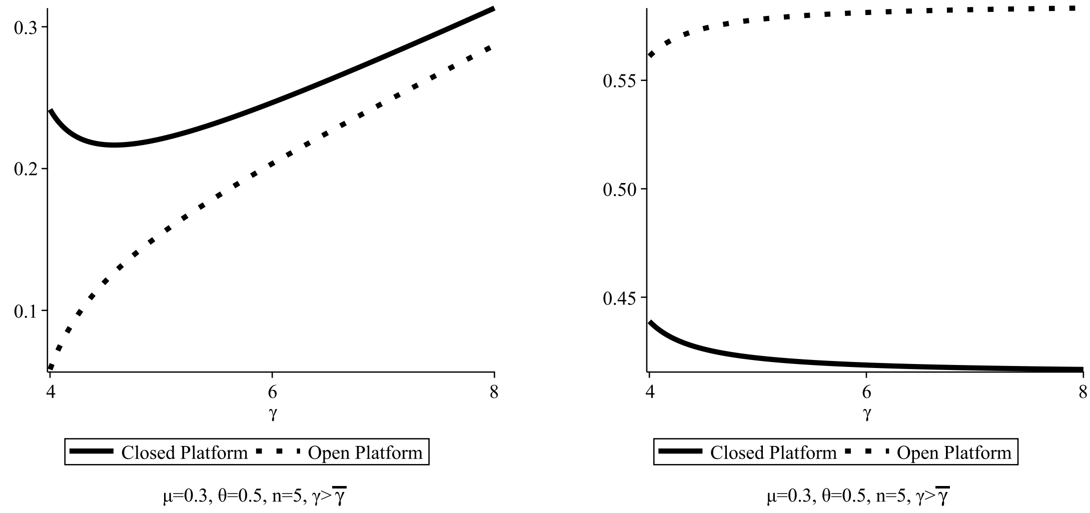
(b) The open platform has a greater number of hardware users than the closed platform.

Proof. See Appendix B. □

Lemma 5.2 leads directly to the first proposition:

Proposition 5.1. *If high-income users have sufficiently strong preferences for the software quality ($\gamma > \overline{\gamma}$), then the closed platform sets a higher software quality standard than the open platform, and the open platform attracts greater software variety.*

Figure 5.2: The software quality standards set by two platforms and software variety when user preference for software quality is sufficiently high



(a) Software quality standard (b) Software variety

Proof. See Appendix 5. □

The intuition of this proposition is that the closed platform gains more from software quality than what it loses from variety because of its direct control over hardware and software. When high-income users have a high preference for software quality, the closed platform is willing to sacrifice revenues in the software market, due to the reduced number of developers, and grab more profit from high-income users in the hardware market. By contrast, the open platform only controls the software market and has a greater incentive to lower its quality standard to access more profit from more developers joining the platform. Consequently, it is more likely to observe a sizeable number of developers joining the open platform (Figure 5.2b). Intuitively, though developers can gain higher revenues from a larger fraction of high-income users joining the closed platform, they also face high development costs of meeting the quality standard set by that platform. The trade-off shifts more developers to the open platform. Since there is a greater number of software varieties in the open platform, low-income users find it optimal to join that platform, resulting in a greater share of low-income users. The important question remaining is what the role of high-income user preference for software quality in driving the software quality standard set by the platform is.

Corollary 5.2. *If high-income users preference for software quality is higher, the closed platform has an incentive to raise its software quality standard if and only if the high-income users have sufficiently high preference for software quality ($\gamma > \bar{\bar{\gamma}}$). Instead, the open platform always improves its quality standard when high-income users have a higher preference for software quality.*

Proof. See Appendix B. □

Corollary 5.2 describes the effects that high-income user preference for software quality has on the decisions made by the two platforms to change their quality standards. Interestingly, when high-income users' preference for software quality becomes higher, the open platform always finds it profitable to raise its quality standard, whereas this is not the case for the closed platform. This because the more high-income users value high-quality software, the more profit the platforms would gain if it improves their quality standard. Since the open platform sets the low quality standard, the gain from raising quality always exceeds the loss caused by reduced varieties. Figure 5.2a illustrates how the platforms would change the software quality standard as the high-income user preference for software quality increases. As can be seen, at a certain value of γ, while the open platform still benefits from increasing its standard quality, the closed platform may find it profitable to lower its quality standard. It is because when γ is not sufficiently high, the gain from raising software quality standard for the closed platform cannot compensate for the loss in reducing varieties.

5.4 Concluding remarks

In the context of two asymmetric competing platforms, we show that when high-income hardware users have a sufficiently strong preference for software quality, the closed platform has a greater incentive to specialise in quality standards, whereas the open platform specialises in variety. As a result, high-income users tend to adopt the closed platform, and low-income users prefer joining the open platform, leading to market segmentation by type of income. As an example, at the early stage, Apple has established strict quality control for its developers and has targeted high-income users, while Google has been more lenient with developers, and offers now, a greater number of varieties. Equally important, the quality standards set by platforms are driven by high-income user preferences for quality. Higher user preferences for software quality can induce higher quality standards set by the closed platform and the open platform. This helps explain why Apple and Google recently have removed low-quality applications to ensure high-quality applications in their stores. These quality control actions are possibly driven by the fact that users now have a higher preference for apps quality, especially Android users. Because Android hardware producers first target the low-income users at the beginning to achieve a critical mass of installed base, then they start to produce high-end products with higher quality and prices. This attracts a greater proportion of high-income users to buy Android products. As a result, this drives the Android user preference for software quality to be higher, and Google finds it profitable to improve its quality standard. Although we do not formalise the welfare analysis, the implication of this policy on overall consumer welfare is expected to be positive. In the case of Apple and Google Android, there is a potential welfare loss for low-income users as a result of decreasing variety, but this loss is expected to be very minimal since the number of mobile applications is very large and most of the users did not use these bad apps. On the other hand, this policy would lead to a larger gain in the welfare of the high-income user group, as this group of users would enjoy higher quality apps.

This work still has several limitations and there is room for future research. First, we do not perform the welfare analysis to evaluate the impacts of the platform's exclusion strategy on consumer surplus and developer surplus. Second, we do not account for the multi-homing of developers in the model. It would be interesting for future works to analyse how minimum quality standards chosen by platforms affect developer's decision to single-home versus multi-home. Third, we assume that hardware has the same quality for simplification, but this can be relaxed in future work. This is also useful to understand whether hardware quality has any impact on the platform decision of targeting software quality over variety. On the other hand, since there is still a limited number of works on platform governance strategies, this area has great potential for future research. For instance, it would be interesting to look at how platforms can use the recommendation system (reviews/ratings/ranking) to control the quality and influence the competition in the market. Another direction is to investigate the impacts of multi-homing and compatibility on platform governance design, as platforms are more likely to use governance rules on the multi-homers instead of single homers. Finally, future research can try to answer which strategy is optimal for platforms by incorporating different governance rules and compare the equilibrium outcomes.

Chapter 6

Digital platform mergers and innovation: evidence from the cloud computing market

6.1 Introduction

The recent wave of mergers and acquisitions by big tech firms has raised a special concern for competition authorities about the potential harm to competition and innovation in digital platform markets. This has attracted a recent stream of the literature on big tech platform mergers and acquisitions. Three influential reports by Furman et al. (2019), Scott-Morton et al. (2019), Crémer et al. (2019) have argued that that one of the shortcomings of current merger control is the difficulty in predicting the effect of the mergers on both competition and innovation in the future. This difficulty comes from the highly innovative and fast-changing nature of digital platform markets, and to evaluate the future effects, competition authorities need to account for this uncertainty (Argentesi et al. 2019). Therefore, more ex-post analysis about the impacts of mergers and acquisitions on competition and innovation in digital platform markets is necessary and will form a good reference for competition authorities in future cases. This research aims to tackle this gap in the literature. In this paper, we will contribute to this early growing literature by investigating the M&A activities in the cloud computing market, and the impacts of these on innovation.

Our empirical analysis is based on the data on the cloud computing industry in the US, a highly innovative market that has grown exponentially in the last decade. In 2019, the total spending worldwide for cloud services has increased by 37%, according to Synergy Research Group. The cloud computing market is a very interesting case to study the relationship between mergers and innovation for several reasons. First, this is a peculiar market with 3 out of the 5 biggest tech firms competing aggressively: Amazon, Microsoft, and Google. These firms have large spending on R&D and also are active in mergers and acquisitions. They have accomplished many acquisitions recently to gain more market share and market power in this market. Outside these firms, other players in the market are also active in acquisition activities with 430 acquisitions of US companies in the last 10 years (source: Crunchbase). Second, the market has a high degree of concentration as the leading firms have more than 50% of the market (Synergies Research Group). Third, Scott-Morton et al. (2019) argue that there is likely a concentration in innovation in the cloud computing market, as the innovative activities are mostly carried out by big digital firms. This implies that other firms in the market may not be willing to invest in innovation since they can not compete against leading firms. Finally, the cloud computing firms also have diverse business models, as firms can operate in a vertically integrated structure, or a multi-sided platform (MSP) structure, or a combination of both. Therefore, it would be interesting to examine whether mergers have any impacts on the innovation outcome of the industry, and how these impacts differ between leading firms vs niche firms and MSP vs non-MSP firms. Surprisingly, to our best knowledge, there has not been any study addressing these issues. In this research, our target is to provide an analysis of the impacts of mergers and acquisitions on the innovation in the US cloud computing market and provide useful policy implications for competition authorities. For our empirical analysis, we construct our unique dataset from several sources: the merger data from Crunchbase, the company financial data from Thomson Reuters Worldscope database, and the patent data downloaded from USPTO websites.

While there is a growing branch of research on mergers in digital markets, acquisition strategies of tech firms have not drawn much attention from researchers, except Gautier & Lamesch (2020). This work aims to fill this gap by investigating the merger strategies of firms in the cloud computing market. By studying the data on merging activities, we provide descriptive evidence that shows that there are two different acquisition strategies by two different groups of firms in the market. The leading firms in the market like Amazon, Microsoft, or Google follow the strategy of acquiring young startup firms. This is probably due to two reasons. First, these firms already have leading technologies and a large customer base, thus, they prefer acquiring young firms with innovative ideas or complementary technologies, which can further entrench their market position. Second, this type of acquisition enables these firms to escape from the scrutiny of the competition authority. On the contrary, niche firms like Cisco, Rackspace, or Dell tend to acquire established firms in order to catch up with the leaders. The purpose of these acquisitions is not only technologies, R&D, or innovation assets, but also the large customer base and data. This would enhance the chance of niche firms to gain more market share and profits, hence, narrow the gap with leading firms.

Previous literature has provided empirical evidence of the impacts of mergers on innovation in different markets like pharmaceutical or HDD, but there is still a lack of studies examining this issue in digital platform markets. This work aims to contribute to this aspect by analysing the effects of mergers in the cloud computing market on the innovation outcome of merged entities. Following previous literature, we employ the patent counts as the measurement for innovation outcome and estimate the effect of merger events on the changes in patenting activity of merging entities before and after mergers. We construct our control group by using propensity score matching and then combine this with the DiD estimator as in Haucap et al. (2019). Different from many other studies, our empirical results suggest that there is not necessarily any evidence that mergers have negative impacts on the patent output in the cloud computing market. Interestingly our results provide evidence that mergers increase the innovation of leading firms and MSP (multi-sided platform) firms significantly more than niche firms and non-MSP firms.

The rest of the paper is organised as follows. The next part will discuss the related literature. Part 3 provides an overview of the cloud computing industry. Then the data and descriptive evidence are described in part 4. Part 5 discusses the empirical strategy. Part 6 present the results and discussions with conclusions are included in part 7.

6.2 Literature review

This work is related to the branch of long-standing literature on the relationship between competition and innovation. The earliest discussion on this relationship was dated back to more than 50 years ago with two schools of thought: Schumpeter (1942) and Arrow (1962). The former suggests that competition would discourage the incentive of firms to innovate as they will receive less potential profit. Whereas, the latter disagrees and claims that firms in a more competitive market have more incentive to innovate due to the profit displacement effects. These contradicting perspectives lead to the beginning of expansive literature, which tries to answer the big question of whether competition is good or bad for innovation. However, there is still yet any consensus amongst economists about whether competition impacts negatively or positively on innovation.

