Platform Competition in the Tablet PC Market: the Role of Application Quality

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Abstract

In the market for tablet PC devices, competition occurs between two dominant platforms: the iOS-based and the Android-based platform. While the former is fully controlled by Apple, which both produces the devices and manages the app store, Apple Store, the latter is vertically disintegrated, with devices produced by competitive manufacturers and the app store, Google Play, controlled by Google. In this paper, we focus on studying the effects of the quality of applications distributed in each dedicated app store on the equilibrium in the tablet PC market (indirect externality). First, we build a simple theoretical model, which provides basic insights into the equilibrium outcomes. Combining data on iOS and Android tablets sales with data on the top 1000 mobile applications in Apple Store and Google Play for five European countries, we then estimate a structural model to quantify the effects of such indirect externality. Estimates confirm our theoretical predictions and we find that: 1) the tablet market is significantly affected by the externality accruing from the quality of apps; 2) The exclusion of low quality apps leads to the gain of both platforms in terms of market shares and profits; 3) The gain is larger for Apple.

Keywords: tablet market, mobile application, externality, iOS, Google Play, quality.
JEL classifiers: L14, L86

1 Introduction

The introduction of digital distribution platforms for mobile operating systems (OS) developed by Apple and Google in 2008 has marked an important milestone for the booming of mobile platforms. Since its beginning, the number of mobile applications (apps) has grown exponentially, counting by the end of June 2018, about 2 million apps in each of the two largest online platforms, Apple Store and Google Play, which together covered more than 90% of the market. Taking advantage of the growing app industry, a new generation of hardware - tablet PC - was launched by Android in 2009 and followed by Apple in 2010. According to Statista.com, in 2014, around 840 million people across the globe used a tablet at least once per month, equivalent to over 20 percent of the world's total population; this figure is forecast to rise to over 1.41 billion by 2020.

The two competing dominant platforms in the tablet PC market: the iOS-based and the Android-based platform follow two distinctive business models. Of interest for our paper, the former is vertically integrated by Apple, which controls both the devices production and the app store, Apple Store, while the latter is an open platform, with devices produced by competitive manufacturers without OS license fee and the app store, Google Play, managed by Google. Our paper contributes to the rich literature on the relevance of network effects in high-tech markets; since the papers by Katz and Shapiro (1986) and Church and Gandal (1992), it has been proved that by attracting more users and developers hi-tech firms can earn the strategic advantage that is needed to gain and preserve market dominance. In this article, we focus on the tablet PC market and answering the question of how the quality of the apps distributed in each dedicated app store affects the outcome of the tablet market. This is a classic form of indirect network externality related to the availability of complementary products.

In the previous literature, indirect network effects are typically related to the number/variety of complementary products. Because the number of applications now exceeds 2 million in both Apple Store and Google Play, it may be not meaningful to estimate the effect of increasing the number of applications available in the store, as this effect would be potentially negligible. For this reason, rather than the number of applications, we focus on the externality generated by the quality of the apps available on the dedicated store. It is very reasonable to assume that the higher the quality of applications developed within a platform, the higher the utility from adopting a tablet for that platform, and the larger the demand.

We first introduce a simple theoretical analysis aimed at studying competition between two incompatible platforms by adopting a classic Hotelling horizontal product differentiation model. We model the game as two stages, where consumers first select the platform and then, given their choice, their most preferred tablet model, with consumer preferences for tablets being affected by the quality of the applications available for that platform. Then we construct an econometric model relying on the discrete choice literature for product differentiation. The demand for tablets is modelled as a random coefficient nested logit demand function, where the nest captures the heterogeneity in operating systems. The reason for this choice is that typically users make their decision in two stages. In line also with our theoretical arguments, we assume that they first choose the operating system, and then one of the models of tablets with that operating system. On the other hand, since our target is analyzing competition in the tablet market, it is necessary to estimate own price and cross price elasticities of demand for both Apple and Android tablets. Therefore, in addition to nested logit structure, we also present random coefficients for the tablet characteristics and price following Nevo (2001), which allow different consumer preferences towards prices and solve the problem of unrealistic price elasticities in the simple nested logit model. Estimations are based on a sample made of three waves of product-level data for tablets and apps distributed in 5 European countries (Germany, France, Italy, Spain, and the UK) over the period September 2013-February 2014.

In addition to the demand side, we also incorporate the cost function and derive the pricing equation. This system of simultaneous equations enables us to estimate the primitives on the tablet market and, most importantly, to evaluate the counterfactual analysis of what the equilibrium prices market shares and profits of tablet manufacturers would have been if the platforms exclude low quality applications from the application store. Our main findings are that there are significant network externalities from the application quality on the tablet demand. Specifically, and in line with our theoretical model, the results of the counterfactual experiment suggest that market shares and profits of both platforms would increase if they remove low quality apps from their stores. Equally important, our estimations suggest that exclusion of low quality applications generates larger profits for Apple than for Android tablet producers. According to this result, Apple has more to gain from increasing the quality of its apps than Android producers; interestingly, this provides a possible rationale for why in Apple Store the distribution of apps undergoes a much stricter quality check than in Google Play.[1]

The outline of this paper is the following. In the next section, we discuss the relevant literature. The third section is then devoted to introduce a simple theoretical model; this analysis will provide some predictions to be tested in the empirical part. The fourth section develops the econometric model while Section 5 provides a description of the data and summary statistics. Section 6 presents the estimation strategy and the empirical estimation, along with a discussion of the main results. Section 7 concludes.

2 Literature review

Our paper contributes to the stream of literature examining the existence of network effect in the context of complementary products. One of the early theoretical works is the paper by Church and Gandal (1992), where they assume that complementary goods are incompatible between hardware technologies, and the benefit/effect from joining the network only depends explicitly on the consumption of software. In their model consumer preferences are homogenous, meaning that consumers derive the same utility from all available software products. Hence, only the software variety drives the network externality. Under these assumptions, consumer preferences are captured by the symmetric CES utility function. The market outcomes for both hardware and software markets are derived by solving two equations, one for hardware adoption and the other for software consumption, given the free-entry condition for software firms. The result implies that the size of the network effect depends on the number of software firms, which is determined by the software development cost. If these costs are large, the number of software

[1] See Comino et al. (2018) for a discussion of the different approaches towards quality control between Apple Store and Google Play.

firms will be small and the result is Bertrand competition in the software market. 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 in the variety of software. These papers model the extent of consumer adoption and ignore software provision. The first empirical work which estimates 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 CDs titles has a significant effect on the adoption of CDs players. They formulate a rudimental dynamic model, where both consumers and developers are infinite-lived and make the decision of purchasing and supplying simultaneously. The CD players' price in their model is assumed to be exogenous and hardware heterogeneity is neglected.

There are various empirical papers that examine indirect network effects in digital markets, such as markets for personal digital assistants (Nair et al. 2004), and video games ((Clements and Ohashi 2005), (Corts and Lederman 2009), (Lee 2013)). Similar to Church and Gandal (1992), 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 the hardware demand, which enables them to fit the model into an econometric framework and 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 in the hardware demand, and from the hardware installed base to the software supply. Their findings also suggest that the size of the cross-network effect can be enhanced by the improvement of hardware product's quality, as that increases the consumer demand directly through the utility, and indirectly, through the positive feedback from software variety.

To the best of our knowledge, Lee (2013) is the first paper to address the heterogeneity problem and examine the differential impact of software on hardware demand by using both hardware and software data. His work aims at quantifying the effect of vertical integration in the form of exclusive software on the market equilibrium and social welfare. He develops a dynamic model, which specifies consumer's hardware and software adoption based on the underlying product's characteristics as well as software provision, which is assumed to follow the first-order Markov process. In a counterfactual exercise, he studies the absence of exclusive contracts and demonstrates that sales would have increased in absence of exclusive contracts.

The papers by Sun (2013) and Kim (2012) are the closest papers to ours. Both papers examine the interaction between the smartphone market and the application market, which is similar to the objective of this study. The former investigates how branding can be changed by application adoption in the store. He conforms to the bulk of previous literature and estimates the indirect network effect by employing the total number of applications as the key control variable and neglects application heterogeneity. His main findings are that app stores have a considerable positive effect on the expansion of smartphones brand value, this while the rate of expansion varies within brands by virtue of different two-sided platform strategies. For instance, iPhone is able to enhance the smartphone branding more substantially than Blackberry, as it is more open to developers. Because the installed base is unobserved by researchers, his paper estimates the equation of installed base in the equilibrium framework, which differs from ours. In addition, his work focuses on measuring the impact of cross-network externalities on the brand value of smartphones and does not look at the competition between hardware producers. The latter empirically evaluates the contribution of applications to smartphones adoption growth and explores how this contribution is determined by the quality of the app store. Kim's paper uses both smartphone and application characteristics to estimate a structural smartphone demand and exploit heterogeneity in application demand to determine the differential contributions of applications on smartphone demand, as in Lee (2013). Comparing to Lee's work, Kim additionally tackles the issue of consumer selection as they have their preference for both smartphones and apps, which depends on demographic characteristics. Moreover, in Kim (2012) it is carried out a hypothetical experiment where Android users are given iPhones and iOS users are offered Android-based smartphones, as to investigate the correlation between smartphone taste and application taste. The estimates suggest that correlation exists, as iPad users tend to consume more apps, and iOS apps often provide more utility to users. Due to lack of data, the paper uses app rank as a proxy for app quantity, with consequences on the unbiasedness of the estimates. Furthermore, the software provision is disregarded in her equilibrium analysis.

