UNIVERSITÀ DEGLI STUDI DI PADOVA

dSEA

Thanh Doan

Office of Communications

Fabio Maria Manenti

University of Padova

Franco Mariuzzo

University of East Anglia

PLATFORM COMPETITION IN THE TABLET PC MARKET: THE EFFECT OF APPLICATION QUALITY AND INTEROPERABILITY

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Platform Competition in the Tablet PC Market: The Effect of Application Quality and Interoperability*

Thanh Doan† Fabio M. Manenti‡ Franco Mariuzzo§

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Abstract

Apple iOS is a closed platform; Google Android is open. In this paper, we combine tablet-level data with data on the quality of the top 1000 mobile applications from these platforms and estimate a structural demand model. We exploit variations over three periods and five European countries to find out whether quality of applications affects tablet demand. We then run two counterfactuals motivated by a stylized theory. In line with our model, the first counterfactual suggests that an improvement in app quality benefits tablet producers on that platform. The effect on demand is more pronounced for Android tablet devices. The second counterfactual hints that tablet producers adopting the store with lower quality applications (Google) gain the most from cross-platform app interoperability. We also show that interoperability stimulates the adoption of tablet PCs and generates consumer surplus on tablet demand. To reinforce the message from the theory, we use the predicted primitives of the structural demand estimation to calibrate our simple model and compare its results to those of the two counterfactuals. The results are similar.

Keywords: app quality, Android, interoperability, iOS, tablet demand.
JEL classifiers: L13, L15, L51, L63

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†Office of Communications. Email: thanh.doan@ofcom.org.uk.

‡Dipartimento di Scienze Economiche ed Aziendali "M. Fanno", Università di Padova (Italy). Email: fabio.manenti@unipd.it

§School of Economics and Centre for Competition Policy, University of East Anglia (UK). Email: F.Mariuzzo@uea.ac.uk

1 Introduction

The introduction of digital distribution platforms for mobile operating systems, developed by Apple and Google in 2008, marked a milestone for the rapid growth of the mobile app market. Since their launch, the number of mobile applications (apps) using Apple and Google operating systems has grown exponentially. By the end of the first quarter of 2022, about 3.3 million apps were available in Google Play and nearly 2.11 million in Apple App Store (source, Statista.com), the two largest app stores by far. This astonishing app growth brought to the market a new generation of hardware – the tablet PC. Apple delivered its first generation of iPad devices in early 2010, followed closely by several other manufacturers.

The wide availability of applications is undoubtedly one of the explanations for the success of tablets; nonetheless, an empirical evaluation of the exact role of apps and the relevant policy in the tablet market is still missing. Filling this gap is essential, especially considering the characteristics of the tablet market tightly dominated by two alternative platforms: the iOS-based and the Android-based platforms. Of interest in our paper, these platforms adopt two different business models and represent most of the tablet market. The iOS-based platform, vertically integrated by Apple, controls the production of devices, and manages the Apple app store. The Android-based platform is open, with competitive and independent manufacturers producing the devices and Google managing the app store (Google Play).

We study how the quality of the apps (measured by user reviews) distributed in each dedicated app store affects the outcome of the tablet market. In particular, we show how, due to the different vertical structures of the two platforms, the quality of the apps in the two online stores has a differential impact on tablet producers. Following the previous literature (Binken and Stremersch, 2009; Kim et al., 2014), we employ the average user rating to measure 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 the 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 and Stremersch, 2009).

We first introduce a stylized theoretical analysis aimed at representing the impact of app quality in the strategic interactions among two incompatible platforms. Platform competition is modeled with a classic Hotelling framework, where stores are both horizontally and vertically differentiated—vertical differentiation accrues both from tablet characteristics and, key for our scope, from the quality of the apps available in the stores of the two platforms. We model a two-stage game, where consumers first select the platform (operating system) and then, according to their choice, are given their most preferred tablet model. Consumer preferences for tablets are affected by the quality of the applications available for that platform. Our theory applies to a specific functional form and allows us to derive a series of testable predictions. We then construct an econometric model relying on the discrete choice literature for product differentiation to test their validity. In the empirical analysis, we employ a different functional form, hence it nicely complements our theory. More specifically, in line with our two-stage theoretical framework, we choose the random coefficients nested logit model proposed by Grigolon and Verboven (2014), where the nest captures the heterogeneity in operating systems. We account for observable and unobservable price sensitivity, as in Nevo (2001). This allows us to estimate richer own-price and cross-price elasticities of demand for both Apple and Android tablets and relate those to profitability and welfare.

The sample used in our estimation consists of three waves of quarterly product-level data for tablets and apps distributed in five European countries (Germany, France, Italy, Spain, and the UK) over 2013Q3-2014Q1. We recover consumer demographics from a Eurostat dataset. We jointly estimate demand and pricing equations to investigate the role of an app's quality in the tablet market.

In the last part of the paper, we simulate two counterfactual analyses to study two alternative policies. First, we evaluate how tablet manufacturers' equilibrium prices, market shares, and profits would change if platforms opt to increase the quality of the available applications. Then, we study what would happen if the quality of the apps were the same in the two stores. We conduct these two counterfactuals on practical grounds. Guaranteeing a certain average quality of their apps has always been one of the objectives of the platforms. Since the beginning, Apple has adopted a strict quality control system, and only developers meeting certain requirements can publish apps on the Apple App Store (see Comino et al., 2019). This policy has played a central role in Apple's strategy toward app quality. On top of this, in 2016, Apple removed thousands of outdated and non-compliant applications from its online store. Google, which, unlike Apple, does not have a similar quality check, periodically removes low-quality, malware, and abandoned apps (see Wang et al., 2018).[1] Our first counterfactual embraces these platform-quality strategies by discussing the impact of increasing the weighted average quality of app stores on the tablet market.

We obtain an increase in app quality by removing the lowest quality apps from the app stores,

[1]In 2019, Google announced that it would have started reviewing more carefully the apps by developers without any track records. See details at: `https://tinyurl.com/mr3uwjxc`.

one store at a time until the weighted average app quality increase reaches a certain level and then recompute the new equilibrium in the tablet market. Our findings confirm that improving app quality impacts the tablet demand. For example, in the UK, Apple's market shares and profits are estimated to increase by 9.44 (base points) and €2.52 million (about 2%), respectively. Android tablet producers would improve their market shares and profits by 17.81 (base points) and €1.39 million (again about 2%), respectively. Our estimations reveal that, due to the different vertical structures of the two platforms, Android tablets' demand expansion tends to be larger than Apple.

The second counterfactual is policy driven. Apple and Android devices are incompatible, and the two ecosystems are not interoperable. To reach users of both devices, app developers must produce two versions of their apps, a practice known as multihoming. Multihoming, however, is far from being effective, and it still represents a relatively marginal phenomenon (see, Hyrynsalmi et al., 2016). The absence of interoperability confers platforms in a bottleneck position for developers and adopters. This position is a source of concern for authorities and policymakers (Morton et al., 2019; Furman et al., 2019; Crémer et al., 2019; Kades and Morton, 2021; OECD, 2021). When multihoming is ineffective, an alternative way to address such concerns is by mandating interoperability (Bourreau et al., 2022). With interoperable platforms, apps could freely be installed on all devices, regardless of which platform they originated from. Consequently, app quality differences between platforms are leveled. With this counterfactual, we aim to study what would have been the effects on the tablet market had the two stores been subject to interoperability and the quality of the two app online stores been the same.

We find that imposing the same app quality through interoperability would favor the Android tablet producers. For example, to remain in the UK again, the profits of Android tablet manufacturers grow by more than €3.5 million with interoperability; those of Apple are reduced by around €1.1 million. Indeed, our data reveals that on Google Play, the average app quality is lower than in the Apple App Store; hence a policy that mandates interoperability would increase the average Android app quality, pushing the demand in favor of Android tablets. Interestingly, though, we find that forcing interoperability between platforms stimulates overall tablet adoption and enhances consumer welfare in the tablet market (in the UK, the estimated increase in consumer surplus due to interoperability amounts to about €6 million).