Gilbert & Newbery (1982) relaxes Arrow (1962)'s assumption about the non-competitive threat to the incumbent, and shows that a dominant incumbent may have more incentive to innovate under competitive threat from potential entrants. Whereas, others have shown that this relationship has not always been true and depends on the technology levels of the incumbent and entrants (Vickers 1985, Boone 2001). Aghion, Bloom, Blundell, Griffith & Howitt (2005) and Aghion, Blundell, Griffith, Howitt & Prantl (2005) suggest that it is not necessary that either Schumpeter or Arrow's view is wrong as the relationship is not strictly positive or negative but an inverted U-shape relationship. They proposed a growth model where the industry can be either neck-to-neck firms or one leader-one laggard firm. When competition is soft, there is a larger fraction of the neck-to-neck industry, in which the innovation incentive is increasing in the degree of competition, as competition would decrease the pre-innovation rents relatively to post-innovation rents. On the other hand, when the competition is fierce, there is a larger fraction of the laggard industry, in which competition would dampen innovation as it increases the pre-innovation rents and reduces the post-innovation profits. Shapiro (2012) shares the similar view and argues that there is no essential contradiction between Schumpeter (1942) and Arrow (1962). He explains this as the former's argument implying the more intense competition post-innovation discourages firms to innovate and the latter's view saying more severe competition pre-innovation encourages firm's incentive to innovate.[1]

While there has been extensive literature on the impacts of competition on innovation, the literature answering the question of how mergers affect the innovation by firms is relatively small and new. Several papers (Motta & Tarantino 2017, Federico et al. 2017, 2018) have pointed

[1]For more detail of this literature, see the comprehensive survey by Jullien & Lefouili (2018).

out that the arguments by Schumpeter and Arrow can not be always applied directly to the analysis of the impacts of mergers on innovation. This is because on the one hand mergers soften competition as the number of firms is reduced. On the other hand, mergers enable the two merging firms to coordinate in innovation decisions after the merger and internalize the externalities they exert on each other's demand, which is the so-called *innovation diversion effect*. The coordination effect of mergers on innovation has been discussed thoroughly by Federico et al. (2017), Federico et al. (2018),Denicolò & Polo (2018), and Bourreau et al. (2019). Federico et al. (2017) propose a stylized model of multiple research labs investing in innovation to invent a new product. They show that after a merger between two labs, the merging entity has an incentive to reduce R&D investment. The intuition here is that this decision would enable merging firms to avoid cannibalization effects on sales when both labs are successful with the R&D investment. However, their results are based on the key assumption that after the merger, the entity would maintain both labs as active, which is criticised by Denicolò & Polo (2018) who claim that this assumption does not always hold. Denicolò & Polo (2018) show that the merging entity's optimal strategy might be to shut one research unit and spend more investment on the other one. This is because closing down one lab would reduce the competition and innovation diversion effect, which induces a higher incentive to invest more in the remaining one. When this is the case, the merger eventually results in higher total R&D investment and consumer welfare. Federico et al. (2018) extend the Federico et al. (2017) model by studying the interaction between the price coordination effect and innovation diversion effect after the merger. They find that while the former effect tends to boost the incentive to innovate, the latter effect would discourage the firm's innovation incentive. Bourreau et al. (2019) contribute to the literature by decomposing the impacts of mergers on innovation into four different effects: the innovation diversion effect, the margin expansion effect, the demand expansion effect, and the per-unit return to innovation effect. They show that while the first two effects are negative, the third one is positive and the sign of the last effect can be either negative or positive.

Although these above theoretical works analyse different aspects of the merger effect on innovation, they share a similar consensus this effect can be negative or positive, depending on the industry setting. However, on the empirical side, most works using firm-level data to evaluate the impacts of mergers on innovation, share the common finding that mergers have negative impacts on innovation in general. Our work contributes directly to this branch of literature by examining a novel industry: cloud computing platform, which has not been yet studied in previous literature on mergers and innovation. The main issue in the literature when empirically analysing the effects of mergers on innovation is how to measure innovation. The previous literature suggests two common proxies for measuring innovation: R&D investment and patents. However, both measurements have their own pros and cons, and need to be considered carefully when turning to the interpretation of the results. While R&D is a good indicator of the firm's incentive to invest in innovation, it should be considered as innovation input instead of output. Large R&D investment does not necessarily turn to good innovation outcomes. Moreover, now we see more conglomerate firms operating in many different industries, which means the firm-level data of R&D investment is not always available in some industries as the firm's financial statements only show the total R&D amount. The issue with patents as a proxy for innovation is more trivial as patents can account for both innovation input and output. Nevertheless, not all patents have important impacts and may not lead to commercial value. Constructing citation weighted patent instead of simple patent count can capture the quality of patent activities (Hall et al. 2005), but it still can not reflect truly the monetary value of innovation.

One of the very few works that show some evidence of positive impacts of mergers on innovation is Valentini (2012). Based on the data of mergers in the US medical devices and photographic equipment industry, he estimates the impacts of mergers on patents in terms of different measurements: patent output, impact, generality, and originality. His results suggest that while mergers have a positive effect on patent output, the effects on patent impact, generality, and originality indicator are negative. Other works studying the pharmaceutical industry like Danzon et al. (2007), Ornaghi (2009), or Haucap et al. (2019) show strong consistent evidence of the negative impacts of mergers on innovation measured by either R&D investment or patent count at the aggregated industry level. Similar to these works, we also aim to examine the effect at the industry level of mergers in the cloud computing market on innovation measured by patent output. Instead of focusing on a specific industry or geographical limit, Szucs (2014) collect a dataset consisting of 133 mergers by companies from 25 countries and many different industries and tests whether mergers lead to lower R&D investment of acquirer and target firms. The results confirm that mergers have negative impacts on both R&D investment and R&D intensity of target firms. Unlike the above works, Bennato et al. (2020) focus on the impacts of mergers on innovation at the firm level instead of the aggregated industry level. They analyse three merger cases in the HDD market in 2011/2012: Seagate/Samsung, Western Digital/Toshiba, and Toshiba/Hitachi's 3.5-inch production, and contribute to the literature by employing a more comprehensive set of measurements of innovation: R&D investment and patents as innovation input, number of new models and unit prices as innovation output. They find the mixed effects of mergers on different measurements of innovation. While mergers significantly increase R&D investments in all cases and the number of new models in two cases, they decrease the patent outputs in all cases and unit prices in two cases.

Equally important, this work contributes to the recent hot debate in the literature about the potential impacts of big tech mergers on competition in digital platform markets. The reason for this debate is a growing number of acquisitions by a dominant digital platform without any scrutiny from competition authorities. This raises the question of how these big tech mergers impact competition and innovation in the platform market. Firstly, there is quite a broad consensus among researchers about the positive impacts of big tech acquisitions on entry and innovation. Bryan & Hovenkamp (2020) and Bourreau & de Streel (2020) both suggest that big tech mergers give young firms and start-ups more incentive to innovate and enter the market, in order to be bought at a high price by the dominant firms. Motta & Peitz (2020) also show that in the case when the innovative start-up is financially constrained, the acquisition can help to improve the innovation level in the market. This view is shared by Crémer et al. (2019) and Scott-Morton et al. (2019), which point out that big tech firms can provide acquired start-up with financial strength and management experience and this facilitates innovation. Therefore, it would be interesting and crucial to test empirically are whether mergers and acquisitions facilitate or reduce innovation. However, there is still a lack of studies addressing this question. This research aims to tackle this gap by evaluating the impacts of mergers on innovation in the cloud computing platform market.

In contrast with the first school of thought, Kamepalli et al. (2020) propose a model to examine whether big tech mergers can create a "kill zone", where venture capitalists have little incentive to fund young start-ups. They then employ the Pitchbook data and find empirical evidence that Google and Facebook mergers have decreased both the number and amount of venture capital funding for young start-ups in the same sector as the acquired companies. Whereas, Scott-Morton et al. (2019) suggest that venture capital funding can be a measure for innovation since more funding would encourage young firms to innovate more. They pointed out that in the market where dominant firms keep acquiring to entrench their market-leading positions, venture capitalists may find it not worthy to fund start-ups that develop new technologies to compete for head to head with the giant firm, as the chance of successful entry is very small. This results in a lower level of venture capital investment, which further reduces entry and innovation. Additionally, since the chance of challenging the big tech incumbent is almost zero, innovative entrance may avoid developing new technology to substitute the dominant technology, and focus on the innovation that can be complements to the incumbent products and services. This view is shared by Katz (2020), as he argues a permissive merger policy would discourage the innovation incentive of the new entrant, whose purpose is so-called *entry for buyout*. The intuition behind this is it may be not profitable to invest more in innovation, when the marginal benefits from a buyout deal do not sufficiently cover the investment cost. In the same vein, Letina et al. (2020) study the effect of the merger policy prohibiting killer acquisitions on the innovation outcome. They develop a four-stage game, in which under two policy regimes of prohibiting or permitting acquisitions, firms decide subsequently whether to invest in a research project, to make an acquisition, to commercialize the project, and finally compete in the market. They find that prohibiting killer acquisitions would negatively impact the variety of research projects, as this may encourage the incumbent firm to duplicate the entrant innovation to avoid competition, instead of developing other projects. Whereas, the negative impacts of prohibiting mergers would be negligible if firms have sufficient capability to commercialize the research project.

Although there is a significant number of theoretical works on mergers and acquisitions by big tech firms, there are only two papers that have empirically investigated their merger activities: Argentesi et al. (2019) (Google, Amazon, and Facebook) and Gautier & Lamesch (2020) (Google, Amazon, Facebook, Apple, and Microsoft —GAFAM). Both papers employ Crunchbase dataset like us, and they share the similar view that big platforms are more likely to acquire young startups in the segment/business that they are already active in rather than in the new market, and these companies usually have the complementary products/services/technologies with the acquirer. To the best of our knowledge, Gautier & Lamesch (2020) is the only paper so far explicitly studying the merger strategies by big tech firms. Their main contribution is a novel approach to define market segments based on targeted users instead of products or services. According to their classification, big tech firms are active in six segments: Advertisers, Business, Consumers, Content editors, Merchants, and Platforms. This classification enables the authors to identify the M&A strategies of GAFAM. They conclude that the main motivation of GAFAM acquisitions is to acquire innovative assets, R&D inputs, or talented employees in order to strengthen their market positions in core businesses/segments. They further analyze whether there has been any "killer acquisition" by GAFAM but found no clear evidence. In this paper, we complement these above two works by examining the merging activities and strategies by firms in the cloud computing market.

6.3 Cloud computing market

In this section, we briefly describe the cloud computing market, with a focus on the definitions and features of cloud computing, how the market is divided into segments, and the main competing firms in the market. It is important to understand the segmentation and main players in the market before investigating merger activities in the next section.

Cloud computing is one of the fastest-growing and highly innovative industries and is becoming more and more important for business around the world, with total spending of $96B according to the Synergy Research Group.[2] This promising industry has attracted the participation of three giant tech firms: Amazon, Microsoft, and Google. While Amazon had a head start, followed by Microsoft, Google is the latecomer, who is trying to gain more market share.

What is cloud computing and why there are more and more firms using this type of service? According to Amazon[3], "Cloud computing is the on-demand delivery of IT resources over the Internet with pay-as-you-go pricing. Instead of buying, owning, and maintaining physical data centers and servers, you can access technology services, such as computing power, storage, and databases, on an as-needed basis from a cloud provider". Thus, we can understand cloud computing as outsourcing services taking place over the Internet, which enables firms to access various kinds of technology inputs without directly managing them. Cloud computing is based on the idea of achieving economies of scale via sharing resources. For instance, a cloud provider can serve 100 more companies with a cost similar to serve 10 companies. This results in a much cheaper price for firms to access IT resources via cloud providers comparing to building these resources themselves. In this way, firms can largely avoid upfront IT costs for operating their business, for example, data storage, customer management system, etc. Additionally, firms also can run their own software/applications on the cloud server with much faster speed and higher computing power, which improves efficiency significantly. The huge advantage of using cloud computing services has led to its widespread adoption and rapid expansion worldwide. In 2019, the total spending worldwide for cloud services has increased by 37%, according to Synergy Research Group.

The cloud computing market can be divided into three main segments: Infrastructure as a service (IaaS), Platform as a service (PaaS), and Software as a service (SaaS). IaaS is the service to provide firms' access to computing infrastructures such as networking, data centers, and servers, etc. Within the cloud providers' infrastructure, firms run their own applications

[2]https://www.srgresearch.com/articles/incremental-growth-cloud-spending-hits-new-high-while-amazon-and-microsoft-maintain-clear-lead-reno-nv-february-4-2020

[3]https://aws.amazon.com/what-is-cloud-computing/

and software. PaaS offers access to a cloud platform environment that allows and supports firms to develop, manage, and host their own application and software. SaaS provides the access to cloud-based software. Instead of buying a license and installing software, firms can access providers' applications via a website or an API. Within these three segments, there are three different types of services: public cloud, private cloud, and hybrid cloud. Public cloud is the type of service where the provider is responsible for all management, maintenance, security, and upgrades. Whereas, private cloud allows firms to host their own data center, in which they have exclusive rights to manage, maintain, and upgrade. Finally, hybrid cloud is the mix between public cloud and private cloud, in which firms can flexibly choose to use a partly public and partly private cloud. Table 6.1 documents the global revenue of public cloud in the main service segments. As can be seen in the table, the revenues of the IaaS and PaaS segment is quite similar, with the IaaS being slightly higher. Whereas, SaaS is the largest segment, as the revenue is significantly higher and exceeds the total revenue of the other two segments. This is not surprising as SaaS is the most popular type of cloud computing service used by enterprises and individuals. It is because SaaS is incredibly easy to use without managing any platform or infrastructure.