The first difference of our work from these two papers is that we focus on the tablet PC market and develop an equilibrium framework with structural tablet demand and supply and take into account the role of unobserved consumer heterogeneity. We develop the theoretical framework based on Armstrong (2006) to capture the effect of apps quality on tablet demand and to provide intuitions behind the empirical results. Then we construct an econometric model following Berry (1994), BLP, and Nevo (2001) with further control for the quality of complementary applications. We aimed at estimating the network externalities parameters and conducting the counterfactual analysis to provide the evidence for the theory part. The work contributes to the previous literature by integrating app quality into the model, rather than just using app variety to capture the cross-network externalities. Equally important, our concentration is not only on estimating the network externalities, but also the impacts of the externalities on the equilibrium prices, market shares and profits of tablets produced for each platform. From both the theoretical and empirical result, our paper is able to analyse and provide an insightful intuition of the competition between producers in the tablet market, an aspect which is still limited in the literature on smartphones and applications.

3 The theoretical model of platform competition

We assume the tablet market to be characterized by the presence of two alternative platforms based on incompatible operating systems: iOS, developed and controlled by Apple, and Android, an open source operating system developed and maintained by Google. Apple sells an iOS-based device, iPad, and compete with n tablet manufacturers of Android-based tablets. Apple controls Apple Store and Google manages Google Play, the two app stores where device users can download applications, Apple Store for iPad users and Google Play for the users of Android-based devices.

For the reasons that will become clearer below, we assume a two-stage competition process:

Stage 1: in the first stage consumers decide which platform to adopt (inter-platform competition) and, in the case they chose iOS, they buy iPad;

Stage 2: in the second stage those who have chosen Android, decide which product to purchase among the n alternatives (intra-platform competition).

For notation convenience, in the remaining, we use the subscripts $1, 2$ for the iOS/Apple platform and the Android platform respectively.

The two platforms are differentiated along several dimensions; just to mention some of them, Apple's and Android-based devices have different hardware, different reputation/brand recognition, they are based on two incompatible operating systems and, to a large extent, the two dedicated app stores contain different applications. For this reason, we assume that inter-platform competition occurs between two vertically and horizontally differentiated products; formally, we represent inter-platform competition using a simple Hotelling line, with qualitatively different products. Regarding the quality of a tablet, we model it as the combination of the quality of its two main components: hardware and software/applications. More specifically, indicating with z_{hj} the quality of the hardware/recognition of tablets of platform j and with $\bar{z}_{sj}$ the average quality of the apps available in the store of platform j, we assume that the overall quality of platform j's tablets is given by the product $z_{hj}\bar{z}_{sj}$.

We solve the model by backward induction; hence let us start from the second stage when competition occurs between Android producers. As discussed above, platform 2 tablet producers compete for users who in stage 1 have chosen to purchase a device of platform 2. Let us indicate with q_{h2} the mass of these customers. For the sake of simplicity, we model intra-platform competition as a Salop oligopoly model with horizontal product differentiation. We assume that the n producers of platform 2 devices are equidistantly located on a unit length circle with customers who are uniformly distributed along the circle. We further simplify our analysis by assuming that platform 2 producers compete by taking the mass of users q_{h2} as given.

Consumer x's purchasing decision solves $\max_{\rho=i,i+1}\{z_{h2}\bar{z}_{s2} - t(l_\rho - x) - \beta p_i\}$, where firms $\rho = i, i+1$ are the firms between which the consumer is located, and where firm ρ's location is $l_\rho = \rho/n$. The parameter t indicates the unit transportation cost measuring the degree of horizontal product differentiation between Android producers, while β represents the individual's price sensitivity.

Consider the generic firm i, with $i = 1, .., n$; given its price p_i and the price p_{i+1}, the consumer indifferent between its product and that of firm $i+1$ is located at:

$$\frac{2i+1}{2n} + \frac{\beta(p_{i+1} - p_i)}{2t}.$$

By analogy, we can identify the location of the consumer indifferent between firm i's product and that of its left neighbor. Firm i sells to all consumers between these two indifferent customers. As we look at the symmetric equilibrium where firms all charge the same price $p = p_{i+1} = p_{i-1}$, firm i's the total demand is:

$$\frac{1}{n} + \frac{\beta(p - p_i)}{t}.$$

Let us now dedicate a few words to parameter β, customers' price sensitivity. In our estimations, individuals have different income levels and in one of our counterfactuals, we allow income distribution to vary. A natural way to incorporate such income effects in our theoretical model is to assume that individuals have different price sensitivities: a fraction μ has a low price sensitivity, $\beta = \beta_L$, and the remaining fraction of consumers is more sensitive to price, $\beta = \beta_H$, with $\beta_H > \beta_L$. As high-income customers are usually less sensitive to price, the fraction μ of β_L consumers can be considered as high-income customers while the others as low-income customers. Both types of individuals are uniformly distributed on the unit circle. According to this distribution of price sensitivity, firm i's profit function is:

$$\pi_{h2,i} = (p_i - c_2)\left(\mu\left(\frac{1}{n} + \frac{\beta_L(p - p_i)}{t}\right) + (1-\mu)\left(\frac{1}{n} + \frac{\beta_H(p - p_i)}{t}\right)\right) q_{h2},$$

where c_2 is the marginal cost of producing a platform 2 tablet, and q_{h2} is the mass of users that in the first stage have chosen platform 1 and that in stage 2 is assumed to be fixed. Solving for the symmetric equilibrium, $p_i = p = p_{h2}$, it is easy to obtain the equilibrium price:

$$p_{h2} = c_2 + \frac{t}{n\left(\beta_H - \mu\left(\beta_H - \beta_L\right)\right)}. \tag{1}$$

In stage 1, consumers observe hardware qualities, z_{hi}, and the average qualities of the apps available in the two stores, $\bar{z}_{si}$, $i = 1, 2$. They also observe the price of an iPad, p_{h1}, and are able to anticipate the equilibrium price of tablets of platform 2, p_{h2}; with this information they decide which platform to adopt.

As said, inter-platform competition occurs a' la Hotelling; platform 1 is located in l_1 and platform 2 in l_2, with $l_2 > l_1$. Consumers between l_1 and l_2 compare net utilities and choose. The net utilities of the user located in $x \in (l_1, l_2)$ are as follow:

$$u_{h1}(x) = z_{h1}\bar{z}_{s1} - k(x - l_1) - \beta p_{h1}, \qquad u_{h2}(x) = z_{h2}\bar{z}_{s2} - k(l_2 - x) - \beta p_{h2}$$

where x is uniformly distributed in $[0, 1]$. The parameter k represents the unit transportation cost and indicates the degree of horizontal inter-platform differentiation; as before, β represents individuals price sensitivity; the mass of customers is normalized to 1. The indifferent customer is identified by:

$$\tilde{x}_{12}(\beta) = \frac{l_1 + l_2}{2} - \frac{\beta(p_{h1} - p_{h2}) + z_{h1}\bar{z}_{s1} - z_{h2}\bar{z}_{s2}}{2k}. \tag{2}$$

Customers to the left of l_1/resp. to the right of l_2, have to decide whether to adopt platform 1/resp. platform 2, or not to adopt any platform. They adopt if they receive a non-negative net utility; formally, the indifferent customer between adopting platform 1/resp. platform 2 or not adopting are located in:

$$\tilde{x}_{10}(\beta) = l_1 + \frac{z_{h1}\bar{z}_{s1} - \beta p_{h1}}{k}, \quad \text{and} \quad \tilde{x}_{20}(\beta) = l_2 + \frac{z_{h2}\bar{z}_{s2} - \beta p_{h2}}{k}. \tag{3}$$

Consumers located between $\tilde{x}_{10}(\beta)$ and $\tilde{x}_{12}(\beta)$ join platform 1 while those located between $\tilde{x}_{12}(\beta)$ and $\tilde{x}_{20}(\beta)$ join platform 2.[2]

[2] All through this section, we assume that at the equilibrium the model admits an internal solution: $0 <$

As explained above, a fraction μ of consumers has low price sensitivity, $\beta = \beta_L$, and the remaining fraction of consumers has high price sensitivity, $\beta = \beta_H$. As the two types of customers are uniformly distributed on the [0,1] segment and have total mass of 1, the demand for platform 1 is: $\mu(\tilde{x}_{12}(\beta_L) - \tilde{x}_{10}(\beta_L)) + (1-\mu)(\tilde{x}_{12}(\beta_H) - \tilde{x}_{10}(\beta_H))$, and the demand for platform 2 is: $\mu(\tilde{x}_{20}(\beta_L) - \tilde{x}_{12}(\beta_L)) + (1-\mu)(\tilde{x}_{20}(\beta_H) - \tilde{x}_{12}(\beta_H))$.

Using expressions (2) and (3), we can rewrite these demands as follows:

$$q_{h1}(p_{h1}, p_{h2}) = \frac{l_2 - l_1}{2} + \frac{3 z_{h1} \bar{z}_{s1} - z_{h2} \bar{z}_{s2} - (3\, p_{h1} - p_{h2})\,(\beta_H - \mu\, (\beta_H - \beta_L))}{2k}$$

$$q_{h2}(p_{h1}, p_{h2}) = \frac{l_2 - l_1}{2} + \frac{3 z_{h2} \bar{z}_{s2} - z_{h1} \bar{z}_{s1} + (p_{h1} - 3\, p_{h2})\,(\beta_H - \mu\, (\beta_H - \beta_L))}{2k}$$

The profit function of the producer of the tablet in platform 1 given p_{h1} and p_{h2} is therefore:

$$\pi_{h1}(p_{h1}, p_{h2}) = (p_{h1} - c_1) \left(\frac{l_2 - l_1}{2} + \frac{3 \bar{z}_{s1} z_{h1} - \bar{z}_{s2} z_{h2} - (3\, p_{h1} - p_{h2})\,(\beta_H - \mu\, (\beta_H - \beta_L))}{2k} \right) \quad (4)$$

where c_1 is the firm marginal cost of production.