To reinforce our analysis, as a final exercise, we compare the findings of the two counterfactual simulations from the discrete choice model literature with those obtained from calibrating our linear demand model. The conclusions reached by the calibrations are qualitatively in line with those of the simulations.

The outline of this paper is the following. In the next section, we briefly review the relevant literature. We introduce a theoretical model in Section 3 that sets up the predictions to be tested empirically. The fourth section develops the econometric model, while Section 5 briefly describes the data and provides summary statistics. Section 6 illustrates the estimation strategy and discusses the main results. Section 7 concludes.

2 Relevant literature

Our paper first aims to contribute to the literature by analyzing the effect of complementary products on the demand for high-tech goods. This literature has mainly focused on indirect network effects generated by product variety. However, it is quite natural to believe that network effects have a sounder effect in the presence of higher quality complementary products. In this respect, a branch of the literature has accounted for quality as the channel of indirect network effects. Viecens (2006) contributes to this literature with a theoretical model of competition between two-sided platforms, where agent preferences on the two sides of the market are, amongst other things, affected by a measure of quality that depends on the type of sellers that the platform hosts.

The relevance of the quality of complementary products is also acknowledged in Nair et al. (2004). They estimate the effect of the availability of software on the demand for personal digital assistants (PDAs). They observe that the consumer benefit from adopting a given PDA should also be related to the quality of the compatible software. Nonetheless, due to data availability, they estimate demand for PDAs only using an index of quality for software availability, captured by the number of software that has at least one download per day. Along similar lines is the paper by Corts and Lederman (2009), where the authors estimate indirect network effects on the demand for game consoles. In their model, the source of externalities is software variety and quality. For a given console, the number of "hits", i.e., games reaching certain sales thresholds, is seen as a proxy for software quality. In this body of literature, the paper probably closest to ours is Kim et al. (2014). The authors explicitly argue that if one does not account for quality in the estimation, there is a real risk of significantly underestimating the impact of the externalities. In their theoretical framework, built on Church and Gandal (1993), they incorporate the quality dimension into the network externalities by allowing consumers to receive different marginal utilities from complementary products of diverse quality. The theoretical framework is then applied to the game console market. In a way, similar to ours, they employ the customers' review score as a metric for game quality. We complement their work by exploiting the competitive asymmetries between two important platforms and studying two relevant regulatory quality changes.

Our paper also contributes to the literature on platforms as regulators of the activity of participating parties. This policy makes the platform more attractive to users, pushing more consumers to buy a tablet associated with that platform. This strategy shares similarities with the minimum quality standard strategy, which has been applied widely by various platforms through quality certifications.[2] The literature has studied the increase of app quality through the disposal of low-quality apps. Teh (2022) highlights two effects quality control policies have on a seller/developer's competition. The first effect is that removing low-quality apps from the store lowers users' search costs ("search facilitating effect"). This change intensifies competition among developers and stimulates higher-quality apps to restore profit margins.[3] The second effect is that stricter quality control can impact developers' competition in opposite directions via the so-called "entry restriction effect". Platform exclusion of low-quality apps reduces the number of apps in the store, which softens the competition among developers and discourages developers from producing higher-quality apps. The overall impacts of a quality control policy on competition among developers, and consequently on the average application quality, will depend on which effect dominates. Belleflamme and Peitz (2019) point out that in the case of asymmetric information (users are less informed than developers about the quality of mobile applications), removing low-quality sellers/developers may increase the value of platforms to buyers/users as it improves the expected quality. These works offer practical insights into the quality control strategy and the effects on the seller/developer side, albeit none of them provides any explicit evidence of the impacts of such a scheme on the user side. Our first counterfactual analysis complements this literature by empirically studying the effects of increasing app quality (through low-quality apps removal) on the user's demand for tablets.

Our second counterfactual contributes to the literature on technology compatibility and interoperability (see, Katz and Shapiro, 1985; Farrell and Saloner, 1985; Matutes and Regibeau, 1988; Economides, 1989; Katz and Shapiro, 1994, among others). When technologies are perfectly interoperable, users of a given technology can interact with all the other users independently of the technology they patronize. Typically, firms may benefit from interoperability as it allows users to enjoy a higher network benefit that firms can try to seize via appropriate commercial strategies. At the same time, though, fully interoperable platforms tend to be less differentiated to the detriment of the producers that might compete more aggressively on prices. In our second counterfactual, we

[2] For instance, eBay certifies sellers who meet a minimum quality standard by the badge "Top Rated Seller". Other examples are Airbnb's "Super host" and Amazon's "Best Seller".

[3] In agreement with this argument, Hui et al. (2018) find that a stricter quality certification policy by eBay would stimulate entry and intensify competition in the market. This process increases the average quality of sellers as it becomes harder to get the "Top Rated Seller" badge.

discuss the impact of mandating interoperability between Android and iOS platforms. This restriction would mean that all the apps developed for one platform could also run on the other, thus eliminating the difference in the quality of the apps in the two stores. Therefore, in our context, a striking effect of interoperability is the reduction of the vertical differentiation between Android and Apple tablets. Despite narrowing platform differentiation, interoperability predominantly benefits Android-based tablet producers. We also find that it has desirable effects from a social welfare perspective.

3 A stylized model of platform competition

We devote this section to developing a stylized theoretical framework of competition between tablet producers. The aims of this model are twofold. On the one hand, it allows us to obtain conjectures to be tested empirically. On the other hand, it gives us a general understanding of the functioning of the tablet market, allowing us to interpret the results of our estimates.

The tablet market is characterized by two alternative platforms, each operating with two incompatible operating systems. Apple has developed and controls iOS; Google has created and maintains Android, an open-source operating system. Apple produces and sells an iOS-based device, iPad, and competes with n tablet manufacturers with installed Android OS. Apple and Google run their online app stores, Apple Store and Google Play, respectively, where users can download software (mobile applications) for their devices.

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

1. In the first stage, consumers decide which operating system (platform) to adopt (inter-platform competition) and, in the case they prefer iOS, they buy an iPad.

2. In the second stage, those who have chosen Android will decide which tablet to purchase among the n alternatives (intra-platform competition).

For notational convenience, in the remaining, we use the subscript 1 for the iOS/Apple Store platform and the subscript 2 for the Android/Google Play platform. The two platforms differ along several dimensions. To mention some, Apple's and Android-based devices have different hardware, different reputation/brand recognition, and they require two incompatible operating systems. To a large extent, the two dedicated app stores contain alternative applications. For these reasons, it is natural to think that the two platforms are horizontally and vertically differentiated. Formally, we represent inter-platform competition using a simple Hotelling line with qualitatively different products. Concerning the quality of a tablet, we model it as a combination of the quality of its two main components, which are hardware and software (applications). Specifically, we indicate with z_{hj} the quality of the hardware relying on platform j, and with $\bar{z}_{sj}$ the average expected quality of the applications available in the store of the platform j. We assume that the overall quality of platform j's tablets is given by the product between z_{hj} and $\bar{z}_{sj}$, as there is no quality if either is missing. In our empirical analysis, app quality is measured using the weighted average of app rating, where each app quality is weighted by its downloads. This measure allows us to account for the well-known fact in system products according to which the more popular software contributes more to the determination of hardware demand (Binken and Stremersch, 2009).