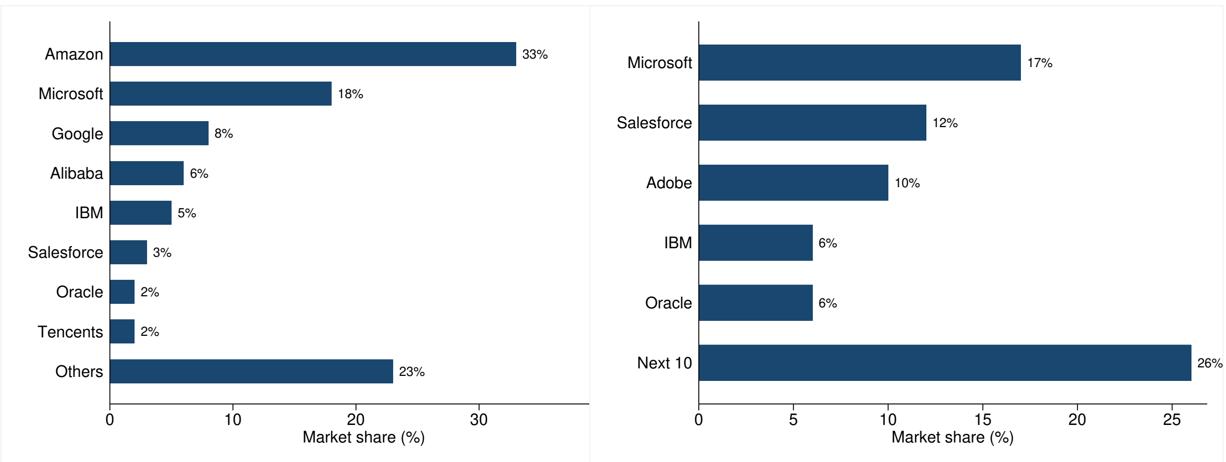
Table 6.1: Worldwide public cloud services revenue forecast (billions of US dollar).

Segment	2018	2019	2020	2021
IaaS	32.4	40.4	50.4	64.3
PaaS	26.4	37.5	43.5	57.3
SaaS	85.7	102.1	104.7	121

Source: Gartner

Figure 6.1: Global market shares by vendors in cloud computing market in 2019

(a) IaaS and PaaS segments (b) SaaS segments



Source: Synergy Research Group

In terms of business model, cloud computing platforms are not necessarily multi-sided platforms, as firms can operate in either a vertically integrated structure or multi-sided structure.[4]

[4]See Karunakaran (2016) for more detail on segmentations and business models in the cloud computing market

In the former case, firms provide both operating systems and their in-house cloud-based applications running on those operating systems, for example, SAP cloud platform. In the latter case, firms provide a market place to connect third-party cloud-based software developers and users, for instance, Amazon Web Service marketplace. All leading firms like Amazon, Microsoft, and Google combine both business models, in which they supply operating systems and in-house applications, and also offer a cloud marketplace. This enables these firms to enjoy benefits from indirect network effects generated by developers to users and vice versa, which would drive more application variety as well as a larger consumer base for these firms. This entrenches their market dominance and maintains their leading positions.

As observed by Crémer et al. (2019), the cloud computing market centralises around several big players, even though there is still a niche market for many fringe firms. With the first-mover advantage, Amazon has dominated the market for IaaS and PaaS with 33% of market share but is under threat from Microsoft and Google. In the SaaS segment, Microsoft is the leading player with 17% of market share due to its advantage of a long-history developing software for PC operating systems. However, this leading position is followed closely by Salesforce and Adobe. To sum up, the cloud computing market is concentrated around big tech firms like Amazon, Microsoft, Google, IBM, etc. The three leading firms obtaining 59% of market share in the IaaS and the PaaS segments, whereas, the top 5 firms take 51% market share in the SaaS segment. As can be seen, although the market is concentrated, no firm can dominate all the segments, and only a few firms are operating in all segments. Amazon is the leading firm in both the IaaS and PaaS but did not participate in the SaaS segment. This is because the cloud computing industry has capacity constraints for any firm. As firms offer more cloud services, fixed and infrastructure costs will be huge and exceed the firm's capacity. That is it is very difficult for any firm to cover all market segments and all services. For example, according to Gartner (2019), there is no single firm offering all 21 categories of services in the PaaS segment, and only 10 out of 360 PaaS vendors can offer more than 10 service categories. Another important point is that the SaaS segment is more competitive than the other two segments with more players obtaining similar shares and the leader acquiring only 17% of market share. The reason for this is that SaaS is a much bigger segment than the others and has many service categories to be offered. This opens up room for many firms competing in this segment, and these firms still make a large amount of profit. Based on the information about the global market shares, we define two groups of firms: leading firms and niche firms. Leading firms are in the top 5 firms in IaaS/PaaS and SaaS segments: Amazon, Microsoft, Google, Salesforce, Adobe, IBM, and Oracle. Whereas the niche firms are the other firms in the market such as Rackspace, Cisco, Dell, etc.

6.4 Data

6.4.1 Merger data and merger strategies

To investigate the merger strategies of cloud computing firms and how mergers affect innovation in the US cloud computing market, we have collected the dataset on US-based cloud computing companies. The dataset is cross-sectional and retrieved from the Crunchbase website, which covers ten years from 2010-2019. This contains information about US cloud computing companies' characteristics such as company name, headquarter location, industries, operating status (whether the company is active or not), founding date, number of employees, funding activities, IPO activities, number of active products, number of investors, and importantly the information on acquisition status (whether the company is acquired or not). US cloud computing firms are active in mergers and acquisitions with a total of 430 acquisitions over ten years. Cisco and VMware had the most number of acquisitions, with nine deals each. The number of acquisitions by leading firms and niche firms are shown in Table 6.2. Surprisingly, Amazon, the leading firm in the market, are not as active as other firms in acquiring other US cloud computing companies, with only four acquisitions. The reason is that Amazon had a first-mover advantage, and already had developed advanced technology and infrastructure. Whereas, to compete with Amazon, the competitors need to buy other firms for their technologies or innovative inventions. Besides, other segment leaders like Microsoft, Google, and Salesforce also acquire only six other companies, which is less than Cisco, VMware, or Rackspace. IBM has less market share than others in the group of leading firms and acquires eight firms, the most among the leading group. This is possible because Amazon, Microsoft, and Google also have other core businesses for which they need to invest in mergers and acquisitions, thus, limiting their budget for acquisitions in the cloud computing industry. Moreover, these leading firms already have advanced technology, a great variety of services, and a large customer base. Hence, to strengthen their market position, their optimal strategy is to acquire companies that offer different products or have complementary innovation projects rather than direct cloud computing competitors that offer similar services. As a result, these leading companies would acquire more firms in adjacent markets such as AI or big data to empower their cloud computing services. Meanwhile, to catch up with the leading firms in terms of technology, range of products and services, and customer base, the niche firms would find it optimal to acquire more cloud computing companies.

Table 6.2: Number of acquisitions by leading vs niche firms 2010-2019

Leading firms		Niche firms	
IBM	8	Cisco	9
Google	6	VMware	9
Microsoft	6	Rackspace	7
Oracle	6	Hewlett Packard	6
Salesforce	5	SAP	6
Amazon	4	Dell	5
Adobe Systems	2	EMC	5

Remark 1: *The niche firms are more active in acquiring US cloud computing companies than the leading firms, but do not complete such high value deals as the leaders.*

In terms of the deal value, the biggest deal is the acquisition of Red Hat by IBM at the price of $34B in 2019. In the top seven leading firms with the largest market shares in the segments (Amazon, Microsoft, Google, Salesforce, IBM, Adobe and Oracle), only IBM, Microsoft, Oracle, and Salesforce had deals in the top ten most value acquisition deals (Table 6.3). This suggests that other leading firms like Amazon or Google are more interested in buying small firms and young startups. Equally important, none of the niche firms have a deal in these top highest valued acquisitions, which implies that niche firms do not have a sufficiently strong financial position to complete such high-value deals. In this case, the alternative option is to acquire a greater number of firms. For example, Cisco and Rackspace have the most number of acquisitions but they have no deal in the top ten highest valued. Interestingly, six deals in this top ten belong to firms, which do not compete in the cloud computing market. Two of these (Broadcom Limited and Nvidia) are firms primarily operating in the semiconductor/chip industry, which provides data storage hardware for cloud data centers (upstream market). Whereas, the rest are conducted by private equity and investment firms, which shows that investors highly value the growth potential of the cloud computing industry.

The difference in the merger and acquisition strategies of the two groups is shown more clearly in Table 6.4, in which we compare the characteristics of targets bought by leading firms (Amazon, Microsoft, Google, Salesforce, Oracle, IBM, and Adobe) and the other strong niche firms (Cisco, Rackspace, Dell, etc.). The key point is that in comparison with acquired targets by the latter, the acquired firms by leading firms are younger, have a smaller number of employees, investors and funding, and have not launched IPO yet. The reasoning behind this is the different purposes of dominant firms and niche firms when making the acquisition. Leading firms only need additional pieces of complementary technology/innovation/products to entrench their market position, which can be found in young startups. Whereas, the other players need to buy established firms with a large customer base and innovative technology to gain more market share and compete against the dominant firms. Another reason for dominant firms buying only young startups is that they can easily escape the scrutiny from competition authorities since young startups normally have not generated a sufficient amount of revenue. Finally, it is also possible that the dominant firms with their superior advantage of data would have a better algorithm to detect young potential firms and optimise their acquisition decision. In contrast, other niche firms with less knowledge, prefer to play safe by buying well-established companies instead of younger firms.

Table 6.3: Top highest valued acquisition in the US cloud computing market

	Target company	Acquired by	Announced date	Price
1	Red Hat	IBM	Oct 28, 2018	$34B
2	CA Technologies	Broadcom Limited	Jul 11, 2018	$18.9B
3	NetSuite	Oracle	Jul 28, 2016	$9.3B
4	GitHub	Microsoft	Jun 3, 2018	$7.5B
5	Mellanox Technologies	NVIDIA	Mar 12, 2019	$6.9B
6	Mulesoft	Salesforce	Mar 20, 2018	$6.5B
7	Informatica	Permira	Aug 7, 2015	$5.3B
8	Rackspace	Apollo	Aug 26, 2016	$4.3B
9	Publicis Sapient	Publicis Groupe	Nov 3, 2014	$3.7B
10	Riverbed Technology	Thoma Bravo	Dec 15, 2014	$3.5B

Table 6.4: Comparison of acquired target characteristics between leading firms (Amazon, Microsoft, Google, IBM, Oracle, Salesforce, and Adobe) and other strong niche firms (Cisco, Dell, Rackspace, etc.)

	Acquired targets of leading firms					Acquired targets of strong niche firms				
Variable	Obs	Mean	Std	Min	Max	Obs	Mean	Std	Min	Max
Age*	40	7.200	5.140	1	18	110	9.336	8.988	1	58
Number of employees*	40	3.175	1.893	1	9	108	4.185	2.427	1	9
Number of investors*	34	4.265	3.068	1	16	83	5.470	3.277	1	16
Funding amount ($M)	31	48.261	78.352	1	350	84	71.993	201.559	1.2	1704
Number of funding rounds	34	3.088	1.864	1	6	84	3.643	2.373	1	12
IPO status	40	0.050	0.221	0	1	95	0.116	0.322	0	1

Note: *: The mean values of two groups are statistically different at 5% significance level. Number of employees is a categorical variable, which take the value 1 if the company has 1-10 employees, 2 if 11-50 employees, 3 if 51-100 employees, 4 if 101-250 employees, 5 if 251-500 employees, 6 if 501-1000 employees, 7 if 1001-5000 employees, 8 if 5001-10,000 employees, and 9 if the company has more than 10,000 employees. IPO status has the value 1 if the company has a successful IPO, 0 other wise.

Remark 2: *While leading firms tend to acquire young startups, the niche firms are more likely to buy well-established firms.*

6.4.2 Data for estimating the impacts of mergers on innovation

Merger data sample

To estimate the impacts of mergers on innovation measured by patents in the cloud computing market, we only select the mergers from 1/1/2011 to 31/12/2014, which include 145 firms acquiring 177 targets. We restricted our sample to this four year period, because first cloud computing is a new market, thus firms do not have many patenting activities before 2011. Second, it is commonly acknowledged in the literature that a merger only has impacts on patent output after several years, since innovation requires a certain amount of time. Therefore, this restriction of the sample enables us to evaluate the impacts on post-merger innovation. For acquirers and targets, we download the data on net sales/revenue, R&D investment, net income, total assets, total debt, gross profit margins from Thomson Reuters Datastream. We then removed the firms with missing data, which results in the final sample of 36 acquirers and 66 targets. Following Haucap et al. (2019), we also combine the value of both acquirers and targets.

Measuring innovation by patent data

Among popular measures for innovation, R&D investment is not applicable in our research as most leading firms in the cloud computing market are operating in many other industries. For instance, Amazon's business is also in the online market place or tablet PC manufacturing, Microsoft also produces personal computers, smartphones, and software. Therefore, it is problematic to identify which amount of R&D investment of these firms is for cloud computing technology. For this reason, we will focus on measuring innovation by the firm's patent activity.

For data on innovation measured by patent, we download the information about 10,382 patents related to cloud technology from the US Patent Office's (USPTO's) Patentsview API. Based on this data, we then construct the measure for innovation by using a simple patent count, which is the number of new patents each year. We only count the patents that have already been granted but assign their dates to the application year instead of the granted year. There are several limitations when measuring innovation by patents. First, it requires a lengthy process and possibly many years for patents to be granted. Therefore, there will be lags in the measurement of patents. For example, the actual number of patents of a company in 2017 may be larger than the count in 2020 if several patent applications filed in 2017 are only granted in 2021. Second, the lengthy and costly process also discourages small firms from patenting their technologies/inventions when the cost outweighs the commercial value of these inventions. In addition to this, technologies/inventions can be protected by other alternative options like trade secrets or copyrights. Hence, patents do not capture all innovation activities and may undermine the innovation output by small firms. Finally, not all patents will lead to inventions/commercial values, and firms may use patents to defend their existing patents rather than innovate. Despite all these limitations, patent activity is still a good measurement for innovation, as it is closely related to innovation output. Furthermore, it is also costly and requires a certain amount of novelty for a patent to be granted. The simple patent count is the most straightforward measure of firm's patent output. The simple patent count is criticised in the literature for its large variation and because it does not account for the quality of each patent. However, this measure is still informative to capture the patenting trend and is thus widely used in the literature.