For later purposes, it is also useful to report the first stage overall profits $\Pi_{h2} = \sum_n \pi_{h2,i}$, enjoyed by the tablet manufacturers in platform 2, given prices:

$$\Pi_{h1}(p_{h1}, p_{h2}) = (p_{h2} - c_2) \left(\frac{l_2 - l_1}{2} + \frac{3 \bar{z}_{s2} z_{h2} - \bar{z}_{s1} z_{h1} + (p_{h1} - 3\, p_{h2})\,(\beta_H - \mu\, (\beta_H - \beta_L))}{2k} \right) \quad (5)$$

We are now in the position to solve for the market equilibrium. Solving the first order condition, and given expression (1), it is possible to derive equilibrium prices and platforms market shares, given software and hardware qualities:[3]

$$p^*_{h1} = \frac{3c_1 + c_2}{6} + \frac{t + n\,(3 \bar{z}_{s1} z_{h1} - \bar{z}_{s2} z_{h2}) + kn\,(l_2 - l_1)}{6n\,(\beta_H - \mu\, (\beta_H - \beta_L))}$$

$$p^*_{h2} = c_2 + \frac{t}{n\,(\beta_H - \mu\, (\beta_H - \beta_L))}$$

Using these values, we can rewrite equilibrium quantities, given expectations on the average quality of the apps available in the two platforms:

$$q^*_{h1} = \frac{l_2 - l_1}{4} + \frac{3 \bar{z}_{s1} z_{h1} - \bar{z}_{s2} z_{h2} - (3c_1 - c_2)\,(\beta_H - \mu\, (\beta_H - \beta_L)) + \frac{t}{n}}{4k}$$

$$q^*_{h2} = \frac{7(l_2 - l_1)}{12} - \frac{\bar{z}_{s1} z_{h1} - \frac{17}{3} \bar{z}_{s2} z_{h2} - \left(c_1 - \frac{17}{3} c_2\right)(\beta_H - \mu\, (\beta_H - \beta_L)) + \frac{17}{3}\frac{t}{n}}{4k}$$

3.0.1 Predictions

From these expressions, we can derive a series of testable predictions on the characteristics of the equilibrium.

The first prediction regards the effect of a change in the average quality of the apps available

$\tilde{x}_{10}(\beta) < \tilde{x}_{12}(\beta) < \tilde{x}_{20}(\beta) < 1$.

[3] It is easy to check that the second order condition is satisfied.

on platform i; from q^*_{h1} and q^*_{h2} if follows immediately that an increase in the quality of the apps available on the dedicated app store of platform i stimulates the demand for tablets i (own effect) and it reduces the demand for the rival platform (cross effect):

$$\frac{dq^*_{h1}}{d\bar{z}_{s1}} = \frac{3}{4}\frac{z_{h1}}{k} > 0, \qquad \frac{dq^*_{h2}}{d\bar{z}_{s2}} = \frac{17}{12}\frac{z_{h2}}{k} > 0 \tag{6}$$

$$\frac{dq^*_{h1}}{d\bar{z}_{s2}} = -\frac{1}{4}\frac{z_{h2}}{k} < 0, \qquad \frac{dq^*_{h2}}{d\bar{z}_{s1}} = -\frac{1}{4}\frac{z_{h1}}{k} < 0 \tag{7}$$

Note also that, in absolute values, own effects are larger than cross effects.

Expressions (6) reveal another interesting observation. If platform 1 hardware quality/reputation is sufficiently larger than that of platform 2, formally if $z_{h1} > \frac{17}{9}z_{h2}$, our model predicts that the impact on demand of an increase in the quality of applications is larger in platform 1 than in platform 2. We cannot test specifically whether this condition on hardware quality is satisfied but anecdotal evidence suggests that it is as, on average, the quality of Android tablets is commonly recognized as being far lower than that of Apple's ones.

These arguments suggest that both platforms benefit from an increase in the quality of the apps available in their store. We can also use our equilibrium prices and quantities to check which platform benefits more. Expressions (4) and (5) provide the first-stage platforms profit functions, given prices and app qualities. The quality of the apps on each platform affects profits both directly, via the effect it has on the number of tablets sold, and indirectly, via the change in prices; totally differentiating the aforementioned profit functions, with respect to $\bar{z}_{si}$, it follows that:

$$\begin{aligned}
\frac{d\pi_{h1}(p_{h1}(\bar{z}_{s1}), p_{h2}(\bar{z}_{s1}), \bar{z}_{s1})}{d\bar{z}_{s1}} &= \underbrace{\frac{\partial \pi_{h1}}{\partial p_{h1}}\frac{dp_{h1}}{d\bar{z}_{s1}}}_{(1)} + \underbrace{\frac{\partial \pi_{h1}}{\partial p_{h2}}\frac{dp_{h2}}{d\bar{z}_{s1}}}_{(2)} + \underbrace{\frac{\partial \pi_{h1}}{\partial \bar{z}_{s1}}}_{(3)}, \\
\frac{d\Pi_{h2}(p_{h1}(\bar{z}_{s2}), p_{h2}(\bar{z}_{s2}), \bar{z}_{s2})}{d\bar{z}_{s1}} &= \overbrace{\frac{\partial \Pi_{h2}}{\partial p_{h2}}\frac{dp_{h2}}{d\bar{z}_{s2}}} + \overbrace{\frac{\partial \Pi_{h2}}{\partial p_{h1}}\frac{dp_{h1}}{d\bar{z}_{s2}}} + \overbrace{\frac{\partial \Pi_{h2}}{\partial \bar{z}_{s2}}},
\end{aligned}$$

as regards platform 2, where (1) and (2) are the indirect own and cross-price effects, and (3) is the direct effect. For the envelope theorem, the own-price effect on equilibrium profits is zero; using the expressions for equilibrium prices and quantities found above, it is possible to show that these two differentials boil down to:

$$\frac{d\pi_{h1}}{d\bar{z}_{s1}} = \frac{3}{2}\frac{p^*_{h1} - c_1}{k}z_{h1} \quad \text{and} \quad \frac{d\Pi_{h2}}{d\bar{z}_{s2}} = \frac{17}{12}\frac{p^*_{h2} - c_2}{k}z_{h2}.$$

Hence, platform 1 benefits more than platform 2 if:

$$p^*_{h1} - c_1 > (p^*_{h2} - c_2)\frac{17}{18}\frac{z_{h2}}{z_{h1}}.$$

Under the very mild condition that Apple's hardware quality is larger than the average quality of Android tablets, $z_{h1} > z_{h2}$, a sufficient condition for platform 1 gaining more benefits from an increase in apps quality than platform 2 is that the equilibrium mark-up in this platform is larger than the mark-up on platform 2. If this condition holds, Apple tends to benefit more from an increase in app quality than the Android producers. The main reason lies in the presence of intra-platform competition which, partially or entirely, washes away the potential benefits of an increase in the quality of Google Play apps that Android tablet producers are able to enjoy.

Wrapping-up, if we reinterpret the average users rating on platform i as the average quality of apps on that platform, the following testable predictions follows immediately:

Prediction 1 (Effects of app quality). *Equilibrium quantities and platform profits are affected by the quality of the apps distributed in the dedicated store: i) the amount of platform i tablets increases with the average users app rating on the same platform and decreases with the average users app rating on platform j - in absolute values, own effects are larger than cross effects; ii) the impact of application quality on tablet demand tends to be larger on platform 1 and, iii) platform 1 benefits more than platform 2 from an increase in the quality of its apps.*

The second prediction is about the effects of income changes. As said, in our model a fraction $1-\mu$ of consumers has a large price sensitivity; it is natural to interpret these consumers as low-income customers who suffer the most from monetary expenses. If we let μ vary, the distribution of income changes; in particular, an increase in μ corresponds to an increase in income as there are fewer low-income users. We can use our equilibrium quantities and prices to evaluate the effects of an increase in μ; formally, the effects on platform market shares of a chance in μ are given by:

$$\frac{dq_{h1}^*}{d\mu} = \frac{(3c_1 - c_2)(\beta_H - \beta_L)}{4k}, \quad \text{and} \quad \frac{dq_{h2}^*}{d\mu} = \frac{(17c_2 - 3c_1)(\beta_H - \beta_L)}{4k}.$$

Under the very mild condition $c_2/3 < c_1 < 17c_2/3$, that is the marginal cost of productions are not extraordinarily different between the two platforms, both these derivatives are positive and the equilibrium market shares increase with income.[4] It is also interesting to notice that:

$$\frac{dq_{h1}^*}{d\mu} - \frac{dq_{h2}^*}{d\mu} = \frac{(\beta_H - \beta_L)(3c_1 - 5c_2)}{3k} > 0 \quad \text{if} \quad c_1 > \frac{5}{3}c_2.$$

In other words, if the cost of producing a tablet for platform 1 is slightly larger than the cost of producing a tablet for platform 2, a condition confirmed by our estimates (see Appendix B) the impact on market shares of an increase in income is stronger for platform 1 tablets than for platform 2. From this discussion the following prediction follows:

Prediction 2. *When the distribution of income changes, such that there are fewer low-income customers, market shares of both platforms increase. If $c_1 > \frac{5}{3}c_2$, the impact of such a change is stronger on platform 1.*

4 Econometric model

In this section we represent the individual decision to buy a tablet and, subsequently, to download mobile applications as discrete.