We solve the sequential model by backward induction. In the second stage, competition occurs between the Android producers. As discussed above, platform 2's tablet producers compete for users that have chosen to purchase a device from that platform in stage one. Let us indicate with q_{h2} the mass of these users. 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's devices are located equidistantly on a unit-length circle with users uniformly distributed on it. We further simplify our analysis by assuming, in the second stage, that platform 2's producers compete by taking the mass of users q_{h2} as given. As in a standard Salop circular model, the consumer located at point x takes his/her purchasing decision by solving $\max_{\mu=i,i+1}\{z_{h2}\bar{z}_{s2} - t|d_\mu - x| - p_\mu\}$, where firms $\mu = i, i+1$ are the firms between which the consumer is located, and where firm μ's location is $d_\mu = \mu/n$. The parameter t indicates the unit transportation cost and measures the degree of horizontal product differentiation between Android producers. The symmetric equilibrium price turns out to be:

$$p^*_{h2} = c_2 + \frac{t}{n}, \tag{1}$$

where c_2 is the marginal cost of producing a platform 2's tablet.

In stage one, consumers observe hardware qualities, z_{hj}, and the average qualities of the apps available in the two stores, $\bar{z}_{sj}$, $j = 1, 2$. They also observe the price of an iPad, p_{h1}, and can 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 at l_1 and platform 2 at l_2, with $1 > l_2 > l_1 > 0$. Consumers between l_1 and l_2 compare their net utilities for buying from the two firms and choose. The net utilities of the consumer located in $x \in (l_1, l_2)$ are as follows:

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

where x is uniformly distributed in $[0, 1]$, and $v \geq 0$ indicates the baseline utility. The parameter k represents the unit transportation cost and indicates the degree of horizontal inter-platform differentiation; the mass of customers is normalized to be one. Using this setting, in the appendix, we discuss how the price that platform 1 charges in equilibrium is:

$$p^*_{h1} = \frac{2v + 3c_1 + c_2}{6} + \frac{t + n\left(3\bar{z}_{s1}z_{h1} - \bar{z}_{s2}z_{h2}\right) + kn\left(l_2 - l_1\right)}{6n}, \tag{2}$$

and the overall quantities of the two platforms are:

$$\begin{aligned} q^*_{h1} &= \frac{l_2 - l_1}{4} + \frac{1}{4}\frac{t}{kn} + \frac{2v + 3\bar{z}_{s1}z_{h1} - \bar{z}_{s2}z_{h2} - 3c_1 + c_2}{4k}, \\ q^*_{h2} &= \frac{7(l_2 - l_1)}{12} - \frac{17}{12}\frac{t}{kn} + \frac{14v - 3\bar{z}_{s1}z_{h1} + 17\bar{z}_{s2}z_{h2} + 3c_1 - 17c_2}{12k}, \end{aligned} \tag{3}$$

where c_1 is the marginal cost of producing a platform 1 tablet.

3.1 Testable conjectures

From these expressions, we derive a series of testable conjectures on the characterization of the equilibrium. The first conjecture regards the effect of a change in the average quality of the apps available on platform j. For example, the variation the platform can achieve by removing low quality apps from its store. From q^*_{h1} and q^*_{h2}, it follows immediately that an increase in app quality on the dedicated store of platform j stimulates the demand for tablets j (own-quality effect) and reduces the rival platform demand (cross-quality effect).[4] Formally:

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

and

$$\frac{dq^*_{h1}}{d\bar{z}_{s2}} = -\frac{1}{4}\frac{z_{h2}}{k} < 0, \qquad \frac{dq^*_{h2}}{d\bar{z}_{s1}} = -\frac{1}{4}\frac{z_{h1}}{k} < 0. \tag{5}$$

Note that, in absolute values, own-quality effects exceed the cross-quality effects. Expressions (4) reveal another interesting observation. If the platform hardware qualities are not too different,

[4] For notational convenience, the same subscript is used for the platform and a tablet.

formally if $z_{h1}/z_{h2} < 17/9$,[5] our model predicts that the impact on demand for an increase in the quality of applications is higher for platform 2's tablets than for platform 1.

These arguments suggest that manufacturers from both platform benefit from an increase in the quality of the apps available in the platform's store. One may wonder which of the two platforms benefits most from an app quality increase and which app quality increase generates the most benefits for consumers. Unfortunately, the model does not allow us to obtain unambiguous predictions on these matters.

Wrapping up, if we reinterpret the weighted average user rating on platform j as the average quality of apps on that platform, then the following testable conjectures follow:

Testable conjecture 1 (Effects of app quality) *Equilibrium quantities and manufacturer profits are affected by the quality of the apps distributed in the dedicated store. First, the number of platform tablets increases with the weighted average users' app rating on the same platform and decreases with the weighted average users' app rating on the other platform – in absolute values, own-effects are larger than cross-effects. Second, the impact of application quality on tablet demand tends to be larger on platform 2. Third, the platform that enjoys the most —in terms of manufacturers' overall profits —of an increase in app quality is a-priori ambiguous, as the increase in quality that generates greater benefits for consumers is ambiguous.*

Although the theoretical model does not delineate the effects on profits and consumer welfare of an improvement in app quality in the two stores, it is helpful to reinforce our empirical results through a calibration exercise. Using the estimated demand primitives, we can check whether the theoretical and the empirical models are aligned.

One of the most debated issues in network industries is the interoperability or standardization of products/platforms. Interoperability is the feature of a product to work with other products or systems without restrictions. In the tablet market, interoperability means that all the apps developed for one platform can also run on the tablets produced for the other platform and vice-versa.[6] Hence, relevant for our scopes, interoperability affects the average degree of app quality available to tablet users. In particular, tablet users of the platform characterized by apps of lower quality benefit from interoperability, as they enjoy the higher quality of the apps of the other store.

[5] We will use the predicted values of the average hardware quality in the two stores to show that indeed this condition holds.

[6] Equivalent to interoperability is a situation where all developers multihome, i.e., they develop apps in both iOS and Android format. Developers benefit from multihoming as it allows them to reach a higher user number. Usually, they develop their app for one platform and, eventually, translate it ("port" in the app jargon) into the alternative operating system. Unfortunately, porting an app can be very costly for developers. This drives the tablet platforms away from achieving an interoperable-like equilibrium. Recently, new tools have been developed that considerably reduce the cost of developing multihoming apps. See discussion at `tinyurl.com/3sw2a83c` (accessed on 12 July 2022).

At the same time, we assume that users of the high-quality platform are unaffected by the policy as they continue to enjoy the higher quality of the apps published in their store. Therefore, we model interoperability by imposing that the average quality of the apps *i*) is the same in both stores and *ii*) is equal to the maximum average quality between the two stores.

In what follows, we study the impact of interoperability under the empirically relevant assumption that, before the policy, the average quality of the apps in platform 1 is higher than in platform 2: $\bar{z}_{s1} > \bar{z}_{s2}$.[7] Hence, $\bar{z}_{s1}$ is the average quality of apps when the policy is implemented.

Let us start by considering the impact on prices. Imposing condition $\bar{z}_{s2} = \bar{z}_{s1}$ in expression (2), we can obtain the equilibrium price of platform 1's tablets with interoperable apps. By subtracting p^*_{h1} from this price, it is easy to see that the policy impacts negatively on platform 1's price.[8] This result is not unexpected, provided the policy implies an improvement in the average quality of platform 2's apps, making the tablets produced for this platform more competitive. Finally, note that as p^*_{h2} is determined entirely by intra-platform competition among Android-based tablet manufacturers, the policy does not impact the price of platform 2's tablets.

We can use expressions (3) to evaluate the impact on quantities. Replacing $\bar{z}_{s2}$ with $\bar{z}_{s1}$ we will obtain the equilibrium quantities of when the policy is introduced. From a comparison of the output levels before and after the introduction of interoperability, it is easy to check that, as expected, the policy positively affects the demand for platform 2's tablets while it reduces platform 1's demand for tablets. Interestingly, it has a positive effect on the overall quantity.[9]

Testable conjecture 2 (Interoperability) *Interoperability: i) this decreases the equilibrium price and quantity of platform 1's tablets, ii) it does not affect the equilibrium price of platform 2's tablets, and it increases the number of platform 2's tablets, iii) it also stimulates the overall demand for tablets.*

Our conjecture allows us to make several interesting observations on the private and social desirability of interoperability. Conjecture 2*iii*) reveals that the overall demand for tablets increases when platforms are interoperable. In other words, when, with incompatible platforms, the average

[7] As we will see, this assumption is supported by the data.