On the other hand, the number of citations is suggested by the innovation literature as closely related to the patent quality. Therefore, citation-weighted patent counts could be a good indicator, which incorporates information about both the number of patents and the quality of patents. However, using this measure can be problematic in our case since our data is quite recent. There is still a high probability that recent patents will be cited more in the next few years, which may suggest that the citation weighted patent may not fully reflect the real quality of patents. Therefore, we will not use this indicator in our main results as it may not correctly capture the innovation trend.

Besides the measure for the outcome variable, we also construct two more indicators to capture the pre-merger patent information of firms, which will be used for estimating the propensity score: citation per patents and patent stock. We compute firm's patent stock in year t by the formula $PS_{it} = (1-\delta)PS_{i,t-1} + P_{it}$ as in Bloom & Reenen (2002), where δ is a discount factor. We set δ to be 0.15, which is common in the innovation literature, and P_{it} denotes the number of new patents of firm i in year t. The patent stock in the year 1998 is set to zero since this is the first year we observe cloud-related patents. We also combine the value of all patent measures for both acquirer and target as one entity.

Table 6.5 presents descriptive statistics of merging entities in the period before the merger. As can be seen, in the pre-merger period, there is not much activity by merged entities as the average new patents in one year is only about 8, and the average patent stocks in only 23.28. Meanwhile, the R&D statistics show that cloud computing is a highly innovative industry as the average R&D to sale ratio is 12.074, implying that cloud computing firms have a high incentive to invest in innovation. The sales, net income, and asset statistics suggest that the firms being active in M&A are all big tech firms with a high amount of revenue and assets. Hence, these firms are likely to make high-value acquisitions, as shown previously in Table 6.3.

Table 6.5: Summary statistics of merged entities based on pre-merger observations

Variable	Mean	Std	Min	Max
Patents per year	7.957	19.313	0	157
Citations weighted patent	79.79	152.27	0	787
Patents stock	23.92	51.816	0	379.37
Net sale (million US$)	23211.837	30785.334	43.716	112069.158
R&D/sale	12.074	7.156	0	32
Net income (million US$)	2782.319	5597.502	-3122.808	23150
Total asset (million US$)	34473.997	45213.610	41.672	220005
Total debt/total asset	13.212	12.193	0	48
Gross profit margin	63.147	18.851	10.78	89.86

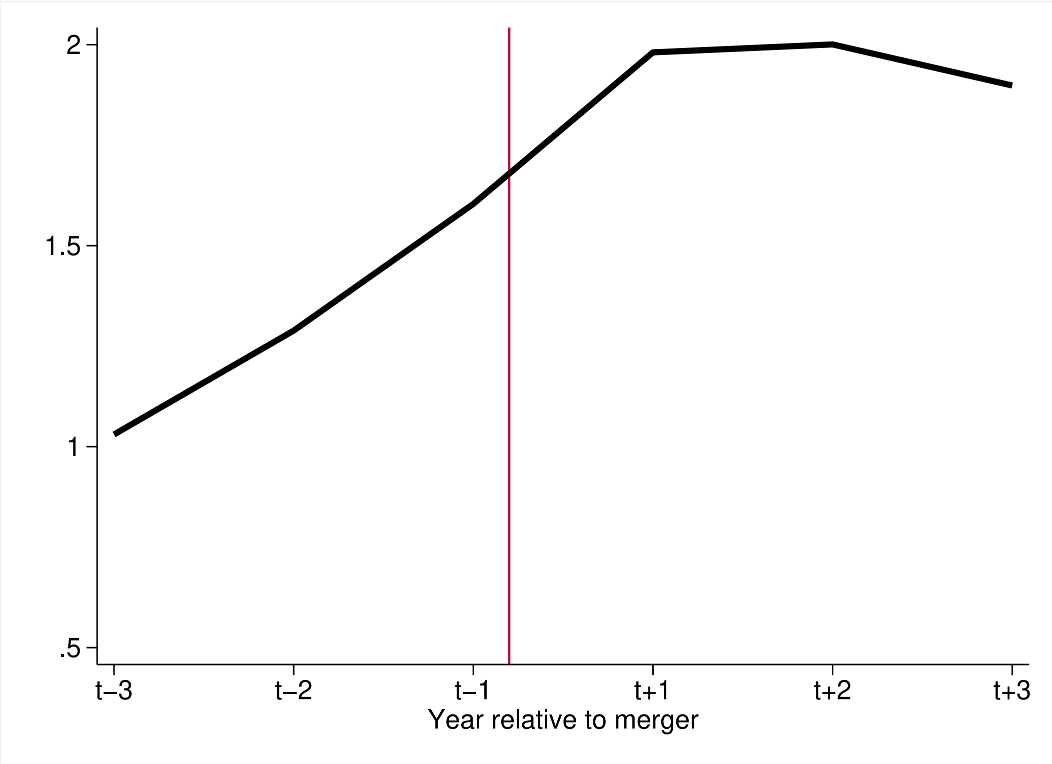
Descriptive evidence-innovation activity before and after

Figure 6.2 illustrates how the patent count (in log) of the merging entities (the combined value of both acquirers and targets) changes after the merger. This descriptive evidence does not account for the causality and time trend, and only visually shows the innovation trend of merging entities before and after the merger. As can be seen in the figure, the number of new patents increases gradually before the merger. Then, it rises significantly in the year after the merger, and falls immediately in year t+2 and year t+3 after the merger, but is still at a higher level than in the pre-merger period. Therefore, this measure may suggest that there would be a potential positive impact of a merger on patent activity.

6.5 Empirical strategy

Following Haucap et al. (2019), we employ propensity score matching to perform a counterfactual analysis and combine this with the DiD estimator to estimate the causal effect of mergers on the innovation of merging entities. Our aim is to estimate the average treatment effect on the treated (ATT), k periods after the merger period t, which is the difference between the actual outcome in the post-merger period and the outcome had no merger taken place in the same period. We denote P^1_{t+k} as the patent output in year t+k in the presence of the merger,

Figure 6.2: Log(patent): before and after



t is the year of the merger

and P^0_{t+k} as the outcome in year t+k in the absence of the merger (the counterfactual). The outcome also depends on a set of control variables X_{t-1}. X_{t-1} only contains pre-merger values in order to avoid the reverse causality problem. MA_t is a dummy, which takes the value 1 if there is a merger in year t, and 0 otherwise. The ATT can be expressed as follows:

$$ATT = E[P^1_{t+k} - P^0_{t+k}|X_{t-1}, MA_t] = E[P^1_{t+k}|X_{t-1}, MA_t] - E[P^0_{t+k}|X_{t-1}, MA_t]. \tag{6.1}$$

The common approach to estimate the ATT in the literature is to construct a panel of firms, including treated firms (merging entities) and a control group of firms, which has similar characteristics but is independent of the merger. Then we can estimate the causal effect by using the DiD estimator. Therefore the key step of this procedure is to identify the control group. However, this can be problematic as it can be difficult to find a perfect comparator in terms of geographical space for the cloud computing market, which is a worldwide market. In terms of product space, it is also challenging to find hi-tech products, which have a similar innovation trend with cloud computing technology. One of the most obvious choices, other cloud computing firms that are not involved in mergers, is questionable as their innovation activities can be indirectly affected by the mergers. Furthermore, as shown in the data section, most of the cloud computing firms are quite young and have not done the IPO, which means it is not possible to gather R&D and financial data on these firms. Fortunately, in our patent data sample, there is a significant number of firms operating in other businesses that own cloud technology related patent. Therefore, we employ this group of firms as the control group. These firms are potentially a valid control group since they are not competing directly with merged entities in the cloud computing market. However, this does not mean that these firms' innovation is fully independent of the treatment, which is one condition for unbiased ATT estimates. For example, Samsung is a firm that owns cloud related patent and does not compete in the cloud computing market. On the other hand, Samsung still needs to use many cloud services offered by Amazon. If merging activities strengthen Amazon's market power, which enables it to raise the price. This would encourage Samsung to invest more in cloud innovation to be less dependent on Amazon services. When firms in the control group are not independent of the effect of mergers, this would bias the estimates and the sign of the bias depends on whether innovation in cloud technology is substituted or complementary between the treated group and control group. Nevertheless, it would be difficult to formally test such a relationship.

The second condition that needs to be satisfied is the control group needs to be similar to the treatment group in terms of both characteristics and innovation pattern before the treatment (parallel trend). To deal with this condition, we first estimate the propensity score (the predicted probability of conducting a merger) from the Probit model $\hat{Pr}(MA_t = 1|X_{t-1})$. To estimate the propensity score, we employ various control variables, including the number of new patents (log) lagged 1-3 years relative to the merger, and other variables lagged 1 year relative to the merger: number of citation per patent, patent stock, net sale/revenue (log), R&D to sales ratio, net income, total assets, total debt to assets ratio, and gross profit margin. For the case of firms conducting multiple mergers, if these mergers are within a year, we consider this as one merger with multiple targets and consolidate the values of all firms involved. When these mergers are in different years, we treat these as separate observations. [5] Then we construct our control group which has similar characteristics and innovation patterns with the treatment group by using nearest neighbor matching methods. The similarity and parallel innovation patterns are shown in the results part, which satisfies the second condition.

Once constructing two matched groups of treatment and control, we can estimate the ATT by using the DiD estimator as in the following specification:

$$\Delta lnP_{i,t+k} = \beta_k + \gamma_k MA_{it} + \epsilon_{kit}. \tag{6.2}$$

Where γ_k is the ATT effects with $k = 1, 2, 3$. To avoid the problem of taking log of zero value, we define $\Delta lnP_{i,t+k}$ as the change in log of (number of new patents+1) from year t-1 to year t+k (Haucap et al. (2019)). One important point about the DiD estimator is that this estimator can only control for time-invariant unobservables, but not time-varying unobservables. Therefore, the challenge when estimating 6.2 is the endogeneity of MA_{it} since the merger decision can be correlated with unobserved time-varying characteristics, which is not eliminated by the DiD estimator. Haucap et al. (2019) suggest using an IV estimator to deal with this issue. However, in this chapter, we have not employed this methodology, as we can not construct valid instruments due to limited data.

Besides the main effect of mergers on the innovation of the merged entities, it is also in-

[5] Szucs (2014) suggests removing these firms with multiple mergers to avoid cofounding effects. However, we could not do this as our sample is already small.

teresting to examine whether this effect would be different for leading firms versus niche firms, or multi-sided firms versus one-sided firms. Leading firms are expected to generate more efficiencies from their acquisitions, which would enhance their innovation outcome. Likewise, firms operating as multi-sided platforms would leverage the effect of mergers by strong indirect network externalities. We will test these heterogeneous effects by estimating the following equations:

$$\begin{aligned} \Delta lnP_{i,t+k} &= \beta_k + \gamma_k MA_{it} + \gamma_{k2} MA_{it} \times leader + \epsilon_{kit} \\ \Delta lnP_{i,t+k} &= \beta_k + \gamma_k MA_{it} + \gamma_{k3} MA_{it} \times MSP + \epsilon_{kit}. \end{aligned} \tag{6.3}$$

where *leader* takes the value 1 if the firm is in the leading group, 0 otherwise. MSP is a dummy indicating whether firms have multi-sided platform business model (MSP=1) or not (MSP=0).

6.6 Results

6.6.1 Fixed effect estimation results

Before analysing the results from propensity score matching, we run a simple DiD fixed effects regression, which ignores the selection bias and endogeneity of merger decisions. To be specific, based on the sample of merging firms only, we regress several patent measurements on the dummy $PostMA$, which take the value 1 for all post-merger observations of the merged entities. We also control for the time and firm fixed effects. The results are presented in Table 6.6. As can be seen in Table 6.6, there is no evidence that merger events would increase the number of new patents of merged entities. Whereas the effect of mergers on citation per patent measure is negative but not statistically significant. However, these results can be misleading as the ignorance of selection bias and endogeneity can lead to biased and inefficient estimates.

Table 6.6: Fixed effect regressions

	(1)	(2)	(3)
	log(patent)	log(citation weighted patent)	log(citation per patent)
$PostMA$	0.039	0.147	-0.077
	(0.253)	(0.382)	(0.191)
N	396	396	396

Notes: $p < .01$: *** $p < .05$: ** $p < 0.10$: *. Table shows the results of linear regressions. $PostMA$ is an indicator which take a value of 1 in all post-merger periods for the merged entity. Variables are based on consolidated companies before and after M&As. Robust standard errors in parentheses.

6.6.2 Results from propensity score matching

We first begin with the results of estimating the propensity score (the probability of conducting a merger), which is reported in Table 6.7. The results show that patenting activities would increase the probability of merging, but these effects are not statistically significant. Most of the other estimated coefficients are also not statistically significant, except the coefficient for gross profit margin. This suggests firms with higher profitability are more likely to be involved in merger activities.