[4]In order to reassure there reader that this condition on firms' marginal cost of production is satisfied, in Appendix B we show the estimated average marginal costs of producing iPads and Android tablets.

4.1 Demand for tablet

When choosing which tablet to purchase consumers observe the tablet characteristics - one of these being the price - along with information on how many mobile applications, and of which quality, are available for downloads in a digital platform compatible with the operating system that tablet relies on. Consumers choose a tablet which maximizes their utility and one of their choices is not to buy a tablet (outside option). Since tablets are associated with a specific operating system, we model tablet choice in two levels. In the first level, users face the alternative choice between purchasing either an iPad, or an Android-based tablet, or no tablet at all. In the second level, users select their preferred tablet within that operating system. Adding this first layer to the choice is needed because when users choose a tablet they are stuck to use the operating system that is associated with that tablet.

In this section, we present the random coefficients nested logit model. This econometric model is fairly general, as it allows for: product-level utility, individual preferences on the price and app externality, unobserved tablet characteristics, individual unobserved heterogeneity for the operating system, and an idiosyncratic random variable. There are T markets (in our data these are combinations of countries and quarters) but in the notation below we drop out the market subscript for notational convenience. In each market, there are I consumers and $J+1$ products (where the $+1$ is the contribution of the outside option). The products belong to one of three groups: $g = 0$ (outside option), $g = 1$ (iOS), $g = 2$ (Android). The utility of user i buying tablet j in OS g is:

$$u_{ij} = x_j\beta - \alpha_i p_j + \varphi z_g + \xi_j + \zeta_{ig} + (1-\rho)\epsilon_{ij}, \tag{8}$$

where x_j is the vector of observed tablet characteristics, p_j is the price, α_i is a random coefficient. z_g is the average quality of applications available in operating system g. The term ζ_{ig} is common to all products using operating system g, and has a unique probability distribution function that depends on the within segment correlation parameter ρ, with $0 \leq \rho < 1$. ϵ_{ij} is assumed to be identically and independently distributed extreme value. $\zeta_{ig} + (1-\rho)\epsilon_{ij}$ is also distributed to be an extreme value random variable. As 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. We follow BLP and (Nevo 2001) to model the distribution of consumer specific taste parameters. The random coefficients are additive in observed and unobserved individual characteristics, denoted D_i and v_i, respectively. $P(D)$ is a nonparametric empirical distribution function and v_i is assumed to be a multivariate standard normal distribution. This is formally described in matrix notation by:

$$\begin{pmatrix} \alpha_i \end{pmatrix} = \begin{pmatrix} \alpha \end{pmatrix} + \Pi D_i + \Sigma v_i,\ D_i \sim P_D,\ v_i \sim P_v = N(0,1). \tag{9}$$

The vector (α, φ) capture the mean marginal utility of the price and average quality of the applications downloaded by users in an online store. Π is a matrix of coefficients that measures how individual tastes vary with observed demographics. Σ is a scaling matrix, which allows each element in v_i to have different standard deviations (Nevo (2001)). By denoting the mean utility of tablet j with $\delta_j = x_j\beta - \alpha p_j + \varphi z_g + \xi_j$ and deviations from that utility with $\mu_{ijg} = [-p_j]'(\Pi D_i + \Sigma v_i)$, it is possible to compact the utility in equation (8) to:

$$u_{ij} \quad = \quad \delta_j + \mu_{ijg} + \zeta_{ig} + (1-\rho)\xi_{ij}. \tag{10}$$

Consumers purchase the tablet that maximizes their utility. The presence of random coefficients in the utility (heterogeneity in preferences that we do not observe) combined with the parametric assumption of the error term yields to the conditional probability of consumer i choosing tablet j

$$\phi_{ij} = \frac{exp((\delta_j + \mu_{ijg}))/(1-\rho)}{exp(I_{ig}/(1-\rho))} \frac{exp(I_{ig})}{exp(I_i)}, \tag{11}$$

where I_{ig} and I_i are McFadden (1978)'s "inclusive values", defined by:

$$\begin{aligned} I_{ig} &= (1-\rho) ln \sum_{j=1}^{\mathcal{J}_g} exp((\delta_{jg} + [-p_j]'(\Pi D_i + \Sigma v_i))/(1-\rho)) \\ I_i &= ln(1 + \sum_{g=1}^{G} exp(I_{ig})), \end{aligned} \tag{12}$$

in which case $\mathcal{J}_g$ is the set of tablet models belonging to nest g, so that for G nests the sum of cardinalities is $\sum_{g=1}^{G} |\mathcal{J}_g| = J$. Next, by defining A_j the support of individual characteristics associated to product j, it is possible to solve for product j's market share as a solution of:

$$s_j = \int_{A_j} dP_{\varepsilon} dP_v dP_D \tag{13}$$

where P denotes the population distribution function of three different multivariate distribution functions. Following BLP, the integral of equation (13) can be approximated numerically by simulation:

$$s_j = \frac{1}{ns} \sum_{i=1}^{ns} \phi_{ij} = \frac{1}{ns} \sum_{i=1}^{ns} \frac{exp((\delta_{jg} + [-p_j]'(\Pi D_i + \Sigma v_i))/(1-\rho))}{exp(I_{ig}/(1-\rho))} \frac{exp(I_{ig})}{exp(I_i)} \tag{14}$$

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

4.2 Tablet producer profit maximization

Multiproduct 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 to be linear in product characteristics (some observed w and some unobserved ω):

$$c_j = w_j \gamma + \omega_j. \tag{15}$$

Tablet manufacturer m produces $\mathcal{J}_m$ of $\mathcal{J}$ tablets. Given the demand (share) function in equation 13, the profit of tablet manufacturer m is:

$$\pi_m = \sum_{j \in \mathcal{J}_m} (p_j - c_j) s_j I \tag{16}$$

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

$$s_j + \sum_{r \in \mathcal{J}_m} (p_r - c_r) \frac{\partial s_r}{\partial p_j} = 0. \tag{17}$$

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

$$\Delta_{jr} = \begin{cases} -\dfrac{\partial s_r^T}{\partial p_j^T}, & \text{if } r, j \in \mathcal{J}_m, \\ 0, & \text{otherwise,} \end{cases} \tag{18}$$

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

$$s - \Delta(p - c) = 0. \tag{19}$$

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

$$\begin{aligned} p &= c + (\Delta)^{-1} s, \\ b &= (\Delta)^{-1} s. \end{aligned} \tag{20}$$

Substituting in the expression for the marginal cost, we obtain a pricing equation to estimate:

$$p - b = w\gamma + \omega. \tag{21}$$

5 Descriptive Data

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 and then discuss the variables that are relevant for the empirical analysis.

5.1 Tablet data

The tablet data was purchased from IDC CEMA. The dataset 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) over 15 quarters, starting from 2010Q3 and ending with 2014Q1. A total of 775 products are observed during this time frame and countries, for a total of 12,337 observations (as products are differentiated by various specs). 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. We label a combination of country-time as a market, so that the number of markets is (15×5=75). The variables in the data that vary by markets are unit sales, prices, and the number of products.

To give an insight of variation of sales, (average) price and the number of models over time, we display in Figure 1 their trend for the UK market. As can be seen, the unit sales of iPad exceed those of Android until 2012Q2. Thereafter the sales of Android-based tablets rise dramatically and surpass those of iOS. This is consistent with the different strategies adopted by the two platforms. While Android is an open platform licensed to many producers, iOS is vertically integrated by Apple. Thus, the number of Android tablet models evolves more rapidly than the number of iOS models, resulting in higher unit sales. Seasonality is also noticeable, with clear Christmas period peaks. Interestingly, but perhaps not surprisingly, sales peaks coincide with model variety peaks. The overall trend for average price is decreasing because a fraction of old product versions grew larger with a variety expansion. Except for the last quarter of each year, the statistics in all other quarters are consistent with the nature of demand, since when the price falls/rises, sales surge/drop. In terms of operating system (OS), 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.

Figure 1: **Tablet unit sales, average price, and number of tablet models sold in the UK market between 2010Q3 and 2014Q1**

(a) Sale units and average prices (b) Number of models

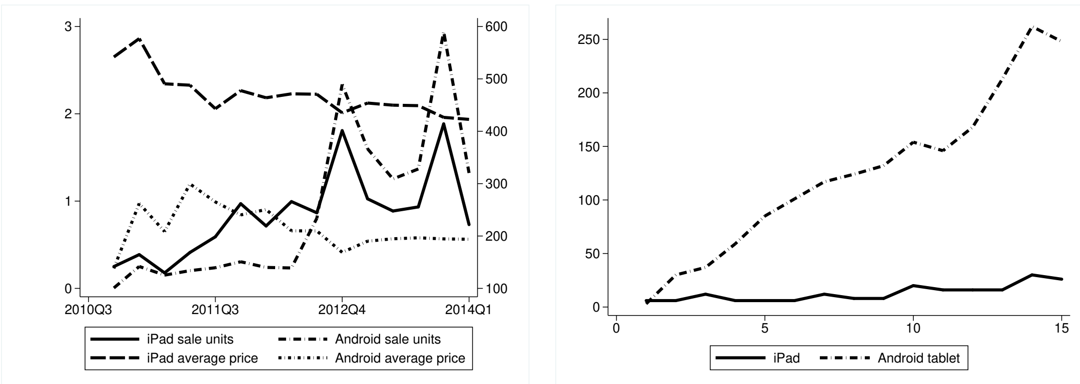


Table 1 summarizes, by platform, the characteristics of tablets. The table highlights a large variation in price and characteristics.