[8] Formally, with interoperability, the price of platform 1 tablets is

$$\frac{3c_1 + c_2}{6} + \frac{2vn + t + n\left(3z_{h1} - z_{h2}\right)\bar{z}_{s1} + kn\left(l_2 - l_1\right)}{6n}.$$

Subtracting from this expression, the equilibrium price of platform 1's tablets when the platforms are not interoperable, it is easy to see that this difference is $z_{h2}(\bar{z}_{s2} - \bar{z}_{s1})/6 < 0$, which is negative.

[9] Formally, indicating with q^*_{hjI} the number of platform i's tablets with interoperability, it turns out that for $z_{h1} > z_{h2}$: $q^*_{h1I} - q^*_{h1} = z_{h2}\left(\bar{z}_{s2} - \bar{z}_{s1}\right)/(4k) < 0$, and $q^*_{h2I} - q^*_{h2} = 17z_{h2}\left(\bar{z}_{s1} - \bar{z}_{s2}\right)/(12k) > 0$. Using these expressions, one can notice that the overall impact of the policy is $(q^*_{h1I} - q^*_{h1}) + (q^*_{h2I} - q^*_{h2}) = 7\left(\bar{z}_{s1} - \bar{z}_{s2}\right)/(6k)$, which is clearly positive.

quality of the apps on platform 1 is higher than on platform 2, interoperability has the remarkable effect of stimulating the adoption of tablet technologies. In terms of impacts on manufacturers' profits, conjectures *i*) and *ii*) imply that the overall profits of tablet manufacturers on platform 2 grow while those on platform 1 decrease. Finally, interoperability has a positive effect on consumers; as with interoperability, p^*_{h1} is reduced, while p^*_{h2} remains unchanged, and given the positive impact on overall tablet adoption, consumers' welfare increases when interoperability is introduced.

4 Econometric model

We devote this section to providing intuition on our empirical model. Despite using a different functional form, our empirical analysis complements the theory and wishes to verify whether this too confirms our theoretical predictions.

There are T country-period markets, each having I_t potential consumers. The consumer i in market t can choose between buying one of the J_t new tablets sold in that market, or a composite outside good, $j = 0$. The indirect utility associated with buying tablet j in the market t is expressed as:

$$u_{ijt} = \underbrace{\beta_0 + \underbrace{\beta_s x^s_{jt}}_{E(\alpha_i)\bar{z}_{sjt}} + \underbrace{x^h_{jt}\beta_h}_{E(\alpha_i)z_{hjt}}}_{x_{jt}\beta} -\alpha_i p_{jt} + \xi_{jt} + \zeta_{igt} + (1-\rho)\epsilon_{ijt}, \tag{6}$$

where x_{jt} is a vector of observed tablet characteristics, among which there is a key variable for this work, which is *the expected (weighted) average quality* of mobile applications.[10] Note that we model hardware and software quality as additive since only products with a minimum level of hardware and software quality will be marketed. In this respect, there is less of a need to interact with these terms, as we do in the theoretical model. The list of tablet characteristics includes storage capacity, screen resolution, screen size, and the connection to the internet (if there is one). Some tablet characteristics are market-invariant; others, like the price, p, tend to vary both over product and market (jt) or over group and market (gt) in case of expected (weighted) average mobile application quality. Groups are created based on the operating system; g=0 is the outside options, g=1 is iOS, g=2 is Android. As often is the case, not all product characteristics are observed by the

[10] Note that in equation (6) we specify $\underbrace{\beta_s x^s_{jt}}_{E(\alpha_i)\bar{z}_{sjt}}$, and similarly for the hardware characteristics, to account for the fact that in the theoretical model the price has coefficient one, and therefore $\bar{z}_s$ and z_h are expressed as a willingness to pay in monetary value.

researcher. Those unobserved characteristics are captured by the variable ξ_{jt}. The coefficients βs are constant, while the coefficient on prices, α_i,[11] is random —this is to account for heterogeneous price sensitivity.[12] The term ζ_{igt}, common to all the products that use the same operating system in the market, is a random variable with a 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 an identically and independently distributed extreme value, and so is the composite term $\zeta_{igt} + (1-\rho)\epsilon_{ijt}$ (see Cardell, 1997). As in Nevo (2001), the random coefficient is given by the sum of its mean and dispersion around the mean. The dispersion depends on a market-specific income distribution and an unobservable variable of individual heterogeneity drawn from a standard normal.

The parameters of interest of the above utility function can be estimated using random coefficient methodologies though due to the presence of groups, we employ the random coefficients nested logit version described in Grigolon and Verboven (2014).

Given the parametric assumption of the error term, the probability that the consumer i in market t prefers product j is,

$$\phi_{ijt}(x_t, p_t, \xi_t, y_i, v_i, \theta) = \frac{exp\left((x_{jt}\beta - \alpha_i p_{jt} + \xi_{jt})\,/\,(1-\rho)\right)}{exp\left(I_{ig}/\,(1-\rho)\right)} \frac{exp\left(I_{ig}\right)}{exp\left(I_i\right)}, \tag{7}$$

where θ denoted the set of all parameters. McFadden's (1978) inclusive values I_{igt} and I_{it} are the result of the log sums:

$$\begin{aligned} I_{igt} &= (1-\rho)\ln \sum_{l=1}^{J_{gt}} exp\left((x_{lt}\beta - \alpha_i p_{lt} + \xi_{lt})\,/\,(1-\rho)\right), \\ I_{it} &= \ln\left(1 + \sum_{g=1}^{G_t} exp\left(I_{igt}\right)\right). \end{aligned} \tag{8}$$

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

The market share of the product j in market t, s_{jt}, can be obtained by integrating equation (7) with respect to the income distribution and the distribution of individual unobserved heterogeneity,

[11] In our empirical section, $\alpha_i = \alpha + \sigma\nu_i + \pi y_i$, where ν_i is a draw from a standard normal distribution and y_i is a draw from the observed income distribution (it varies by country but here we maintain the notation light and omit that subscript).

[12] Only the price variable has a random coefficient. We experimented by adding a random coefficient to app quality, but the estimated standard deviation was always close to zero and thus removed that coefficient to save computational time. We opted for removing that random coefficient to speed up the estimation procedure and avoid quasi-multicollinearity. Behind this choice, there was also a lack of theoretical justification for having a different marginal effect on quality between stores.

which can be done via Monte Carlo simulations (see Nevo, 2001; Berry et al., 1995). This integration gives a set of J_t market share (demand) functions for each product/market, i.e., the system of equations from the demand side that we estimate.

Our empirical methodology also accounts for a system of J_t pricing equations for each market, which results from multiproduct firms choosing the optimal prices of their differentiated tablets. This is a classic Bertrand differentiated profit maximization with constant marginal costs.

4.1 Instruments

The presence of unobserved product heterogeneity leads to the endogeneity of the price and the average application quality entering the demand, which we identify using the instruments described below. This correlation may lead to an upward bias of the price parameter estimated using OLS due to a positive correlation between price and quality. Consequently, the markup derived from the pricing equations will be overestimated and lead to several negative marginal costs. The empirical IO literature has advanced instruments able to cope with this endogeneity (see Hausman and Taylor, 1981; Berry, 1994; Berry et al., 1995; Berry and Haile, 2014). Besides the price endogeneity, the effect of application quality also raises endogeneity concerns. This is because the unobserved tablet quality can drive tablet sales and, consequently, tablet installed base, which impacts the decision of developers to produce higher-quality applications. Following the previous literature (see Nair et al., 2004; Corts and Lederman, 2009), we employ the average tablet characteristics of products within the same segment as instruments for application quality.