Table 6.7: Estimation results of propensity score

Variable	Coefficient	Std
log(patent_t-1)	0.279	0.264
log(patent_t-2)	-0.149	0.302
log(patent_t-3)	0.118	0.308
Citation per patent	0.008	0.005
log(patent stock_t-1)	0.267	0.294
log(sale)	0.809	0.535
R&D/sale	-0.040	0.030
Income	-0.076*	0.043
log(asset)	-0.792	0.489
Debt/asset	-0.002	0.015
Gross profit margin	0.047***	0.013
N	500	
R-squared	0.211	

Notes: $p < .01$: *** $p < .05$: ** $p < 0.10$: *. Dependent variable is 1 in the case of a merger. Time varying regressors are lagged one year relative to the merger. Regression includes time fixed effects.

Although there is a significant difference between the unmatched groups of treatment firms and control firms, after the nearest neighbor matching, there are more balancing properties as shown in Table 6.8. Most importantly, we can not reject the equality of means of the propensity score between the two groups. Moreover, the mean value of characteristics like sales, income, assets, debt/assets, and profit are not statistically different across treatment and control groups. Thus, we can say that firms in the treatment and control group after matching have a similar probability of merging, and characteristics in the pre-merger period, which shows the validity of the control group. We also plot the average trajectories of log patents for merged entities relative to the respective control firms after matching, which is illustrated in Figure 6.3. As can be seen in the figure, before the merger at year t, the innovation patterns of merged entities and control firms display a parallel trend. Hence, the condition that treatment firms and control firms behave similarly is met. After mergers, both merged entities and control firms increase their patent activity in year t+1. Then while the number of patents by merged entities becomes flat in year t+2 before a fall in $t + 3$, the control group experiences a gradual decrease in t+2 and t+3. Interestingly, although experiencing a fall in year 3 after mergers, the level of patents by merged entities is still higher than the pre-merger level. Whereas, in the case of control firms, the level of patents in year $t + 3$ is slightly lower than the pre-merger value in year $t - 1$. This visually shows that mergers may have positive impacts on the patent activity of merged entities.

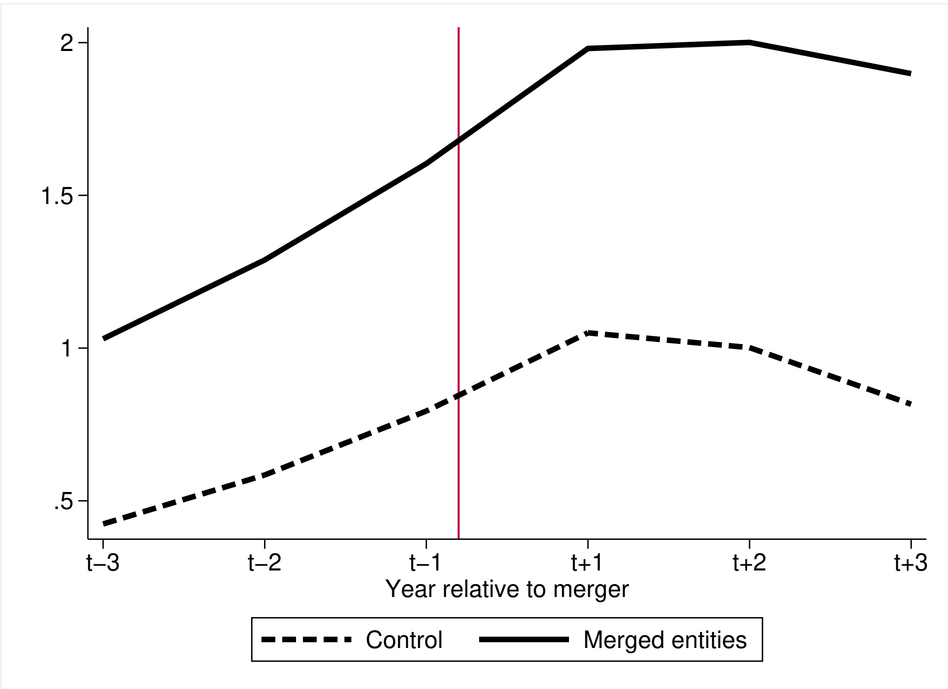
The main results of the estimated ATT effects of mergers on patents of merged entities are

Table 6.8: Balancing property after matching

Variable	Treated	Control	t-stat	p-value
Propensity score	0.179	0.153	1.388	0.169
log($patents_{t-1}$)	1.604	0.794	3.707	0.000
log($patents_{t-2}$)	1.289	0.585	2.942	0.004
log($patents_{t-3}$)	1.030	0.424	3.026	0.003
Citation per patent	12.216	7.842	0.661	0.510
log($patentstock_{t-1}$)	1.380	0.630	3.430	0.001
log(sale)	15.456	15.457	-0.000	0.999
R&D/sale	12.074	9.573	1.941	0.055
Income	2.782	1.537	1.472	0.145
log(asset)	15.845	15.710	0.327	0.744
Debt/asset	13.212	13.828	-0.262	0.794
Gross profit margin	63.147	61.930	0.269	0.788

Notes: Table shows mean differences between treated (merging entities) and control observations for the matched sample based on the propensity score.

Figure 6.3: Trajectories of log patent count for merged entities and control group



t denotes the time period in which the merger takes place.

documented in Table 6.9. For interpretation, merged entities would increase the number of new patents by 13%, 21%, and 31% in the first year, second year, and third year respectively after mergers. The magnitude of the effect is the largest, which is consistent with the visual evidence in Figure 6.3. However, these effects are not statistically significant, even at 10 % significance level. Therefore, we can not confirm any evidence that mergers impact positively on innovation activities of merging firms in general. This is probably because not all mergers generate enough synergies/efficiencies to boost the innovation outcome. Besides, these results also suggest that there is not necessarily any harm caused by mergers to innovation.

Table 6.9: Average treatment effects on the treated (ATT) estimation results

	(1)	(2)	(3)
	Δ log(patent)		
	t+1	t+2	t+3
MA	0.121	0.189	0.272
	(0.148)	(0.157)	(0.173)
N	102	102	102

Notes: $p < .01$: *** $p < .05$: ** $p < 0.10$: *. Table shows regressions based on the matched sample after using propensity score matching. Dependent variable is $ln(patents_{t+k} + 1)$ - $ln(patents_{t-1} + 1)$, where t refers to the year of the merger. Robust standard errors in parentheses. MA is an indicator variable which takes on a value of 1 if a firm is involved in a merger.

On the other hand, Table 6.10 documents the results of heterogeneous effects of mergers on innovation by different groups of firms. These effects on leading firms versus niche firms are presented in the first three columns. The estimated coefficient on the interaction term between two dummies of merger event and leading firms is positive and statistically significant in year 3 after the merger. Mergers would be estimated to increase the innovation measured by patents of leading firms by 137% higher than other firms in year 3 after the merger. This confirms that while mergers may not have an overall significant impact on merged entities, leading firms still benefit from their acquisitions to improve significantly their innovation outcome. The intuition here is that leading firms can generate more synergies from mergers, and fully capitalize these effects to boost their innovation, compared to other niche firms. Moreover, as analyzed above, leading firms are more likely to acquire young startups with talented people and innovative projects. Hence, mergers would enable these projects to be successful, and drive greater innovation outcomes.

The last three columns show the results of how mergers affect MSP firms versus non-MSP firms. As expected, the coefficients for the interaction between MA and MSP are highly positive and significant in both period t+2 and t+3. For instance, MSP firms would be estimated to increase their innovation by 75% higher than non-MSP firms 3 years after the merger. This is possible because of the role of indirect network effects. By acquiring other firms with different/complementary products, MSP firms could expand their range of products/services, which attract more users, and subsequently, drive more developers to join their cloud marketplace. This would lead to more sales revenue, which enables firms to spend more on R&D investment and eventually generate a greater innovation outcome.

When facing the trade-off between building and buying, firms may prefer to use acquisitions to acquire competitors' patents and technologies instead of developing themselves. Hence, one can question whether the results above are actually driven by the firm's acquisitions in the following years after the period in our data sample. While it is true that the leading firms and MSP firms in our analysis continue to acquire other cloud companies after our data sample period, this does not affect the above results/findings because of two reasons. First, most of the targets acquired by leading firms and MSP firms are young companies/startups, which do not have any patents or very few patents. Second, even when these targets have a number of patents, these patents have not been reassigned to acquirers, which means that our measurement of patents for leading/MSP firms is not affected by these acquisitions.

Table 6.10: Effects on leading vs niche firms and MSP vs non-MSP

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ log(patent)					
	t+1	t+2	t+3	t+1	t+2	t+3
MA	0.103	0.171	0.239	0.086	0.136	0.206
	(0.147)	(0.155)	(0.169)	(0.145)	(0.153)	(0.171)
MA x *leader*	0.457*	0.461*	0.861***			
	(0.244)	(0.240)	(0.256)			
MA x MSP				0.293*	0.455***	0.560***
				(0.167)	(0.162)	(0.189)
N	102	102	102	102	102	102

Notes: $p < .01$: *** $p < .05$: ** $p < 0.10$: *. Table shows regressions based on the matched sample after using propensity score matching. Dependent variable is $ln(patents_{t+k} + 1)$ - $ln(patents_{t-1} + 1)$, where t refers to the year of the merger. Robust standard errors in parentheses. MA is an indicator variable which takes the value of 1 if a firm is involved in a merger. *leader* is a dummy variable which has the value of 1 if the firm is in the group of leading firms. MSP is an indicator which takes the value 1 if firms have multi-sided platform business model.

Our results are consistent with theoretical evidence by Bourreau et al. (2019), and Jullien & Lefouili (2018) that mergers can have overall positive or negative impacts on innovation. The key policy implication from our result is that mergers do not necessarily lead to less innovation. Our intuition here is in the cloud computing market, most of the merger cases are young startup firms acquired by big tech firms, and this type of merger is more likely to promote innovation in this specific market. As mentioned in the descriptive evidence, the leading firms in the cloud computing market prefer to acquire young firms that develop complementary products instead of substituted products. Thus, the merger would not generate any cannibalization effect, which discourages the innovation incentive. On the other hand, since leading firms in cloud computing acquire young startups because of their talented employees, innovative assets, or R&D projects, the merger would generate synergies, for instance allowing startups to have enough funding to develop their innovative projects successfully. These synergies would enhance significantly the innovation outcome, which results in new or higher quality products/services and increases consumer welfare. On the other hand, mergers in the cloud computing market do not necessarily soften the competition in the market, as the main players remain the same. They are competing intensely to acquire more market share, and profit in this expansive market. Therefore, there is no evidence to believe that innovation is harmful because of M&A weakening competition in the market. To sum up, prohibiting startup acquisitions by big tech firms may do more harm than good. However, this does not mean that competition authorities should not scrutinise merger cases between big tech firms and young startup firms, especially when the young startup firms have great potential to be successful and be able to challenge the dominant firms, for example, large customer base or superior technologies.

6.7 Conclusions

While there are increasing discussions and debates among both researchers and practitioners on whether M&A by big tech firms harm innovation, there has not been any ex-post analysis providing empirical evidence to address this. This work aims to fill this gap by attempting to study merger activities and their impacts on innovation in the cloud computing market.

Our first descriptive evidence suggests that there are two different M&A strategies by two different groups of firms: leading firms and niche firms, which are defined by their market shares. While leading firms are more likely to target young startups, niche firms prefer to acquire longer established firms. This result complements previous studies on merger activities and strategies (Argentesi et al. 2019, Gautier & Lamesch 2020), as they only focus on big tech mergers' strategies, but do not analyse the case of a specific market. Most importantly, in addition to descriptive evidence, we provide an ex-post merger analysis to evaluate the impact on the innovation activity of merged entities. Our results suggest that mergers have positive impacts on innovation measured by the patent output of leading firms and MSP firms in the cloud computing market. This confirms previous theoretical findings in the literature that the effects of mergers on innovation is not always negative and can be positive. The intuition here is that in the cloud computing market, synergies are likely to occur between big tech firms with strong funding resources and project management experience, and young start-ups with talented employees and innovative ideas. And these synergies are more pronounced in the case of leading firms and MSP firms, thanks to their ability to capitalize them better or leverage them via indirect network effect. This will eventually generate positive effects on the innovation outcome of these firms. Our results help to ease some of the rising concerns about the potential harms of mergers and acquisitions in the digital platform market.

However, our study still has several limitations and can be extended in several ways. First, we only have a small sample of merging firms over a short period of time relative to other studies. The potential solution is to expand the number of merger cases by looking at extra merger cases in Europe and Asia. Since firms in the cloud computing market are genuinely competing globally, it is sensible to not limit merger cases in terms of geographical borders. To deal with the short time frame, we can employ quarterly data instead of yearly data to enrich the variation over time. Nevertheless, the issue here is the firms' financial data like revenue, R&D, income may not be available quarterly. Secondly, firms with multiple mergers can likely cause some co-founding effects, which bias the results. However, we can not exclude these firms as suggested in the literature due to our small sample. This problem can be solved when we extend our sample. Finally, we have not dealt with the endogeneity of merger decisions by IV regression as in previous studies. Our work can be extended by evaluating the impacts of mergers on the innovation activity of non-merging competitors in addition to merged entities as in Haucap et al. (2019). Furthermore, it would be interesting to analyse the effects of mergers on the entry and exit in the cloud computing market by using survival analysis.