5.2 Data used in the estimation

5.2.1 App data

The app data was bought from Priori Consulting Analytics. It is made of 6 monthly panels of top 1,000 ranked (most downloaded) apps in Google Play and Apple Store in each of 5 European countries (the UK, France, Germany, Spain and Italy). The period covered by the data is September 2013 - February 2014. Therefore, there are 30 time-country markets.

Out interest in this dataset is to recover a measure of app quality. After 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 app rating of each app in our application dataset as a proxy of app

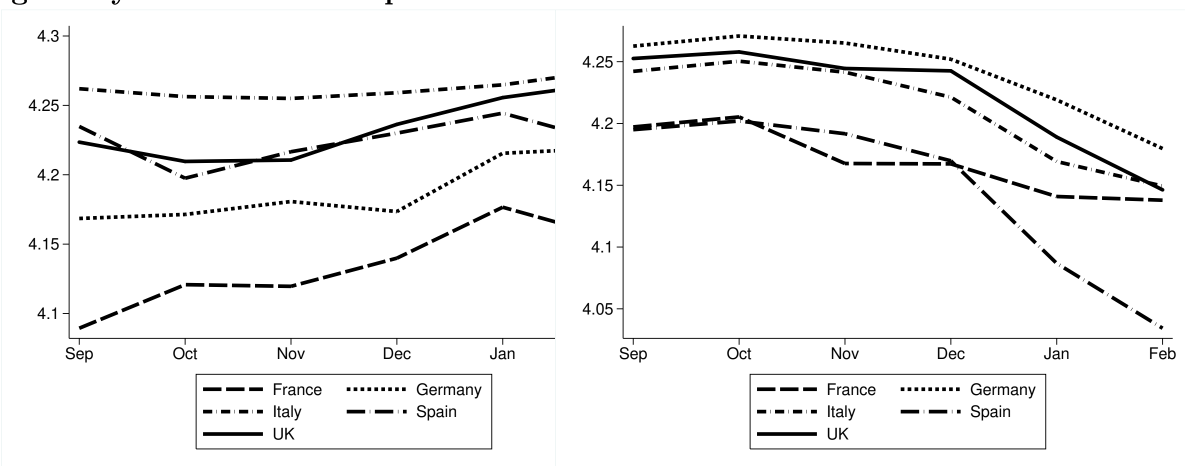
Table 1: **Summary statistics by OS**

	N	Screen size (inches)		Storage (GB)		Average price (EUR)	
		Mean	Std	Mean	Std	Mean	Std
iOS	977	9.22	0.8	41.86	30.72	493.76	112.9
Android	9271	8.62	1.39	20.03	29.73	236.79	144.23
BlackBerry OS	175	7	0	37.03	19.47	259.35	130.58
Windows	1714	10.5	1.18	90.54	95.14	785.88	516
Windows RT	170	10.32	0.25	45.74	15.89	479.92	106.29
Android&Windows	20	11.6	0	625	128.25	1036.65	129.5
webOS	10	9.7	0	24	8.43	195	108.47

quality. The average rating of users of an app is an indicator of how good and reliable the app is. This measure influences users in their decision to download the app. For each market, we calculate the weighted average app rating and use this measure as a source of average software quality and study its effect on tablet demand.

Figure 2 displays the weighted average app rating by period and country (by market). In most countries, the weighted average rating in Google Play store is slightly higher than that in Apple Store. The rating of an app is country invariant; thus variation in rating across countries is only possible if countries have a different portfolio of top apps. This is the case in our data for two reasons. First, because it is not necessarily that an app is top in all countries in the same period (or in any period) and second, equally important, because there are apps that are local and therefore distributed only in that country. As can be seen in the figure, there is variation of app rating over time and across countries.

Figure 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

Table 2 presents sources of variation of app rating by country, time, OS, category, and developer. It can be seen that most of the variation in app rating is due to developers.

The analysis presented in table 2 is aggregate. However, it is important to highlight the difference between the perceived quality of the same application in the two stores. Figure 3

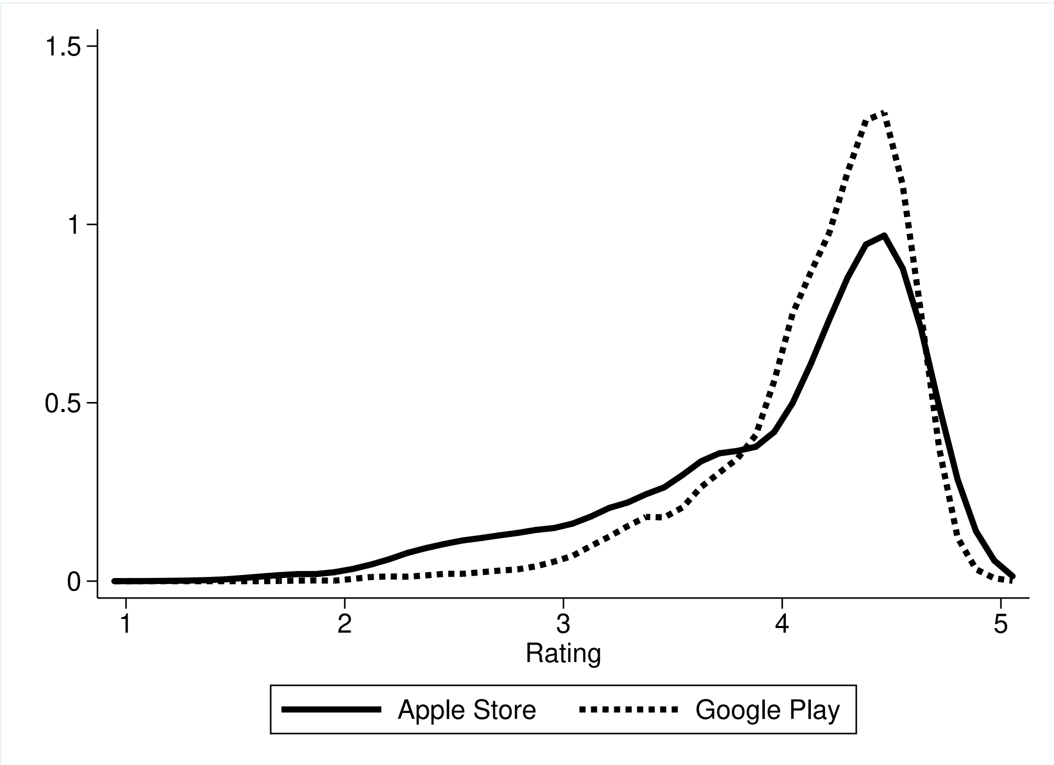
Table 2: App rating source of variation

Dependent Variable	N	Explanatory Variable			R-squared (%)
Apprating	29966	Country Dummies			0.02
Apprating	29966	Time Dummies			0.52
Apprating	29966	OS Dummy			0.09
Apprating	29966	Category Dummies			0.66
Apprating	29966	Developers Dummies			29.56
Apprating*	29966	Country Dummies	Time Dummies	OS Dummy	30.96
Apprating*	29966		Time Dummies	OS Dummy	30.94
Apprating*	29966	Country Dummies		OS Dummy	30.45
Apprating*	29966	Countries Dummies	Time Dummies		30.56

*: includes category and developer fixed effects.

shows for the subset of multihomed apps, the distribution of app rating in the two stores. The average app rating in Google Play has a lower dispersion and higher frequency of high app ratings. The difference between the two distributions can have two reasons. First, it could be the result of an actual quality difference between stores induced by different software and quality control by the platforms (see Comino et al (2018)). Secondly, it could be the result of selection of users with the heterogeneous preference for quality into the two stores. For instance, it could be that higher income users have higher standards for quality and prefer iPads over Androids tablets. This selection could lead to more rigid reviews in app stores. In the empirical analysis, we will study this conjecture by verifying whether the selection to the store based on income is correlated with app rating.

Figure 3: **Kernel density estimates of multihomed apps in both stores in 5 countries in Feb 2014**



A linear regression of app rating by store against a set of controls app characteristics and the multi-homed dummy variable proves that the rating tends to be larger in Google Play than in Apple Store.

Table 3: The effect of multihoming on average rating

Variable	Apprating	
	iOS	Android
Age	-0.004	0.004
	(0.000)	(0.000)
Version	0.007	-5E-06
	(0.002)	(0.862)
Inapp	0.072	0.073
	(0.012)	(0.009)
Multihoming	-0.011	0.057
	(0.007)	(0.007)
N	14976	14996
R-squared	0.827	0.843

Robust standard errors in parentheses, all specifications include the intercept, time, category and developer fixed effects.

5.2.2 Combining the app and tablet datasets

This section provides insight into the dataset used in the estimations. As one of the objectives of the paper is to estimate the effect of cross-network externalities, the two datasets (tablet and mobile application) will need to be both available in the market. The side effect of this is a reduction in the original number of tablet observations. The time periods do not coincide (months versus quarters), but the countries do. Tablet data are quarterly and span a longer period (2010Q3-2014Q1), while the app data are monthly and are limited to the time sub-period 2013M9-2014M2. In an attempt to have enough overlapping periods for calculating the network effect variable we select three months that overlap with three quarters. These are 2013M9, 2013M11, and 2014M2 and match these to the quarters of tablet data 2013Q3, 2013Q4, and 2014Q1. Of course, the downside is that the tablet data are limited to three quarters only, narrowing down the number of observations from 12,337 to 4,849. Furthermore, since only data for applications distributed in App Store and Google Play are observed, the tablet observations need a further cut to be associated to models compatible with these two stores. Finally, we drop out 54 observations that have too tiny market shares, in order to avoid outliers. This leaves us with 3,750 tablet observations.