In the nested logit version of the demand estimation, the price endogeneity has both a direct effect on the demand, as well as an indirect effect, as prices enter the within segment market share function–making this endogenous as well. 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 and app quality) from the set of other tablets produced by the same manufacturer. These instruments assume that they are the result of long-term decisions. In the short term, they are postulated to be uncorrelated time-varying unobserved product heterogeneity. Based on this assumption, the above instruments are exogenous and meet the independent moment conditions. The Hausman and Taylor's 1981-type instruments exploit the assumption that multi-product firms have a common cost structure and, once we have control over the firm's fixed effect, the average price of other products by the same firm can be used as an instrument.

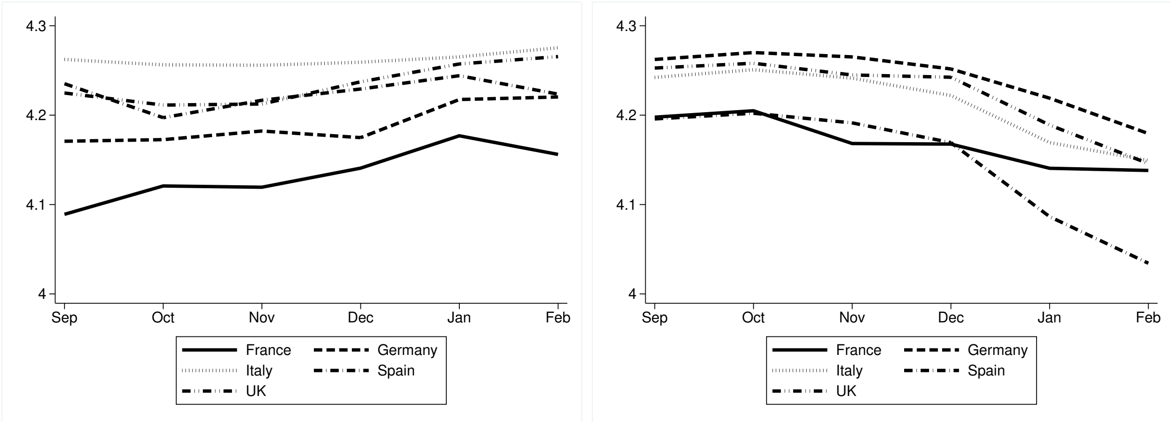
We also employ the regression tree approach (Leo Breiman and Olshen, 1984) to capture any non-linear effects of tablet characteristics on prices and within market shares. This process enables us to generate a set of instruments for both the prices and within market shares. The list of instruments used, in addition to the exogenous product characteristics $\tilde{x}$,[13] 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 the screen resolution (log) of other products by the same firm), h_4 (sum of storage of other products by the same firm), h_5 (average screen resolution of products within the same segment), h_6 (average screen size of products within the same segment), h_7 (average storage of products within the same segment) and three instruments constructed using a regression tree approach: h_8 (a dummy taking value one if Storage>12 and zero otherwise), h_9 (a dummy taking value one if Storage>48 and Screen size>7.9 and zero otherwise), and h_{10} (a dummy taking value one if Storage≥24 and zero otherwise). The first stage of the regressions and selected instruments are presented in Table (A.1) in the annex. Combinations of the above instruments are used for various types of regressions.

5 Data

In our empirical work, we combine three datasets. The first dataset is on the new tablet market, maintained by IDC CEMA. The dataset contains product-level information on tablet characteristics such as model name, model ID, producer name, operating system (OS), CPU type, connectivity, screen size, screen resolution, storage, prices, and unit sales for five European countries: France, Germany, Italy, Spain, and the UK. The original dataset is a panel of 15 quarters, starting from 2010Q3 and ending with 2014Q1, but for this analysis, which requires matching with other data, we only use the quarters 2013Q3, 2013Q4, and 2014Q1.

The second dataset is given by consumer demographics obtained from Eurostat, European Union Statistics on Income and Living Conditions (EU-SILC) survey 2013. The data from this survey consists of cross-section and longitudinal multidimensional micro data on labor, education, health, income, poverty, social exclusion, and living conditions in all EU countries. While the information on labor, education, and health are collected at the individual level, social exclusion and living conditions information is obtained at the household level. Our variable of interest, income, is decomposed into detailed components such as gross cash or near-cash employee income, gross non-cash employee income, etc., and is collected at personal levels. We sum all the income components to obtain the individual income levels and use a random sample of this variable in our analysis.

[13] $\tilde{x}$ is the list of covariates of x with the exclusion of average application quality.



(a) Apple Store

(b) Google Play

Figure 1: The weighted average rating (quality) of the top 1000 ranked apps in the App Store and Google Play in five countries Sep 2013 - Feb 2014

The third dataset that we use is made of mobile application data. This dataset, assembled by Priori Consulting Analytics, is made of six-monthly panels of the top 1,000 ranked (based on downloads) apps in Google Play and Apple Store in each of the five European countries mentioned earlier. The period covered by the data is 2013M9-2014M2. Our interest in this dataset is, in this work, limited to have 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 one to five. The average rating of users of an app is an indicator of how good and reliable the app is; hence, for each market (country-period), we compute the weighted (by downloads) average app rating of the apps and use this as a proxy of the average quality of the apps distributed in the store. We weigh apps to account for the fact that popular apps contribute more to the average quality than less popular ones. Nonetheless, in the appendix, Table A.4, we show how results change if we use other metrics based on top or bottom apps. Figure 1 displays the weighted average app rating by period and country (by market). In most countries in the early period, the weighted average rating in the Google Play Store is slightly higher than that in Apple Store but becomes lower than in Apple Store in the last period in all the countries. 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 or in the weighted average version we use, if they have different country downloads. This is the case in our data for three reasons. First, it is not necessarily true that an app is at the top in all countries in the same period (or in any period). Second, equally important because there are apps that are local, i.e., apps distributed only in that country.[14] Third, had the top 1,000 apps been the same in

[14]In our dataset, an app is defined as local if it generates more than 40% of its revenues within a single country.

all countries, the weighted average could differ due to download distributions (the weights) being country specific. As can be seen in Figure 1, there is a variation of app ratings both over time and across countries.

The number of observations on tablets is 4,849. However, since only data for applications distributed in the App Store and Google Play are observed, we keep only tablet observations associated with models compatible with these two stores. Additionally, we drop 54 tablet models that have too tiny market shares, to avoid outliers in our estimation. This leaves us with 3,753 tablet observations. The market size is assumed to be a quarter 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 1.

Table 1: Summary statistics of relevant variables

	N	Mean	Std.dev	Min	Max
Key variables					
market share (s)	3753	4.27E-04	0.001	1.48E-07	0.023
price (p)	3753	261.830	167.860	37.740	1050.000
screen size	3753	8.648	1.366	7.000	13.300
storage	3753	20.846	19.401	0.512	128.000
log screen resolution	3753	13.835	0.658	12.858	15.226
connectivity	3753	1.344	0.475	1.000	2.000
app rating	3753	4.196	0.059	4.034	4.275
income (in 100K)	500	0.272	0.177	0.052	0.995

Notes: Connectivity is one if the connectivity is WIFI and two if WIFI/3G or WIFI/4G. We take the log of the product of width and height for the value of screen resolution. For example, the resolution 1920x1080 will be $\ln(1920 \times 1080)$. From the survey on consumer data, we randomly draw 100 individuals for each of the five countries. 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 (5150 and 99500 EUR, respectively). We rescale income by dividing it by 100K.

6 Results

In this section, we first present the results of the joint demand and supply equation estimations for tablets and then discuss the counterfactual analyses aimed at studying the role of app quality. The estimates of the demand for tablets and the pricing equation are documented in Table 2.