Chapter 7

Summary and discussion

The booming of digital platforms/markets has drawn great attention from researchers and practitioners in the last two decades, which lead to incredible growth in the number of research works on platforms and digital markets. Despite these substantial works, there are still many aspects of digital platforms/markets that have been largely ignored or unexplored. This thesis contributes to a branch of the digital platform/market literature; not previously (fully) addressed by economic researchers.

The thesis began by introducing digital platforms and a literature survey on platform competition and relevant competition policy. The purpose of this chapter was not to provide a comprehensive survey but to guide readers through the definition, features, how platforms compete, and recent debates in competition policy for digital platform markets. Within this chapter, we also identified several gaps that should be addressed in future research.

Previous literature has devoted to studying price competitions between symmetric platforms but has not paid enough attention to asymmetric competition and the role of quality. The subsequent three chapters of the thesis contribute to this aspect by studying the asymmetric competition between a closed versus an open platform in the context of the hardware (tablet PC)-software (application) market and investigate the role of software quality. In Chapter 3, we developed a simple two-stage game, which we use to capture the asymmetry between a closed and open platform. we utilize this model to study the impact of software quality on equilibrium outcomes in the hardware market. We solve this game by backward induction and compute the effect of software quality on hardware market shares and prices of the two platforms. The results show that software quality impacts the own platform (own-effect) positively and has a negative effect (cross-effect) on the other platform, with the former effect being greater than the latter. Based on the equilibrium outcome, we study two possible policies that can affect the software quality: exclusion of lowest quality apps and forcing interoperability, which led to two hypotheses to be empirically tested in Chapter 4.

In Chapter 4, we aim to test the theory developed in Chapter 3 based on the three waves of product-level data on tablet and top 1000 applications in iOS and Android in 5 European countries. We first estimated the effect of application quality on tablet demand by employing the structural demand estimation in the previous literature as in Berry et al. (1995), and Grigolon & Verboven (2014). The estimation results imply that there is a positive significant impact of application quality on tablet demand. The structural demand model allows me to conduct counterfactual analyses to test the two hypotheses We set in the previous chapter. The counterfactual results confirm the support of two hypotheses: the exclusion of lowest quality apps led to an increase in both market shares and profits of tablet producers in the two platforms, with larger gain for Apple, and the compulsory interoperability across platforms would benefit Android tablet producers while worsening Apple market shares and profits. Interestingly, both policies are consumer welfare-enhancing. This suggests that a policymaker may have an incentive to encourage platforms to remove low-quality apps or forcing interoperability across platforms. Chapter 3 and Chapter 4 shed light on asymmetric platform competition in the tablet PC market, a market that has not been studied well in previous literature.

In a similar context of asymmetric platform competition, Chapter 5 studies how platforms decide when facing the trade-off between software quality and variety. This question has been studied in the literature by Hagiu (2011), as he investigates whether symmetric platforms have an incentive to exclude low-quality users by leveling up the quality standard. We contribute to this discussion by modeling asymmetric platforms and find an interesting result. When users have a sufficiently strong preference for software quality, the platform choices diverge. While the closed platform chooses a higher software quality standard, which results in a smaller software variety, the open platform sets a lower quality standard to attract greater software variety.

While the previous three chapters have been dedicated to studying platform competition in the case of a closed versus an open and emphasize the role of quality, the last chapter of the thesis brings a different flavor: mergers and innovation in the digital platform market. The literature on the relationship between mergers and innovations in the digital market has been emerging incredibly in recent years, with many extensive theoretical works on this topic. However, there are only a few empirical studies to address, directly, the question of how mergers affect innovation in the digital platform market. Chapter 6 of the thesis tackled this gap by providing an empirical analysis of mergers and innovation in the cloud computing market, one of the emerging digital markets. First, we examine the merger strategies by cloud computing firms and find that while leading firms like Amazon, Microsoft, or Google tended to acquire young innovative firms, niche firms like Cisco or VMware are more likely to buy well-established companies. Then, we employ the merger data from Crunchbase, along with the patent data from the US Patent Office, and estimated the causal effect of mergers on innovation —measured by patents of merged entities. The main results show a positive but insignificant impact of mergers on innovations in general. This suggests that mergers do not necessarily harm innovation in the market. Interestingly, there are positive and significant moderating effects of whether a firm is leading in the market or a multi-sided platform on the innovation outcome. Specifically, mergers are estimated to positively impact innovation —measured by patents of market leaders and multi-sided firms. This result supports the theory in previous literature that mergers in the digital market can enhance innovation when there are sufficient synergies.

This Ph.D. thesis provides insights into both firm's strategies and competition policy. In Chapter 3 and Chapter 4, it is shown that application quality is a driver of the demand for tablets and that platforms can gain market shares and profits by excluding low-quality apps. These results are useful to explain why Apple and Google have recently been more active in controlling the application quality. They also help to deepen the understanding of platform strategies in other markets. For instance, an online platform can detect and remove low-quality sellers to improve the buyer's experience, and in this way, encourage more users to visit the marketplace. Besides, this strategy also results in higher consumer welfare, suggesting that a regulator may be prone to force platforms to impose stricter controls for quality. For example, by setting a minimum quality standard that platforms need to meet. Additionally, Chapter 5 results suggest that compulsory application interoperability across platforms can enhance consumer welfare. Therefore, a policymaker may find it socially optimal to impose compulsory interoperability for applications on all platforms. Moreover, the finding in Chapter 5 that platforms find it profitable to set a higher quality standard when users have a high preference for software quality has an interesting implication for other platform markets. For example, based on consumer's past purchases and activities, platforms can identify whether consumers have a strong preference for quality, in which case, platforms should focus on improving quality instead of variety. Finally, Chapter 6's findings imply that merger control should not be too prohibitive against acquisitions by big tech firms like Amazon, Microsoft, or Google. These mergers can generate high-innovation outcomes—at least when measured by patents.

Appendices

A Appendix for Chapter 4

A.1 Robustness check: different measures of application quality

The average rating of users of an application is believed to represent a trustworthy measure of how good the application is, and influence as such the downloading of that application by users.

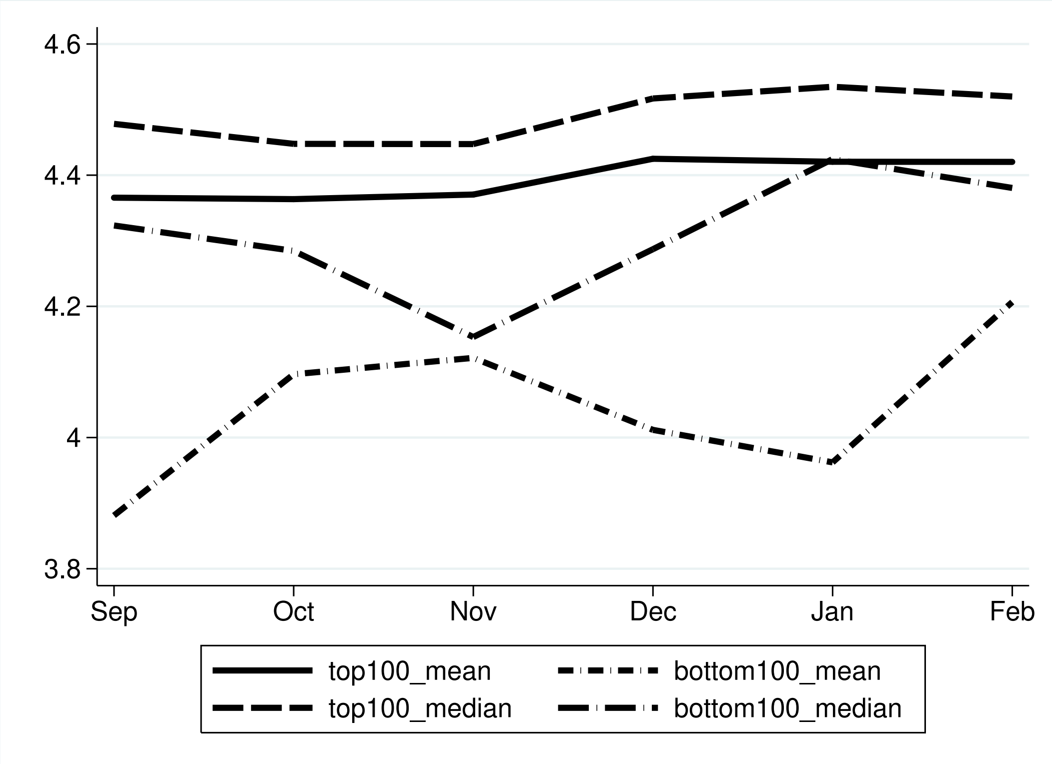


Figure A.1: Weighted average and median application rating of top and bottom 100 applications of the 1000 most downloaded applications in the UK App Store during the period 2013M09-2014M02

Figure A.1 shows that both the weighted average and the median ratings of the top-ranked 100 apps are substantially higher than for applications ranked 901st-1000th in the UK App Store; this because users tend to prefer applications with higher ratings, as these ratings signal quality.

We carry out a sequence of robustness regressions to check whether our results based on an overall weighted average quality of applications are consistent with different measures of app ratings. We re-estimate the RCNL model documented in the last pair of columns of Table 4.2 base on the measures of quality: weighted average ratings of top 100 apps in the store, weighted average ratings of top 200 apps in the store, the weighted average rating of apps ranked 901-1000, the weighted average rating of apps ranked 801-1000 and the median rating of top 1000 apps. The robustness check results are reported in Table A.1. When application quality is proxied by the median, the result of the app quality coefficient is the largest. Whereas, the results when using the weighted average of top 100 applications and top 200 apps are very similar, with both being positive and significant. In contrast, the estimated coefficients when application quality measure by apps ranked 901-1000, apps ranked 801-1000 are not statistically significant. Intuitively, these results reveal the fact that the top apps dominate the effect of app quality in the tablet market. Thus, we should put more weight on these apps, and thus the weighted average rating is a preferred measure of application quality.

Table A.1: Different measures of application quality

	Top 100		Top 200		Apps 901-1000		Apps 801-1000		Median	
	Parameter (1)	SE (1)	Parameter (2)	SE (2)	Parameter (3)	SE (3)	Parameter (4)	SE (4)	Parameter (5)	SE (5)
Demand side										
Constant	-16.165**	0.031	-15.914**	0.035	-15.117**	3.329	-15.738**	3.081	-16.587**	0.275
Storage	0.005**	0.001	0.004 *	0.002	-0.004	-0.005	0.003	0.001	0.003	0.004
Screen resolution	0.610**	0.044	0.583**	0.065	0.475**	0.159	0.447**	0.049	0.483**	0.116
Screen size	0.103**	0.016	0.094**	0.026	0.037	0.043	0.037	0.024	0.076**	0.027
Connection	0.285**	0.042	0.265**	0.071	0.065	0.127	0.052	0.075	0.207 *	0.10
Application quality	0.952**	0.130	0.980**	0.175	0.932	0.874	1.167	0.678	1.417**	0.410
Price (β_{p})	-0.010**	4E-04	-0.009**	0.001	-0.007**	0.002	-0.007**	0.001	-0.008**	0.001
Price (σ_{p})	0.007**	0.001	0.007**	0.003	0.005	0.058	0.005	0.022	0.005	0.018
Price (π_{p})	0.014**	6E-04	0.013**	0.001	0.012 *	0.006	0.013**	0.002	0.011**	0.004
Correlation ρ	0.657**	0.014	0.665**	0.025	0.524**	0.102	0.522**	0.078	0.670**	0.083
Pricing equation										
Constant	0.318**	0.066	0.219	0.828	0.536	24.524	1.118	2.466	0.639	5.532
Storage	0.004	0.003	0.004	0.010	-4E-04	0.053	-0.001	0.033	0.004	0.006
Screen resolution	0.247**	0.013	0.251**	0.042	0.156	1.902	0.116	0.346	0.216	0.427
Screen size	0.121**	0.024	0.123**	0.030	0.204	0.308	0.202	0.799	0.128**	0.026
Connection	0.269**	0.062	0.277 *	0.112	0.317	1.971	0.306	3.420	0.285	0.211
Model Statistics										
N	3753		3753		3753		3753		3753	
Pseudo R^2_D	0.675		0.666		0.596		0.616		0.678	
Pseudo R^2_S	0.649		0.654		0.416		0.381		0.632	
J-stat	16.823		17.051		13.541		27.895		20.413	
N mc<0	10		10		142		162		11	
Average PCM	0.280		0.292		0.508		0.517		0.317	

Notes: Table presents the results of the random coefficients nested logit estimation when we use different measures for application quality. PCM: price cost margin. Significance level: *: $p < 0.05$, **: $p < 0.01$. e: Application quality is treated as endogenous. Time, country and firm fixed effects are included both in the demand and pricing equations but not reported. Instruments: $h_1, h_2, h_4, h_6, h_7, h_8$

A.2 Additional tables

Table A.2: Instrument strength of demand side-First stage regression results

Variables	Price		Ln(sjg)		Application quality	
	Parameters	SE	Parameters	SE	Parameters	SE
Cons	-1349.835**	182.425	-8.780**	4.865	5.204**	0.108
Storage	2.058**	0.066	-0.026**	0.000	-4E-05	3E-05
Screenres	82.808**	2.247	0.306**	0.060	4E-04	0.001
Screensize	16.915**	0.857	-0.151**	0.023	-5E-05	0.001
Connectivity	62.854**	2.155	-0.464**	0.057	0.001	0.001
h_1	-0.152	0.135 *	0.003 *	0.001	2E-05	3E-05
h_2	0.624**	0.042	-0.005**	0.001	7E-05**	2E-05
h_3	0.035**	0.015	-0.002**	0.000	-4E-05**	9E-06
h_4	19.677	18.726	0.182	0.499	-0.153**	0.011
h_6	-8.566 *	3.937	0.070	0.105	0.019**	0.002
h_8	-6.128 *	3.086	0.075	0.082	-2E-04	0.002
Statistics						
N	3753		3753		3753	
F-stat instr	41.850		11.830		47.680	
F p-val	0.000		0.000		0.000	

Notes: Table presents the results of the first-stage IV GMM estimation with dependent variables price, log within the market share, and application quality (endogenous variables in the regression. Significance level: *: $p < 0.05$, **: $p < 0.01$. Time, country and firm fixed effects are included but not reported.