The market size is assumed to be half of a country's population. Given this assumption, the market share of each tablet model in a period can be calculated by taking the ratio between the unit sales and the market size.

The summary statistics of the variables that will be used in the estimation are documented in table 4.

Table 4: Descriptive statistics main variables for estimation

	Mean	Std.dev	Min	Max
Variables entering the tablet estimation				
market share (s)	2.3E-04	5.26E-04	2.53E-08	0.01
price (p)	261.1	170.12	37.74	1050
screen size	8.65	1.37	7	13.3
storage	20.95	20.02	0.51	250
log screen resolution	13.83	0.66	12.86	15.226
app rating	4.13	0.068	4.03	4.28

5.2.3 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 values of income (outliers) in the estimation, we restrict the income variable to its 5^{th} and 95^{th} 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 price and apprating. As our timeline lasts only for three quarters, we assume that the income of individuals is permanent.

6 Estimation

6.1 Estimation strategy

In this section, we discuss how to estimate simultaneously the demand and supply equations for the tablet market, previously presented in the econometric model section. A critical issue in demand estimation is how to address the price endogeneity caused by the correlation between demand unobservables, inclusive of unobserved quality, and supply unobservables, comprehensive of cost shifters. This correlation may lead to an upward bias of the price parameter estimated using OLS, due to a positive correlation between price and quality. As a consequence, the markup derived from the pricing equations will be overestimated, and cause a large number of negative marginal costs. The empirical IO literature has advanced instrumental variables to cope with this issue (see Hausman and Taylor (1981), Berry (1994), Berry et al. (1995)).

The joint estimation of demand and supply has the advantage of increasing the efficiency of estimates, but comes at the cost of a more complicated procedure and slower computation. Our interest is in estimating the non-linear parameters: α, ρ, Π and Σ and the cross-network effect parameter φ. We employ a nonlinear General Method of Moments method.

The vector of unobservable individual characteristics v is drawn from a multivariate standard normal distribution. To accelerate the computation, the empirical distribution of income is the only observed demographic included in D. For a given initial value of parameters in Π, Σ, and α, we compute the mean utility levels δ that equate the predicted market shares to the observed market shares, and then derive the marginal costs c by subtracting the estimated markups from the observed prices. This step allows us to recover the unobserved characteristics on both demand and cost side, ξ and ω, from

$$\begin{aligned} \xi &= \delta - \alpha p - x\beta \\ \omega &= mc - w\gamma. \end{aligned} \tag{22}$$

Indicating with θ_1 the vector of linear parameters (β, φ, and γ), and with θ_2 the vector of non-linear parameters (α, ρ, Π, and Σ), we have the set of all parameters $\theta = [\theta_1, \theta_2]$. We minimize the GMM objective function following the underlying assumptions put forward in Berry et al. (1995) (BLP), which are: unobserved demand and supply shifters are mean independent of demand and supply observable characteristics. The estimation procedure relies on BLP and is augmented by the use of demographics as in (Nevo 2001) and nested logit parameter as in Grigolon and Verboven (2014).

6.2 Instruments

We use instruments to deal with the price endogeneity. In the nested logit version of the demand estimation, the price endogeneity has a direct effect but also an indirect effect as prices enter the within segment market shares. Following previous related literature, we employ two sets of instruments: BLP-type and Hausman and Taylor (1981)-type. The BLP-type instruments are computed as the sum of each observed product characteristic (excluding the price) over the set of other tablets produced by the same manufacturer. To deal with the endogeneity of within product market shares, we refine the logic to products sold by other manufacturers in the same segment. These instruments assume that they are the result of long term decision and in the short term they are assumed to be uncorrelated time-varying unobserved product heterogeneity. Based on this assumption, the above instruments are exogenous and meet the independent moment conditions. In addition, we also construct as instruments the sum of the other products distributed in other segments as in Grigolon and Verboven (2014). The Hausman and Taylor (1981)-type instruments exploit 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. We also employ the regression tree approach 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 is:

z_2: Sum of screen resolution of other products by the same firm.

z_7: Average price of other products by the same firm.

z_8: Sum of storage of other products by the same firm.

z_{13}: The average price of other products of the other firms.

Rt_1: The instrument generated by using the regression tree- a dummy with the value 1 if Storage>12 and 0 otherwise.

Rt_2: The instrument generated by using the regression tree- a dummy with the value 1 if Storage>48 and Screen size>7.9; 0 otherwise.

Rt_3: The instrument generated by using the regression tree- a dummy with the value 1 if Storage≥24 ; 0 otherwise.

We test for instruments strength and report in table 8. The results show that all of instruments are valid and strong.

6.3 Empirical results

In this section, we present the results of the joint demand and supply equation estimations for tablets. We then discuss the counterfactual analysis aimed at studying the role of indirect network effects generated by users and developers. The tablet demand and supply estimation results are documented in the following table.

6.3.1 Tablet demand-supply

7 Main Results

Table 2 Demand-Supply Estimation Results

	Logit		Nested Logit		RC Logit		RC Nested Logit	
	Parameter	SE	Parameter	SE	Parameter	SE	Parameter	SE
Demand Side								
Mean valuation (β)								
Constant	-31.440**	3.361	-12.762**	2.107	-30.223**	2.949	-16.040**	0.037
Storage	0.004	0.005	0.001	0.001	-0.002	0.003	0.003**	0.001
Screen resolution	1.382**	0.189	0.227**	0.047	1.245**	0.112	0.395**	0.042
Screen size	0.077	0.042	0.045**	0.016	0.014	0.021	0.058**	0.015
Connection	0.336*	0.148	0.068	0.039	0.270**	0.080	0.174**	0.041
Price (α)	-0.013**	0.002	-0.002**	0.000	-0.016**	0.001	-0.006**	0.000
Apprating (φ)	1.302**	0.381	1.575**	0.480	1.322*	0.569	1.676**	0.122
Nesting Parameter								
ρ	NA		0.854**	0.001	NA		0.765**	0.018
Standard Deviation (σ)								
Price (σ_p)	NA		NA		0.015**	0.038	0.005*	0.002
Interaction with D								
Price*Income (π_p)	NA		NA		0.018**	0.005	0.009**	0.000
Supply Side								
Constant	-5.304	8.886	-7.529**	0.148	-3.252**	0.536	0.023	0.097
Storage	0.009**	0.000	0.027**	0.001	0.008**	0.001	0.003	0.003
Screen resolution	0.466**	0.032	0.628**	0.036	0.397**	0.038	0.241**	0.038
Screen size	0.274**	0.016	0.220	0.014	0.189	0.016	0.130**	0.036
Connection	0.561**	0.030	0.708**	0.035	0.405**	0.035	0.264	0.175
Model Statistics								
N	3753		3753		3753		3753	
R2D	0.383		0.987		0.484		0.705	
R2S	0.717		0.676		0.761		0.567	
N. mc ¡ 0	120		281		23		18	
Jstat	6.294		5.149		1.029		8.180	
Average price-cost margin	0.424		0.486		0.407		0.323	

Note: $p < 0.05$: *.$p < 0.01$: **. The time, country and firm fixed effects are included in the estimation but not reported. Instruments: [Logit: D=Rt_1, Rt_3, z_7], [Nested Logit: D=Rt_1, Rt_2, Rt_3, z_2, z_7, z_8], [RC Logit: D=Rt_1, Rt_2, Rt_3, z_7, z_{13}], [RC Nested Logit: D=Rt_1, Rt_2, Rt_3, z_2, z_7, z_8]

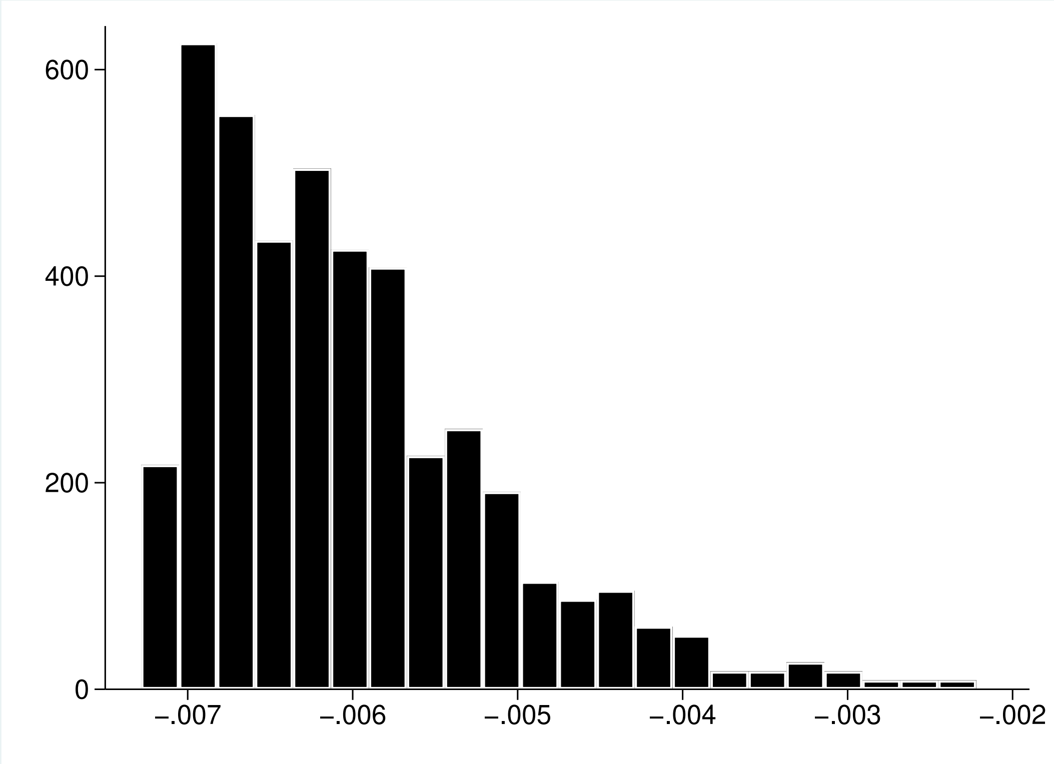
The first two pair of columns shows the results of a logit and nested logit joint demand and supply GMM estimates. The nested logit estimation captures a richer variation of demand as the pseudo R-squared is significantly larger than in logit model. The estimated within segment coefficient, ρ is 0.854 and statistically significant from zero and one; suggesting strong correlation in individual preferences toward tablets within the same nest. The price coefficient in the nested logit is smaller in terms of absolute value, which results in an increase of the number of negative marginal costs, relative to the logit model. The estimated coefficient on indirect network externality (app-rating) is positive and significant, confirming the existence of a positive feedback effect from the application market to the tablet market.