The first pairs of columns show the results of a simple OLS estimation of nested logit tablet

Table 2: Demand and pricing joint estimation results

	OLS NL		GMM NL		GMM NL^e		GMM RCNL		GMM 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	-12.992**	0.034
Storage	-0.002	0.003	0.001	0.001	0.001	0.001	0.006	0.005	0.006**	0.001
Screen resol.	0.827**	0.047	0.186**	0.047	0.493 *	0.208	0.370**	0.096	0.549**	0.050
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	0.291**	0.043
App quality	-0.196	0.321	-0.536**	0.130	1.077**	0.135	0.376	0.205	0.473**	0.147
Price ($-\alpha$)	-0.008**	0.000	-0.002**	0.000	-0.018**	0.000	-0.006**	0.002	-0.009**	0.001
Price (σ)							0.006	0.044	0.007**	0.001
Price (π)							0.011**	0.004	0.012**	0.001
Correlation ρ	0.264 *	0.104	0.859**	0.018	0.885**	0.001	0.740**	0.108	0.735**	0.019
Pricing equation										
Constant	-12.585**	0.037	-7.228**	0.157	0.023**	0.001	0.314	0.482	0.587**	0.071
Storage	0.016**	0.001	0.029**	0.001	0.473**	0.002	0.004	0.011	0.004	0.002
Screen resol.	0.762**	0.037	0.516**	0.037	0.237**	0.015	0.233**	0.072	0.236**	0.014
Screen size	0.384**	0.016	0.263**	0.015	0.628**	0.034	0.114	0.117	0.114**	0.024
Connection	0.882**	0.035	0.681**	0.034	0.061	0.117	0.269 *	0.137	0.267**	0.039
Model Statistics										
N	3753		3753		3753		3753		3753	
Pseudo R^2_D	0.684		0.987		0.989		0.697		0.716	
Pseudo R^2_S	0.769		0.678		0.702		0.681		0.652	
J-stat	5E-15		2.121		2.664		13.446		12.492	
N mc<0	1049		431		368		8		9	
Average pcm	0.513		0.460		0.429		0.272		0.249	

Notes: 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: [Nested Logit: D=$h_1, h_2, h_4, h_8, h_{10}$], [Nested Logit^e: D=$h_1, h_2, h_4, h_6, h_7, h_8$], [RC Nested Logit: D=$h_1, h_2, h_4, h_8, h_{10}$],[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.1, where it is shown that the instruments that we have chosen are valid and strong. pcm=price-cost margin.

demand and supply without controlling for the endogeneity of price, within market share, and application quality. Most of the estimated coefficients on the demand side, especially the estimated coefficient for application quality, are not statistically significant due to the endogeneity. Ignoring this problem leads to biased estimates, which results in a large number (about 28%) of negative marginal costs. On the other hand, the price coefficient and within-nest correlation parameter have the expected sign and range and are statistically significant.

The following two pairs of columns present the results of nested logit joint demand and supply GMM estimate *without* and *with* controlling for the endogeneity of application quality. The GMM estimator reduces the bias and improves the efficiency of the estimates, and 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 in 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 demand for tablets is positively affected by the quality of available apps. Controlling for the endogeneity of within market shares has corrected the downward bias of the OLS estimates. The estimated ρ parameter is statistically significant both from zero and one—implying a strong within-group (operating system) correlation of individual preferences. The price coefficient in all nested logit specifications is relatively small in absolute value. The price elasticity of demand is not sufficiently picked by the within-market share correlation coefficient, resulting in a high number of negative marginal costs after correcting for the endogeneity (431 and 368, respectively).

The results of the random coefficients nested logit (RCNL) model with and without controlling for the endogeneity of application quality are presented in the pairs of columns (4) and (5). The first rows of results are the mean marginal effect on the utilities (βs). Both estimations show similar estimated coefficients on the tablet characteristics like storage, connection, screen resolution, and screen size, with the former generating tinier standard errors. After accounting for the endogeneity of application quality, the estimated app quality parameter becomes statistically significant. The results suggest that treating application quality as exogenous would lead to biased estimates.

The number of negative marginal costs drops from above 350 in the NL specification to only 8 in RCNL. We choose RCNL with application quality treated as endogenous as our preferred model. In contrast to the Nested Logit model, the nesting parameter in RCNL remains highly statistically significant from zero and one, but the magnitude is smaller. Along with this parameter, our focus is on the price parameters. The mean coefficient on the price ($-\alpha$) is negative and statistically significant. The dispersion around the mean price effect induced by the unobserved and observed individual characteristics (recall that we only control for one observable individual characteristic, which is income) are all significant. As one would expect, high-income individuals are less elastic to price changes.[15] This heterogeneity also has implications for the pass-on effect of a quality change.

The bottom panel of Table 2 displays the results of the pricing equation. We observe that improvements in tablet characteristics like higher storage, more refined screen resolution, and larger screen size positively affect the marginal cost of producing and distributing tablets. For instance, to manufacture and distribute a tablet with an inch larger screen size, the marginal cost would increase by $\exp(0.113) - 1 = 0.1196$ or 11.96%.

We use the estimates reported in column (5) to quantify consumer valuation for hardware and software, as well as the marginal cost and other relevant statistics. We document, in Table A.2 in the appendix, the relevant information for each country and last period. The surplus generated by the average Apple tablet quality (z_h) is estimated to be just over €1,000, whereas app quality

[15] See Figure (A.1) in the appendix, which depicts the distribution of price sensitivity for all markets. There is sufficient heterogeneity in price sensitivity.

($\bar{z}_s$) is predicted just below or borderline above €200. The weighted marginal cost ranges between €229.48 in Spain and €278.24 in the UK; the average price is between €420-440. As expected, the figures for an Android OS tablet are lower. The willingness to pay for an average hardware quality is around €900, and the corresponding one attributable to the app quality is in the proximity of €190. The average price and marginal cost are below those of Apple's products, ranging between €190-210 and €130-160, respectively. We also provide information on the market shares and the number of products. The larger market share of the Android-based tablets is sufficient to generate greater profits for Android than for Apple. In addition to their value in quantifying this market, these statistics are also helpful in calibrating our theoretical model. Our theory though was not able to provide an answer to some effects. Later on, we will use the statistics from Table A.2 to check what the theoretical model would have suggested about the sign of the changes.

We document the own- and cross-price elasticities averaged over products and segments in Table 3. We separate the cross-price elasticities into the same and 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 products across segments. This is the result of a significant grouping parameter. Segment-level cross-price elasticities are reported in the last pair of columns. They show the average percentage change in the market share of a product in the nest if the prices of all products in that nest (same group) or other nests (different groups) increase by 1%. It is not surprising that the cross-price elasticities are small between different segments, as the market has not tipped towards either of the two platforms.

6.1 Two counterfactual analyses of quality variations

We run two counterfactual analyses. In the first one, we study what would have happened to the demands for tablets, prices, profits, and consumer surplus if platforms increase the average quality of the apps in their stores. In the second counterfactual we show what would have been the effect on the demands for tablets, prices, profits, and consumer surplus if a regulator would affect app quality by imposing interoperability of apps between the two platforms.

6.1.1 Counterfactual 1: Increasing apps quality

Earlier, we showed that the average application quality in the app store impacts the tablet demand positively. As discussed above, platforms increasingly play a regulatory role, deciding what third

Table 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	-8.532	0.243	0.006	6.327	0.149
Android	-5.424	0.015	5E-04	3.759	0.122

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 2. Product-level cross-price elasticities are averaged across products from the same segment and the different segments. 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 increase by 1%.

parties can or cannot do or which third parties can or cannot participate in the platform. Among these regulatory activities, platforms can implement quality control strategies aimed at increasing the average application quality. To analyze the effect of such strategies, we perform a counterfactual experiment. We study what tablet demand, price, and profit would have been had the average application quality increased. Specifically, we obtain such an increase by withdrawing low-quality applications from one store at a time so that the average quality of this store grows by 0.05, which is about one standard deviation (see Table 1).