Table A.3: Changes in average app rating when excluding 10 % of lowest quality apps and imposing interoperability

Exclusion of 10% low quality apps					Interoperability/Comparability Intervention				
Country	OS	Top 1000	Top 900	Change	Country	OS	Before	After	Change
France	iOS	4.155	4.333	0.178	France	iOS	4.155	4.155	0.000
	Android	4.138	4.192	0.054		Android	4.138	4.155	0.017
Germany	iOS	4.219	4.335	0.116	Germany	iOS	4.219	4.219	0.000
	Android	4.180	4.233	0.053		Android	4.180	4.219	0.039
Italy	iOS	4.275	4.385	0.110	Italy	iOS	4.275	4.275	0.000
	Android	4.149	4.193	0.044		Android	4.149	4.275	0.126
Spain	iOS	4.223	4.335	0.111	Spain	iOS	4.223	4.223	0.000
	Android	4.034	4.065	0.031		Android	4.034	4.223	0.189
UK	iOS	4.266	4.380	0.114	UK	iOS	4.266	4.266	0.000
	Android	4.146	4.206	0.060		Android	4.146	4.266	0.120

Notes: Table presents the absolute changes in the average rating of both iOS and Android apps in the case where we exclude 10% of the lowest quality apps (apps with rating ranked between 901 and 1000) in the two stores, and the case where we impose compatibility/interoperability across the two stores.

Table A.4: Global tablet PC market shares by OS

Year	iOS	Android	Windows
2013	33.93	62.36	3.50
2014	27.57	67.33	5.09
2015	23.90	67.40	8.60
2016	22.40	66.20	11.30
2017	25.63	61.06	13.31
2018	25.67	58.34	15.98
2019	25.70	56.50	17.80

Source: Statista (2019)

B Appendix for Chapter 5

B.1 Derivation of equilibrium outcome

Solving for the first order of conditions of (5.5) with respect to p_1^h, p_1^s, p_2^s, z_1^s and z_2^s to derive the equilibrium outcomes:

$$\begin{aligned}
p_1^{s*} &= \frac{\mu\theta^2}{12}(Q_{H1}^{he} - Q_{H2}^{he}) + \frac{1}{3}(Q_{H1}^{he} + Q_{L1}^{he} - Q_{H2}^{he} - Q_{L2}^{he}) \\
p_2^{s*} &= \frac{\mu\theta^2}{12}(Q_{H2}^{he} - Q_{H1}^{he}) + \frac{1}{3}(Q_{H2}^{he} + Q_{L2}^{he} - Q_{H1}^{he} - Q_{L1}^{he}) \\
p_1^{h*} &= \frac{\mu J\gamma(z_1^{se} - z_2^{se}) + 2\alpha c(1-\mu)J + (n_1^{se} - n_2^{se})J + J + 1 - \mu}{2(1-\mu)\alpha J} \\
p_2^{h*} &= \frac{\mu J\gamma(z_2^{se} - z_1^{se}) + 2\alpha cJ(1-\mu+2J) + (n_1^{se} - n_2^{se})J + 3J + 1 - \mu}{2(1-\mu+2J)\alpha J} \\
q_1^{s*} &= \frac{\mu\theta^2(Q_{H1}^{he} - Q_{H2}^{he}) + 4(Q_{H1}^{he} + Q_{L1}^{he}) - 4(Q_{H2}^{he} + Q_{L2}^{he}) + 12}{24} \\
q_2^{s*} &= \frac{\mu\theta^2(Q_{H2}^{he} - Q_{H1}^{he}) + 4(Q_{H2}^{he} + Q_{L2}^{he}) - 4(Q_{H1}^{he} + Q_{L1}^{he}) + 12}{24} \\
Q_{H1}^{h*} &= \mu\frac{1 + \gamma(z_1^{se} - z_2^{se}) + (n_1^{se} - n_2^{se})}{2} \\
Q_{L1}^{h*} &= \frac{(\mu^2 + J(1-2\mu) - \mu)(n_1^{se} - n_2^{se}) + \mu(\mu - 1 - J)\gamma(z_1^{se} - z_2^{se}) + \mu^2 + (J+1)(1-2\mu)}{2(2J - \mu + 1)} \\
z_1^{s*} &= \frac{\theta\gamma Q_{H1}^{he}}{2} \\
z_2^{s*} &= \frac{\theta\gamma Q_{H2}^{he}}{2}.
\end{aligned} \tag{1}$$

Under the assumption that expectations are fulfilled, we can substitute z_1^{se}, z_2^{se}, n_1^{se} and n_2^{se} back to q_{H1}^h, q_{L1}^h to have the system of simultaneous equations:

$$\begin{aligned}
Q_{H1}^h &= \mu\frac{1 + \gamma\theta\frac{Q_{H1}^h - Q_{H2}^h}{2} + \frac{(\mu\theta^2+4)(Q_{H1}^h - Q_{H2}^h) + 4(Q_{L1}^h - Q_{L2}^h)}{12}}{2} \\
Q_{H2}^h &= \mu - Q_{H1}^h \\
Q_{L1}^h &= \frac{(\mu^2 + J(1-2\mu) - \mu)\frac{(\mu\theta^2+4)(Q_{H1}^h - Q_{H2}^h) + 4(Q_{L1}^h - Q_{L2}^h)}{12} + \mu(\mu - 1 - J)\gamma\theta\frac{Q_{H1}^h - Q_{H2}^h}{2} + \mu^2 + (J+1)(1-2\mu)}{2(2J - \mu + 1)} \\
Q_{L2}^h &= 1 - \mu - Q_{L1}^h.
\end{aligned}$$

Solving these we obtain the equilibrium:

$$
\begin{aligned}
Q_{H1}^{h*} &= \frac{\mu}{2} + \frac{2J\mu}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]\gamma^2+12\mu-20J-12} \quad Q_{H2}^{h*} = \mu - Q_{H1}^{h*} \\
Q_{L1}^{h*} &= \frac{1-\mu}{2} - \frac{J}{2}\frac{[\mu\theta(\mu\theta+6)\gamma^2+4\mu-12]}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]\gamma^2+12\mu-20J-12} \quad Q_{L2}^{h*} = 1-\mu-Q_{L1}^{h*}.
\end{aligned} \tag{2}
$$

B.2 Proof

First, we define:

$$
\begin{aligned}
\overline{\gamma} &= \max\left\{\sqrt{\frac{12(2J+1-\mu)}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]}}, \sqrt{\frac{12(1-\mu)^2+8J(1-2\mu)}{\mu\theta[\mu^3\theta+(1-2\mu)(J\mu\theta+\mu\theta+4J)+6(1-\mu)^2-2J\mu^2]}}\right\} \\
\underline{\gamma} &= \sqrt{\frac{4(4J+3-3\mu)}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]}}.
\end{aligned} \tag{3}
$$

Proof of Lemma 1

Proof. To ensure positive market shares for both platform in high income users group:

$$
\begin{aligned}
0 &< Q_{H1}^{h*} < \mu \Leftrightarrow -\frac{1}{2} < \frac{2J}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]\gamma^2+12\mu-20J-12} < \frac{1}{2} \\
&\Leftrightarrow \left|\frac{2J}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]\gamma^2+12\mu-20J-12}\right| < \frac{1}{2} \\
&\Leftrightarrow |\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]\gamma^2+12\mu-20J-12| > 4J \\
&\Leftrightarrow \gamma > \sqrt{\frac{12(2J+1-\mu)}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]}} \\
\textit{or} \quad & \quad \gamma < \sqrt{\frac{4(4J+3-3\mu)}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]}}.
\end{aligned} \tag{4}
$$

+) If $\gamma > \sqrt{\frac{12(2J+1-\mu)}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]}}$, we have:

$$
\begin{aligned}
&\frac{12(2J+1-\mu)}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]}\frac{4(3-\mu)}{\mu\theta(\mu\theta+6)} \\
&= \frac{4[\mu(1-\mu)(\mu\theta+6)+2J(\mu\theta+\mu+5)]}{\mu\theta(\mu\theta+6)[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]} > 0 \\
&\frac{12(2J+1-\mu)}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]} - \frac{4(5J+3-3\mu)}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]} \\
&= \frac{4J}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]} > 0.
\end{aligned}
$$

which leads to:

$$
\begin{aligned}
\gamma^2 &> \frac{4(3-\mu)}{\mu\theta(\mu\theta+6)} \quad \textit{and} \quad \gamma^2 > \frac{4(4J+3-3\mu)}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]} \\
\Leftrightarrow &\quad [\mu\theta(\mu\theta+6)\gamma^2+4\mu-12] > 0 \\
\textit{and} &\quad \mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]\gamma^2+12\mu-20J-12 > 0 \\
\Leftrightarrow &\quad \frac{[\mu\theta(\mu\theta+6)\gamma^2+4\mu-12]}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]\gamma^2+12\mu-20J-12} > 0.
\end{aligned}
$$

Thus, $Q_{L1}^{h*} < \dfrac{1-\mu}{2} < 1-\mu$. Platform 1 has a positive share in low income group if and only if:

$$
\begin{aligned}
& \frac{1-\mu}{2} - \frac{J}{2}\frac{[\mu\theta(\mu\theta+6)\gamma^2+4\mu-12]}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]\gamma^2+12\mu-20J-12} > 0 \\
\Leftrightarrow\ & \mu\theta[\mu^3\theta+(1-2\mu)(J\mu\theta+\mu\theta+4J)+6(1-\mu)^2-2J\mu^2]\gamma^2 > 12(1-\mu)^2+8J(1-2\mu) \\
\Leftrightarrow\ & \gamma > \sqrt{\frac{12(1-\mu)^2+8J(1-2\mu)}{\mu\theta[\mu^3\theta+(1-2\mu)(J\mu\theta+\mu\theta+4J)+6(1-\mu)^2-2J\mu^2]}}. \qquad (5)
\end{aligned}
$$

+) If $\gamma < \sqrt{\dfrac{4(4J+3-3\mu)}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]}}$,

$$
\begin{aligned}
& \frac{4(4J+3-3\mu)}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]} - \frac{4(3-\mu)}{\mu\theta(\mu\theta+6)} \\
= & -\frac{4(1-\mu)[\mu(2n+2n\theta-\mu\theta)+6(J-\mu)]}{\mu\theta(\mu\theta+6)[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]} < 0 \\
& \frac{4(4J+3-3\mu)}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]} - \frac{4(5J+3-3\mu)}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]} \\
= & -\frac{4J}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]} < 0.
\end{aligned}
$$

Hence,

$$
\begin{aligned}
\gamma^2 &< \frac{4(3-\mu)}{\mu\theta(\mu\theta+6)} \quad \textit{and} \quad \gamma^2 < \frac{4(5J+3-3\mu)}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]} \\
\Leftrightarrow &\quad [\mu\theta(\mu\theta+6)\gamma^2+4\mu-12] < 0 \\
\textit{and} &\quad \mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]\gamma^2+12\mu-20J-12 < 0 \\
\Leftrightarrow &\quad \frac{[\mu\theta(\mu\theta+6)\gamma^2+4\mu-12]}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]\gamma^2+12\mu-20J-12} > 0 \\
\Rightarrow &\quad Q_{L1}^{h*} < \frac{1-\mu}{2} < 1-\mu.
\end{aligned}
$$

Platform 1 has a positive share in low income group if and only if:

$$
\begin{aligned}
& \frac{1-\mu}{2}-\frac{J}{2}\frac{[\mu\theta(\mu\theta+6)\gamma^2+4\mu-12]}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]\gamma^2+12\mu-20J-12}>0\\
\Leftrightarrow\ & \mu\theta[\mu^3\theta+(1-2\mu)(J\mu\theta+\mu\theta+4J)+6(1-\mu)^2-2J\mu^2]\gamma^2<12(1-\mu)^2+8J(1-2\mu)\\
\Leftrightarrow\ & \gamma^2<\frac{12(1-\mu)^2+8J(1-2\mu)}{\mu\theta[\mu^3\theta+(1-2\mu)(J\mu\theta+\mu\theta+4J)+6(1-\mu)^2-2J\mu^2]}. \qquad (6)
\end{aligned}
$$