The results of the random coefficients logit and random coefficients nested logit model are presented in the last two pair of columns. Unsurprisingly, the random coefficients logit model produces similar results as the logit model and the estimation results of random coefficient nested logit model are similar to the nested logit model. The top panel documents the results of the mean marginal effects on the utilities (βs). The tablet characteristics like storage, screen resolution and screen size, as well as the quality of applications have all an expected positive significant effect on the tablet demand. In comparison with the Nested Logit model, the nesting parameter in RC Nested Logit remains highly statistically significant from zero and one, but the magnitude is smaller. The Nested Logit model overestimates the nesting parameter, as it does not account for nonlinearity in the data.

Our main interests are the price parameters. The mean coefficient on the price is negative and statistically significant. The effect of unobserved and observed demographics associated with prices are reported in the middle panel under the name ”Standard Deviation” and ”Interaction with D”. The significant estimates of the standard deviation and the interaction of price with income suggest that the heterogeneity of price is explained both by the observable and unobservable individual characteristics. People with higher income are less elastic to price changes. Figure (4) pictures the distribution of price sensitivity of UK individuals and we can see that there is sufficient heterogeneity for price sensitivity.

The bottom panel displays the results of the supply side estimation, where improvements in tablet characteristics like storage, screen resolution, and screen size are estimated to rise the marginal cost of producing and distributing tablets.

Figure 4: **Frequency distribution of price sensitivity**



7.0.1 Substitution patterns

In the left panel of table 5, we document the own-price elasticities and cross-price elasticities averaged over products and over segments. We separate the cross-price elasticities into cross-price elasticities of products in the same segment and of products in other segments. The average own-price elasticities of Apple's products 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 the competition in the tablet market. As expected competition between products within the segment is more intense than that between products in different segments. This is the result of a significant nesting parameter. This result tells us that products are differentiated across stores. Furthermore, business stealing is stronger within the iOS than within the Android; implying that iPads are more homogenous than Android-based tablets. This is not surprising since there are only several models of iPads but there are large varieties of tablets in Google Play store. Finally, an increase in price will lead to a larger loss of market share of Apple products than Android-based, tablets due to the stronger business stealing effect in the iOS nest.

Segment-level cross-price elasticities are reported in the last pair of columns. They show by how much the market share of a product in the nest increases, on average, if all products in that nest (same segment) or in other nests (different segments) increase by 1%. It is not surprising that these cross-price elasticities for the two stores are similar between different segments, as the market has not tipped towards either of the platforms.

Table 5: Product-level and segment-level price elasticities in the UK 2014Q1

Store	Product-level			Segment-level	
	Own-price elasticities	Cross-price elasticities		Cross-price elasticities	
		Same segment	Different segment	Same segment	Different segment
Logit					
Apple	-6.419	0.022	0.020	0.649	0.602
Android	-3.081	0.002	0.050	0.476	0.478
Nested logit					
Apple	-1.255	0.009	0.003	0.267	0.101
Android	-0.604	0.001	<0.001	0.154	0.080
RC logit					
Apple	-5.665	0.042	0.025	1.208	0.744
Android	-3.237	0.002	0.002	0.570	0.630
RC nested logit					
Apple	-8.094	0.203	0.007	5.900	0.224
Android	-4.534	0.013	0.001	3.325	0.167

7.0.2 Counterfactual analysis

In the tablet results section, we have estimated the network externality parameter and found that there is a positive indirect effect from mobile applications on to the tablet demand. To gain a better insight into their impact, we perform a counterfactual experiment in each of the five country-based tablet markets. We restrict the counterfactual to the final quarter of 2013 - the middle period. The experiment is to study what is the effects on the equilibrium demand, prices and profits of tablet manufacturers when the applications stores control for application quality by excluding 10% of lowest quality application from the store. The intuition here is by doing that, the application store can improve the average app quality, which has impacts on the tablet market. The changes of average app quality in each store are shown in table 9. From the tablet demand-supply estimation, we back out the marginal costs and then compute the new markup. We then calculate the new equilibrium prices and market shares by holding the marginal costs constant. The results of this counterfactual exercise are reported in the table (6).

The results confirm Prediction 1: the increase in the average application rating by excluding 10 % of lowest quality applications in one store generates positive effects on tablet demand and profits of that platform and negative effects on tablet demand and profits of manufacturers selling via the other platform. The absolute values of own-effects are much larger than the cross-effects. It is because competition between tablets across platforms is weak, as shown by the limited substitution pattern highlighted in table 5. An increase in the average app quality in one store leads to a larger gain from the outside option than from the other competitors. In addition, it is very interesting to compare the effects of increasing app quality on tablet demand and profits between Apple and Android producers. The results of K-Smirnov test confirm that the effects are always larger for Apple (except United Kingdom, where the effects are not statistically different). This may be one of the reasons why Apple was more urgent to raise its quality standard for applications published in its store in 2016, as it updated a stricter guidelines for approving these apps. This strategy lead to an increase of tablet market shares worldwide of Apple as shown in table 10. One year later, Google also imposes a stricter control for application quality by removing large number of low quality apps. By contrast, the effects

Table 6: Counterfactual 1-Removing 10% of lowest rating apps in each stores

		France	Germany	Italy	Spain	UK
		Own-effect				
Apple	Price changes (%)	0.136**(R)	0.229(R)	-0.004(F)	0.217**(R)	0.483**(R)
	Market share changes (%)	6.849**(R)	20.556**(R)	29.806**(R)	19.168**(R)	9.898**(R)
		(7.011)	(21.789)	(29.973)	(19.554)	(10.262)
	Profit changes (%)	7.170**(R)	20.785**(R)	29.654**(R)	19.626**(R)	10.942**(F)
		(7.312)	(21.354)	(29.874)	(19.932)	(11.317)
Android	Price changes (%)	-0.002**	0.028	0.017	-0.042**	-0.013**
	Market share changes (%)	5.752**	19.758**	21.745**	12.200**	10.487**
		(5.752)	(19.851)	(21.899)	(12.257)	(10.512)
	Profit changes (%)	5.731**	20.036**	21.532**	12.018**	10.687**
		(5.707)	(19.541)	(20.797)	(11.943)	(10.375)
		Cross-effect				
Apple	Price changes (%)	-0.063**(R)	-0.353(R)	-0.483**(F)	-0.305**(R)	-0.324**(R)
	Market share changes (%)	-0.691**(R)	-3.26**(R)	-1.495(F)	-1.030**(R)	-2.216**(R)
		(-0.622)	(-2.214)	(-1.489)	(-0.981)	(-2.052)
	Profit changes (%)	-0.832**(R)	-3.886** (R)	-2.564**(R)	-1.576**(R)	-2.805**(R)
		(-0.622)	(-3.487)	(-2.516)	(-1.487)	(-2.671)
Android	Price changes (%)	-0.017**	0.028	0.016	-0.095**	-0.081**
	Market share changes (%)	-0.383**	-1.467**	-1.261**	-0.832**	-1.699**
		(-0.339)	(-1.275)	(-1.019)	(-0.639)	(-1.523)
	Profit changes (%)	-0.452**	-1.071**	-1.517**	-1.162**	-2.072**
		(-0.454)	(-1.650)	(-2.183)	(-1.169)	(-2.117)
		Consumer welfare effect (%)				
Apple		2.082	6.461	8.134	5.251	3.984
Android		4.120	13.596	16.101	9.172	6.130

$p < 0.01$: **. We perform the K-Smirnov test for the Counterfactual 1 which the H0 is that the changes for iOS and Android tablets are equally distributed. R:Reject at 5%, F:Fail to reject at 5%. The average changes are in terms of own effects (the average effects of excluding 10% of lowest quality applications in the OS on the each tablet model installed that OS) and cross effects (the average effects of excluding 10% of lowest quality applications in the OS on each tablet model installed the other OS). The total effects on all tablet models in each OS are in parentheses of a rise in application quality on the equilibrium prices of tablets linked to the two stores are not significant[5].

8 Conclusions

This paper examines the role of indirect network externalities of applications on the tablet demand, focusing on the case of iOS versus Android. We combine tablet and app data across 5 European countries over the quarters 2013Q3-2014Q1. We estimate jointly demand and supply equations for tablets. This paper fills the gap in previous literature by incorporating quality of applications into the tablet demand function, as to capture indirect network effects. The estimation results provide evidence of network externalities in the market for tablets. An increase in application quality raises the demand for tablets.