We run such an experiment in each of the five country-based tablet markets, relying on our estimates of the random coefficient nested logit model with application quality treated as endogenous. We run the counterfactual in the last period, the first quarter of 2014 because we wish to highlight variation across countries more than across time. From the joint estimations, we back out the marginal costs. We compute the new markups and calculate the new equilibrium prices and market shares by holding the marginal costs constant since increasing the app quality does not affect the cost of producing tablets. The results of this counterfactual, documented in Table 4 (values non in brackets), confirm Prediction 1.

The increase in the average (weighted) app rating produced by excluding the applications with the lowest quality in the platform has positive spillovers on tablet demand in that platform and on manufacturers' profits (own effect) and a negative impact on tablet demand and tablets and profits of the manufacturers of the other platform (cross effect). The absolute values of the own effects are much larger than those of the cross effects, and this confirms the first two points of Prediction 1. Indeed, competition between tablet producers across platforms is weak, as shown by

Table 4: Counterfactual 1 - Increasing the weighted average rating of each store

	France	Germany	Italy	Spain	UK
Increase in Apple app store quality					
Apple avg price change (€)	0.09	-0.15	-0.03	-1.08	0.13
	[1.24]	[1.26]	[1.25]	[1.25]	[1.25]
Android avg price change (€)	-0.00	-0.12	-0.04	-0.00	-0.08
	[0]	[0]	[0]	[0]	[0]
Apple Market share changes (bps)	3.98	5.95	2.98	3.13	9.44
	[12.43]	[12.56]	[12.49]	[12.48]	[12.52]
Android Market share changes (bps)	-0.43	-0.44	-0.24	-0.22	-1.22
	[-4.14]	[-4.19]	[-4.16]	[-4.16]	[-4.17]
Apple Profit changes (€ thousand)	668.94	2206.49	691.32	676.03	2518.38
	[1163.63]	[2308.46]	[1468.28]	[1560.95]	[1867.45]
Android Profit changes (€ thousand)	-28.21	-182.26	-29.95	-45.98	-292.78
	[-332.70]	[-464.34]	[-312.74]	[-317.31]	[-346.86]
Consumer surplus change (€ thousand)†	642.12	1966.44	664.69	1151.11	1421.76
	[581.81]	[1154.23]	[734.19]	[780.47]	[933.73]
Increase in Google Play app store quality					
Android avg price change (€)	-0.00	-0.05	-0.03	-0.00	-0.04
	[0]	[0]	[0]	[0]	[0]
Apple avg price change (€)	-0.07	-0.79	-0.26	-2.35	-0.09
	[-.36]	[-.36]	[-0.33]	[-0.36]	[-0.32]
Android Market share changes (bps)	13.23	12.43	10.63	10.57	17.81
	[20.24]	[20.22]	[18.69]	[20.26]	[17.89]
Apple Market share changes (bps)	-0.31	-0.10	-0.13	-0.08	-0.96
	[-3.57]	[-3.57]	[-3.30]	[-3.58]	[-3.16]
Android Profit changes (€ thousand)	732.77	1294.24	772.46	760.15	1386.61
	[1625.13]	[2242.36]	[1404.22]	[1504.65]	[1487.02]
Apple Profit changes (€ thousand)	-62.30	-306.02	-69.58	-72.98	-433.47
	[-324.90]	[-644.14]	[-380.02]	[-440.24]	[-463.01]
Consumer surplus change (€ thousand)††	1909.57	2630.61	1772.69	2461.23	2440.65
	[4386.88]	[5686.72]	[3613.65]	[3249.06]	[3519.33]

Notes: We report the calibrations from the linear demand model used in our theory in square brackets. Basis points (bps): 100 bps = 1%. For example, given the original market share of 1.76% of Apple in France (see Table A.2), the market share after the change of 3.98 bps is equivalent to 0.0176+0.000398=0.017998 or 1.7998%. † In percentages, the changes are: 0.56% [1.71%], 0.90% [1.34%], 0.60% [2.08%], 0.68% [1.51%] and 0.81% [2.84%]. †† In percentages, the changes are: 1.67% [12.92%], 1.21% [6.60%], 1.60% [10.25%], 1.45% [6.30%], and 1.39% [10.72%]. The percentage change for profits is around 2% in all countries and stores.

the limited substitution patterns previously highlighted in Table 3, and an increase in the average (weighted) application quality in one store leads to a larger gain from the outside good than from demand from other competitors. Interestingly, while the effects on market shares are large (higher for Android), prices do not seem to change significantly with app quality, and there are instances of negative price changes. The stylized model does not support negative price changes, since a uniform distribution of consumers on the unit Hotelling segment is assumed, generating a linear demand. In this situation, an increment in the app quality on a platform produces a parallel outward demand shift without changing the slope. It follows that prices will go up. Instead, the econometric model assumes a logistic distribution. The demand is a sigmoid shape. It is now possible that the outward demand shift is associated with a flatter inverse demand function. Two effects are in place. First, the outward demand movement pushes prices up. Second, the flatter inverse demand leads to a more elastic pointwise demand whereby a tiny price drop yields a high increase in demand. The simulations tell us that the first effect dominates in France and the UK; in the other countries, the second one dominates.

As expected, platforms benefit from a quality increase of the apps distributed on their store. The theoretical model was unable to provide a clear answer to which of the two platforms benefits the most from this increase in quality. Our simulations confirm this. According to Table 4, in France, Italy and Spain, it is on the Android platform, albeit to a marginal extent, that we observe the highest increase in overall profits of tablet manufacturers. By contrast, in Germany and the UK, Apple's profits in tablet production grow significantly more. Finally, in the table we also report the effects on consumer welfare. Since prices vary little, but quantities do, especially on the Android platform, we find that an app quality improvement boosts consumer surplus, particularly on the Android tablet market.

As mentioned, our theory was inconclusive on several of these effects. However, it is still possible to theoretically corroborate our empirical findings by calibrating the theoretical model using the estimated primitives of consumer valuations for hardware and software, along with those of the marginal cost and the other relevant statistics reported in Table A.2. By inserting these values in the expressions (3), we can calibrate the model to back out the equilibrium market shares, the overall profits of tablet manufacturers in the two platforms, and the consumers surplus. We then impose an increase in $\bar{z}_s$ by 0.05 and calculate how prices, markets share (in base points), profits and consumer surplus change. The results of this calibration are reported in the square brackets in Table 4.[16] The calibration based on the theoretical model largely confirms the empirical simulation.

6.1.2 Counterfactual 2: Compulsory interoperability of apps

In this counterfactual, we study the effects of apps interoperability on tablet demand. As discussed above, platform interoperability is often referred to as a possible remedy to reduce/eliminate the negative effects of bottleneck positions in platform markets.

[16] The calibration has been conducted fixing $l_1 = 0.4$, $l_2 = 0.5$, $v = 0.1$ and $k = 1.5$; as regards the parameter relating to the horizontal differentiation between Android tablet manufacturers we got it from the equilibrium condition (1); knowing the prices, the number of tablet producers and the marginal costs of production (see Table A.2), it is possible to derive the value of t which is compatible with the equilibrium condition. The value of the horizontal differentiation parameter between the two platforms has then been fixed consistently, with $k>t$ as it is natural to assume that the degree of differentiation between platforms is larger than that between tablets of the same platform. At these values of the parameters, the model exists and admits an internal solution.

With interoperable platforms, tablet users can access all the apps in the two stores, regardless of which platform the apps are designed for. The natural way to implement interoperability between platforms in our setting is to impose a leveling of the average quality of the apps in the two stores. More specifically, we set the app quality to be the same in the two stores: equal to the higher of the two (weighted) store averages. In this way, users of the tablets of the platform that, before interoperability, were enjoying apps of higher quality will not be affected by interoperability. In contrast, users of the tablets of the lower quality platform are affected as they can now benefit from apps of higher quality.