Moreover,

$$
\begin{aligned}
& \frac{12(1-\mu)^2+8J(1-2\mu)}{\mu\theta[\mu^3\theta+(1-2\mu)(J\mu\theta+\mu\theta+4J)+6(1-\mu)^2-2J\mu^2]}-\frac{4(4J+3-3\mu)}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]}\\
= & \frac{4J(1-\mu)(\mu\theta+4J+6)}{\mu\theta[\mu^3\theta+(1-2\mu)(J\mu\theta+\mu\theta+4J)+6(1-\mu)^2-2J\mu^2][(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]}>0\\
\Leftrightarrow & \frac{12(1-\mu)^2+8J(1-2\mu)}{\mu\theta[\mu^3\theta+(1-2\mu)(J\mu\theta+\mu\theta+4J)+6(1-\mu)^2-2J\mu^2]}>\frac{4(4J+3-3\mu)}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]}
\end{aligned}
$$

Combining the inequalities 4, 5, 7, we have the necessary and condition for positive market share for both platforms in the two groups as in 3. □

Proof of Lemma 2a

Proof. We have:

$$
\begin{aligned}
Q_{H1}^{h*}-Q_{H2}^{h*} &= \frac{4J\mu}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]\gamma^2+12\mu-20J-12}\\
Q_{L1}^{h*}-Q_{L2}^{h*} &= -\frac{J[\mu\theta(\mu\theta+6)\gamma^2+4\mu-12]}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]\gamma^2+12\mu-20J-12}.
\end{aligned}
$$

When $\gamma>\overline{\gamma}$,

$$
\begin{aligned}
& \gamma^2>\frac{12(2J+1-\mu)}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]}>\frac{4(5J+3-3\mu)}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]}\\
\Rightarrow\ & \mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]\gamma^2+12\mu-20J-12>0.
\end{aligned}
$$

Hence, $Q_{H1}^{h*}-Q_{H2}^{h*}>0\Rightarrow Q_{H1}^{h*}>Q_{H2}^{h*}$. On the other hand,

$$
\begin{aligned}
& \frac{12(2J+1-\mu)}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]}>\frac{4(3-\mu)}{\mu\theta(\mu\theta+6)}\\
\Rightarrow\ & \gamma^2>\frac{4(3-\mu)}{\mu\theta(\mu\theta+6)}\\
\Rightarrow\ & \mu\theta(\mu\theta+6)\gamma^2+4\mu-12>0\\
\Rightarrow\ & -\frac{J[\mu\theta(\mu\theta+6)\gamma^2+4\mu-12]}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]\gamma^2+12\mu-20J-12}<0.
\end{aligned}
$$

Thus, $Q_{L1}^{h*}-Q_{L2}^{h*}<0\Rightarrow Q_{L1}^{h*}<Q_{L2}^{h*}$. □

Proof of Lemma 2b

Proof. Similar to the proof of Lemma 2a, we can show that when $\gamma < \underline{\gamma}$:

$$\begin{aligned}
& \gamma^2 < \frac{4(4J+3-3\mu)}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]} < \frac{4(5J+3-3\mu)}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]} \\
\Rightarrow \quad & \mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]\gamma^2+12\mu-20J-12<0.
\end{aligned}$$

Therefore, $Q_{H1}^{h*} - Q_{H2}^{h*} < 0 \Rightarrow Q_{H1}^{h*} < Q_{H2}^{h*}$. Whereas,

$$\begin{aligned}
& \frac{4(4J+3-3\mu)}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]} < \frac{4(3-\mu)}{\mu\theta(\mu\theta+6)} \\
\Rightarrow \quad & \gamma^2 < \frac{4(3-\mu)}{\mu\theta(\mu\theta+6)} \\
\Rightarrow \quad & \mu\theta(\mu\theta+6)\gamma^2+4\mu-12<0 \\
\Rightarrow \quad & -\frac{J[\mu\theta(\mu\theta+6)\gamma^2+4\mu-12]}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]\gamma^2+12\mu-20J-12} < 0.
\end{aligned}$$

Thus, $Q_{L1}^{h*} - Q_{L2}^{h*} < 0 \Rightarrow Q_{L1}^{h*} < Q_{L2}^{h*}$. □

Proof of Corollary 1a

Proof. Substituting 2 back to 1 and computing the equilibrium price to have:

$$p_1^{h*} - p_2^{h*} = \frac{J}{(1-\mu)\alpha}\frac{[\mu\theta(\mu\theta+2\mu+4)\gamma^2-8]}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]\gamma^2+12\mu-20J-12}.$$

Additionally,

$$\begin{aligned}
\frac{8}{\mu\theta(\mu\theta+2\mu+4)} \quad &- \quad \frac{12(2J+1-\mu)}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]} \\
&= \quad -\frac{4[(1-\mu)(\mu\theta+6)+2J(\mu\theta+4\mu+2)]}{\mu\theta(\mu\theta+2\mu+4)[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]} < 0 \\
\Leftrightarrow \frac{8}{\mu\theta(\mu\theta+2\mu+4)} \quad &< \quad \frac{12(2J+1-\mu)}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]} \leq \overline{\gamma}^2 \\
\frac{8}{\mu\theta(\mu\theta+2\mu+4)} \quad &- \quad \frac{4(4J+3-3\mu)}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]} \\
&= \quad \frac{4(1-\mu)(4J-6\mu-\mu\theta)}{\mu\theta(\mu\theta+2\mu+4)[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]} > 0 \\
\Leftrightarrow \frac{8}{\mu\theta(\mu\theta+2\mu+4)} \quad &> \quad \frac{4(4J+3-3\mu)}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]} = \underline{\gamma}^2.
\end{aligned} \tag{8}$$

Therefore,

+) When $\gamma > \overline{\gamma}$,

$$\begin{aligned}
\gamma^2 &> \frac{8}{\mu\theta(\mu\theta+2\mu+4)} \Rightarrow \mu\theta(\mu\theta+2\mu+4)\gamma^2 - 8 > 0 \\
\gamma^2 &> \frac{4(4J+3-3\mu)}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]} \\
&\Rightarrow \mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]\gamma^2 + 12\mu - 20J - 12 > 0 \\
&\Rightarrow p_1^{h*} > p_2^{h*}. \qquad (9)
\end{aligned}$$

+) When $\gamma < \underline{\gamma}$

$$\begin{aligned}
\gamma^2 &< \frac{8}{\mu\theta(\mu\theta+2\mu+4)} \Rightarrow \mu\theta(\mu\theta+2\mu+4)\gamma^2 - 8 > 0 \\
\gamma^2 &< \frac{4(4J+3-3\mu)}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]} \\
&\Rightarrow \mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]\gamma^2 + 12\mu - 20J - 12 < 0 \\
&\Rightarrow p_1^{h*} > p_2^{h*}. \qquad (10)
\end{aligned}$$

Thus, we have $p_1^{h*} > p_2^{h*}$ when $\gamma > \overline{\gamma}$ or $\gamma < \underline{\gamma}$ □

Proof of Corollary 1b

Proof. We have the difference between hardware users in the two platforms:

$$Q_1^{h*} - Q_2^{h*} = -\frac{J[\mu\theta(\mu\theta+6)\gamma^2 - 12]}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]\gamma^2 + 12\mu - 20J - 12}. \qquad (11)$$

It can be shown easily:

$$\begin{aligned}
&\frac{12(2J+1-\mu)}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]} - \frac{12}{\mu\theta(\mu\theta+6)} \\
&= \frac{24J(1-\mu)}{\mu\theta(\mu\theta+6)[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]} > 0 \\
&\frac{4(4J+3-3\mu)}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]} - \frac{12}{\mu\theta(\mu\theta+6)} \\
&= \frac{-8J(\mu\theta+3\mu+3)}{\mu\theta(\mu\theta+6)[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]} < 0 \\
&\Rightarrow \overline{\gamma}^2 > \frac{12}{\mu\theta(\mu\theta+6)} > \underline{\gamma}^2 \\
&\Rightarrow J[\mu\theta(\mu\theta+6)\overline{\gamma}^2 - 12] > 0 \quad \& \quad J[\mu\theta(\mu\theta+6)\underline{\gamma}^2 - 12] < 0. \qquad (12)
\end{aligned}$$

As in Lemma 5.1, we already have:

$$\begin{aligned}
\overline{\gamma}^2 &> \frac{4(5J+3-3\mu)}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]} > \underline{\gamma}^2 \\
&\Rightarrow \mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]\overline{\gamma}^2 + 12\mu - 20J - 12 > 0 \\
&\textit{and} \quad \mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]\underline{\gamma}^2 + 12\mu - 20J - 12 < 0. \qquad (13)
\end{aligned}$$

Combining 12 and 13, we have the right hand side of Equation 11 is always negative. Thus, the open platform always has more hardware users than the closed platform. □

Proof of Proposition 1

Proof. +) As $z_1^{s*} = \dfrac{\theta\gamma Q_{H1}^{h*}}{2}$ and $z_2^{s*} = \dfrac{\theta\gamma Q_{H2}^{h*}}{2}$, $z_1^{s*} > z_2^{s*}$ if $\gamma > \overline{\gamma}$.

+) Substituting 2 into 1, we can derive:

$$n_2^{s*} - n_1^{s*} = \frac{2J(\mu\theta\gamma^2 - 2)}{\mu\theta[(\mu\theta+6)(1-\mu) + 2J(\mu\theta+\mu+5)]\underline{\gamma}^2 + 12\mu - 20J - 12}.$$

We need to prove the right hand side is positive in both cases: $\gamma > \overline{\gamma}$ and $\gamma < \underline{\gamma}$.

If $\gamma > \overline{\gamma}$. Indeed,

$$\frac{12(2J+1-\mu)}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]} - \frac{2}{\mu\theta} = \frac{2[(2J-\mu\theta)(1-\mu) - 2J\mu\theta])}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]} > 0$$
$$\Rightarrow \quad \overline{\gamma}^2 > \frac{2}{\mu\theta} \quad (\mu < 0.4 \quad \theta < 1).$$

We already show that $\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]\underline{\gamma}^2 + 12\mu - 20J - 12 > 0$ if $\gamma > \overline{\gamma}$, which means that the right hand side of 14 is positive if $\gamma > \overline{\gamma}$.

If $\gamma < \underline{\gamma}$, we have:

$$\begin{aligned}
&\frac{4(4J+3-3\mu)}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]} - \frac{2}{\mu\theta} \\
= &\frac{-2(-\mu^2\theta + 2J\mu\theta + 2J\mu + \mu\theta + 2J)}{\mu\theta(\mu\theta+6)[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]} < 0 \\
\Rightarrow &\ \underline{\gamma}^2 < \frac{2}{\mu\theta} \quad (\mu < 0.4).
\end{aligned}$$

Since $\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]\underline{\gamma}^2 + 12\mu - 20J - 12 < 0$ if $\gamma < \underline{\gamma}$,

$$\frac{2J(\mu\theta\gamma^2 - 2)}{\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]\underline{\gamma}^2 + 12\mu - 20J - 12} > 0 \Leftrightarrow n_2^{s*} > n_1^{s*} \quad if \quad \gamma > \underline{\gamma}.$$

□

Proof of Corollary 2

Proof. We can compute the partial effects of γ on z_1^{s*} as:

$$\begin{aligned}
\frac{\partial z_1^{s*}}{\partial\gamma} &= \frac{(\mu\theta a\gamma^2 - 2(11J+6-6\mu) - b)\,(\mu\theta a\gamma^2 - 2(11J+6-6\mu) + b)}{4\,(\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]\gamma^2 + 12\mu - 20J - 12)^2} \\
where \quad a &= (\mu\theta+6)(1-\mu) + 2J(\mu\theta+\mu+5) \quad \& \quad b = \sqrt{41J^2 + 24J - 24J\mu}. \qquad (14)
\end{aligned}$$

Hence,

$$\frac{\partial z_1^{s*}}{\partial\gamma} > 0 \Leftrightarrow \gamma^2 > \frac{2(11J+6-6\mu)+b}{\mu\theta a} \quad or \quad \gamma^2 < \frac{2(11J+6-6\mu)-b}{\mu\theta a}. \qquad (15)$$

Set $\overline{\overline{\gamma}} = \sqrt{\dfrac{2(11J+6-6\mu)+b}{\mu\theta a}}$ and $\underline{\underline{\gamma}} = \sqrt{\dfrac{2(11J+6-6\mu)+b}{\mu\theta a}}$. Then, the first statement of Corollary 5.2 is proved. Similarly, the partial effects of γ on z_2^{s*} is computed as:

$$\frac{\partial z_2^{s*}}{\partial \gamma} = \frac{\mu^3\theta^3 a\gamma^4 + 12\mu^2\theta^2(3J+2-2\mu)a\gamma^2 + 48\mu\theta(2J+1-\mu)(5J+3-3\mu)}{4\left(\mu\theta[(\mu\theta+6)(1-\mu)+2J(\mu\theta+\mu+5)]\gamma^2 + 12\mu - 20J - 12\right)^2}. \tag{16}$$

The numerator of the right hand side of (16) can be rewritten as:

$$d\gamma^4 + e\gamma^2 + f = d(\gamma^2 + \frac{e}{2d})^2 + \frac{4df - e^2}{d}. \tag{17}$$

Where $d = \mu^3\theta^3 a$, $e = 12\mu^2\theta^2(3J+2-2\mu)a$ and $f = 48\mu\theta(2J+1-\mu)(5J+3-3\mu)$. Because $4df - e^2 = 48\mu^4\theta^4 J(13J+8-8\mu)a^2 > 0 \Rightarrow d\gamma^4 + e\gamma^2 + f > 0$, which leads to $\dfrac{\partial z_2^{s*}}{\partial \gamma} > 0$ $\square$

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