The magnitudes of these effects differ between platforms, with the effect for iPads being larger than for Android-based tablets. To study the importance of these effects on the tablet market, we perform a sequence of counterfactual experiments. First, we separately let each application store remove 10 % of lowest quality applications, and compute the new equilibrium market shares, prices, and profits of tablet producers. The results show that the total profit of Apple increases more significantly than Android tablet manufacturers. Therefore, Apple has an incentive to improve its application quality, for instance, by imposing higher quality standards to the developers.

The paper has several limitations and can be extended in several ways. In the first place, because of the lack of data, we cannot use the variety (number) of applications as a source of indirect network effects, as done in previous literature. Nonetheless, since the number of applications available is enormous (about 2 million), it is legitimate to believe that consumers value applications quality more than variety. A valuable extension of this paper is modelling the indirect network externalities generated from users to developers and estimating jointly the multi-sides of the market to capture the full effect of cross-network externalities. Similarly, it is interesting to unravel the role of indirect network effects in the developer's decision of publishing paid or free applications. Another point deserves investigation is to study possible self-selection in app-rating by store by using information on multihomed apps. In this case, app in different stores may suggest different types of users, with different benchmark values of what is high and low quality, with implications on the reviews for the same product.

Finally, in this work app quality was treated as exogenous. It is worth relaxing this assumption and allow for quality to be a decision variable by developers and estimate a structural model that deals with endogenous quality in addition to endogenous prices.

[5] The aboslute value is smaller than 4%, which is equivalent to less than 5 EUR

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A Robustness Check-Different app rating measurements

The average rating of users of an app can represent how good the app is (the quality) and influence others decision of downloading that app since it affects the ranking in search result.

Figure 5: **The average rating of the top 100 and the bottom 100 apps in the 1000 most downloaded apps in the UK App Store Sep 2013 - Feb 2014**

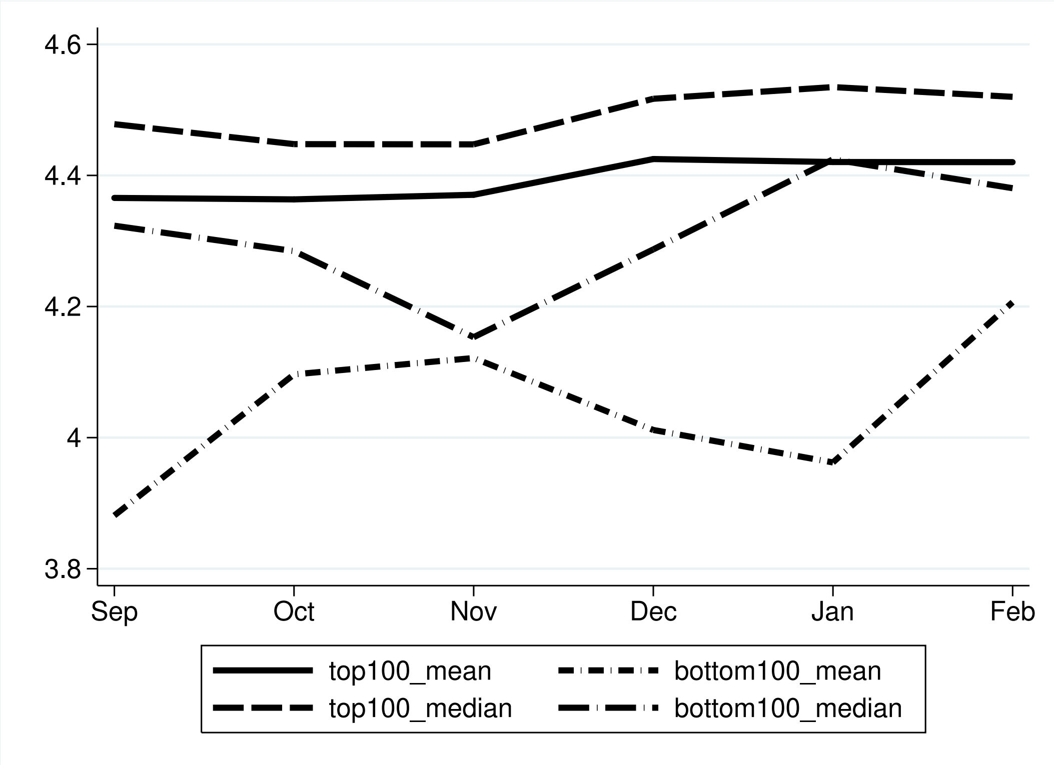

Figure 5 depicts that the weighted average rating of top ranked 100 apps is significantly higher than of apps ranked 901st-1000th in the UK App Store. This is because users tend to prefer apps with higher ratings as it is a signal for high quality apps. It leads to a larger amount of downloads for higher rating apps than the lower ones. We carry out the robustness check to test our results are consistent with different app rating measurements. To check whether the weighted average rating of top 1000 apps in both stores is an appropriate measurement, we replace this with several other measurements: the weighted average rating of top 100 apps in both stores, the weighted average rating of apps ranked 900-1000 (the lowest ranked apps in our data), and the non-weighted average rating of top 1000 apps. Then we estimate the RCNL demand and supply model with each of these. The results are reported in table 7. Our findings are that only the magnitudes of estimated coefficients in the model with the weighted average rating of the top 100 apps are similar to the original model. Whereas, the estimated coefficient on app rating in the model with the weighted average app rating of apps ranked 900-1000 (bottom apps) becomes negative and the estimated coefficients on app rating in the model with non-weighted average apprating are higher than in the original model. Intuitively, these results enunciate that the superstar apps (the top 100 apps) dominate the effect of network externalities generated from the app market to the tablet market. Thus, we should put more weight on these apps and the weighted average rating is a suitable measurement for the network externalities.

Table 7: Robustness check: different app quality measurements

	Unweighted average		Weighted average of top 100 apps		Weighted average of bottom 100 apps	
	Parameter	SE	Parameter	SE	Parameter	SE
Demand Side						
Mean valuation (β)						
Constant	-10.762	4.112	-18.165	0.002	-13.740	2.878
Storage	0.003	0.005	0.002	0.001	0.002	0.004
Screen resolution	0.410	0.211	0.544	0.008	0.396	0.059
Screen size	0.059	0.034	0.070	0.011	0.052	0.027
Connection	0.175	0.121	0.200	0.029	0.154	0.081
Price (α)	-0.006	0.002	-0.008	0.000	-0.006	0.001
Appating (φ	0.367	1.088	1.546	0.005	1.117	0.676
Standard deviation (σ)						
Price	0.006	0.067	0.006	0.001	0.006	0.059
Interaction with D						
Price*Income (π_p)	0.009	0.006	0.011	0.000	0.008	0.006
Nesting Parameter						
rho	0.752	0.141	0.629	0.003	0.754	0.102
Supply Side						
Constant	-0.1	72.677	-0.924	0.002	0.128	4.386
Storage	0.004	0.0323	0.005	0.001	0.005	0.729
Screen resolution	0.251	5.040	0.008	3.862	0.228	0.510
Screen size	0.124	0.288	0.149	0.011	0.128	1.416
Connection	0.287	0.575	0.326	0.024	0.292	1.038
Model Statistics						
N	3753		3753		3753	
R2D	0.692		0.626		0.695	
R2S	0.601		0.586		0.545	
Jstat	7.144		10.498		4.481	
N.mc¡0	14		24		20	

Note: Not reported the firm fixed effect.The estimations include time and firm fixed effects.

B Tables

Table 8: Instrument strength of demand side

Variables	Price		Ln(sjg)	
	Parameters	SE	Parameters	SE
Cons	-1356.983**	116.752	-3.488	3.120
Storage	1.673**	0.083	-0.019**	0.002
Screenres	80.922**	2.242	0.323**	0.060
Screensize	14.913**	1.247	-0.098**	0.033
Connectivity	65.099**	2.150	-0.518**	0.057
Apprating	9.011	26.543	-0.548	0.709
Rtiv1	-6.311*	3.081	0.067	0.082
Rtiv2	-9.478**	3.631	0.239*	0.097
Rtiv3	29.391**	3.207	-0.415**	0.086
Htiv7	0.565**	0.040	-0.005**	0.001
Htiv8	-0.009	0.010	-0.002**	0.000
Statistics				
N	3753		3753	
F-stat instr	57.600		17.700	
F p-val	0.000		0.000	

$p < 0.05$: *.$p < 0.01$: **

Table 9: Changes in average app rating when the stores exclude 10 % of low quality apps

Country	OS	Top 1000	Top 900	Change
France	iOS	4.181	4.231	0.051
	Android	4.265	4.296	0.031
Germany	iOS	4.255	4.333	0.078
	Android	4.241	4.316	0.075
Italy	iOS	4.217	4.305	0.088
	Android	4.192	4.301	0.109
Spain	iOS	4.211	4.336	0.125
	Android	4.244	4.361	0.117
UK	iOS	4.155	4.333	0.178
	Android	4.138	4.192	0.054

Table 10: 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)

Table 11: Weighted average marginal cost of producing a tablet for the two OS in 5 countries (EUR)

OS	France	Germany	Italy	Spain	United Kingdom
iOS	264.86	201.47	249.10	189.08	236.99
Android	110.87	81.60	97.19	71.12	94.21
Cost-ratio between two OS	2.39	2.47	2.56	2.65	2.51

Note: The cost-ratio between the average cost of producing a tablet for iOS and Android satisfies the condition stated in the prediction 2 of the theoretical part.