Similar to the first counterfactual, we restrict the analysis to the last quarter. As shown in Table A.3 in the appendix, the average (weighted) application quality in Apple Store is higher than in Google Play in all countries. Hence, imposing interoperability implies an increase in the average (weighted) quality of the apps for Android tablets.

Table 5: Counterfactual 2 - Compulsory interoperability of apps

	France	Germany	Italy	Spain	UK
Apple					
Avg price changes (€)	-0.02	-0.63	-0.61	-4.76	-0.09
	[-0.12]	[-0.28]	[-0.83]	[-1.35]	[-0.76]
Total market share changes (bps)	-0.10	-0.07	-0.36	-0.37	-2.28
	[-1.21]	[-2.79]	[-8.31]	[-13.51]	[-7.57]
Total profit changes (€ thousand)	-21.52	-240.69	-175.34	-258.22	-1101.68
	[-110.38]	[-504.32]	[-951.43	[-1648.37]	[-1104.71]
Android					
Avg price changes (€)	-0.00	-0.04	-0.07	-0.07	-0.07
	[0]	[0]	[0]	[0]	[0]
Total market share changes (bps)	4.57	9.77	27.16	41.16	43.22
	[6.85]	[15.82]	[47.11]	[76.58]	[42.90]
Total profit changes (€ thousand)	252.98	1017.52	1972.00	2948.12	3530.97
	[549.73]	[1754.07]	[3538.77]	[5838.98]	[3565.07]
Change in consumer welfare (€ thousand)†	658.87	2068.03	4521.99	9505.01	5938.34
	[1576.16]	[4441.18]	[9209.82]	[12542.29]	[8525.65]

Notes: The table shows the effect of imposing compulsory interoperability on the outcome variable of each product in each store. We report the calibrations from the linear demand model used in our theory in square brackets. † In percentages, for the simulations, the changes are: 0.58% [4.35%], 0.95% [5.15%], 4.09% [26.12%], 5.61% [24.30%] and 3.37% [25.96%].

The results of this second counterfactual are in Table (5); they support the second prediction of our theoretical model. Interoperability reduces the prices of Apple products while those of Android tablets remain substantially unchanged. As far as market shares are concerned, it depresses the sales of Apple tablets but stimulates Android sales. This is because imposing interoperability translates into an increase in the average (weighted) quality of the apps available for Android tablets, as Android users can now also download the higher quality apps in Apple App Store. By contrast, the average quality of apps for Apple tablets stays unchanged. This makes Android tablets more attractive relative to Apple iPads, leading to a shift in demand from Apple to Android. The drop in Apple's market shares more than compensates the increase in Android's market shares. Also, this finding is in line with our theoretical prediction and reveals that a policy that mandates platform interoperability promotes the adoption of tablet technologies. The fact that the prices of Android tablets do not vary with the quality of the apps available for this platform confirms their prices are essentially determined by the within platform competition and not between platform competition.

The simulations in Table 5 quantify the profit gains from interoperability for Android tablet producers and the losses for Apple, as well as the higher benefits enjoyed by consumers, following the decrease in prices and increase in quantities. Again, we theoretically support all these findings by calibrating our model using the estimated primitives. Figures are shown in square brackets in Table 5. Due to the differences in functional forms between the theoretical and the empirical model, the results of simulations and the calibrations are quantitatively different but deliver the same qualitative results.

6.2 Robustness checks: different measures of application quality

In our estimates, we used the average rating weighted by downloads as a measure of app quality. We adopted this measure to account for the "superstar effect", which foresees the demand for tablets being driven mainly by the quality of the most downloaded/popular apps. In this section, we want to provide further evidence on this assumption by running our estimations using other measures of application quality. To do so, we select the top 100 and 200 apps based on downloads, along with the bottom 100 (apps ranked 901-1000) and bottom 200 apps (apps ranked 801-1000), and calculate the average (weighted) rating for these apps in the platform in the market.

Figure A.2 in the appendix shows, for the UK Apple App store (but similar patterns hold for the other countries and platforms), the weighted average rating of the top 1,000 apps is close to that of the top-ranked 100 apps and well above the weighted average rating of the bottom 100 apps. This result is not surprising, given that the probability distribution of downloads is heavily skewed on the right and, consequently, a measure of quality based on all apps is close to that one would obtain, relying on superstar apps.

We use these alternative measures of app quality to test the robustness of our empirical exercise. In Table A.4 in the appendix, we replicate the empirical regressions using the four different quality measures for the various markets and platforms. We expect the impact of app quality on tablets to be close to those in column (5) of Table 2 and those for bottom apps not to be statistically different and possibly not different from zero.

The estimated effect of application quality based on the top 100 and 200 apps are very similar. Both coefficients are positive and significant and slightly greater than the effect obtained using the whole sample of apps. The estimated coefficients of application quality measured by the bottom 100 apps and bottom 200 apps are statistically not significant. In line with our expectations, these results reveal that top apps play a dominant role in affecting demand for tablets, while bottom apps have no significant effect. In addition, they suggest that our weighted average rating is a good measure of application quality.

7 Conclusions

This paper examines the role of the quality of applications on tablet demand, focusing on the case of iOS versus Android. Moving from a simple theoretical model of duopolistic competition in the tablet market, we empirically evaluate the theoretical predictions that emerge from the model. We combine tablet and app data across five European countries over the quarters 2013Q3-2014Q1 to jointly estimate the demand and pricing equations for tablets. Our results provide evidence of the relevance of application quality on the market for tablets. A rise in the average (weighted) application quality raises the demand for tablets.

We perform a sequence of counterfactual experiments to study the importance of these effects on the tablet market. First, we separately let each application store increase the quality of its applications and compute the new equilibrium market shares, prices, and profits of tablet producers. The results show that manufacturers on both platforms benefit from an increase in app quality. In terms of demand, we show that the highest impact is on Android tablets. Another interesting exercise we conduct is to study the effect of a regulator imposing the interoperability of mobile applications. When we impose that all applications be the same in both stores, we find that redistribution of application quality plays a key role. Before the counterfactual and in the period of study, Apple has a higher average (weighted) application quality in all markets. Interoperability implies that while the average (weighted) quality of apps for Apple tablets is unchanged, that of Android one's increases. The effect of this rearrangement is that Android tablet producers would gain more market shares and profits from interoperability at the expense of Apple. Interestingly, this policy has a negative and significant impact on Apple product prices, but negligible effects on

Android tablet prices. If the regulator cares only about consumers, we show that this policy should go ahead as it stimulates overall adoption of tablet PCs and enhances consumer surplus.

A valuable extension of this paper is to fully consider the two-sided nature of the tablet market by estimating the effects of application quality on the tablet market and tablet quality on the application market jointly. The lack of enough period of data has prevented us from doing so.

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A Appendix

A.1 The equilibrium of the theoretical model

The second stage equilibrium price of Android tablets is given in expression (1). Going backward, the indifferent customer between platform 1 and 2 is identified by:

$$\tilde{x}_{12} = l_1 + \frac{l_1 + l_2}{2} - \frac{p_{h1} - p^*_{h2} - z_{h1}\bar{z}_{s1} + z_{h2}\bar{z}_{s2}}{2k}. \tag{A.1}$$

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 at:[17]

$$\tilde{x}_{10} = l_1 - \frac{v + z_{h1}\bar{z}_{s1} - p_{h1}}{k}, \quad \text{and} \quad \tilde{x}_{20} = l_2 + \frac{v + z_{h2}\bar{z}_{s2} - p^*_{h2}}{k}. \tag{A.2}$$

Customers located between $\tilde{x}_{10}$ and $\tilde{x}_{12}$ join platform 1 while those located between $\tilde{x}_{12}$ and $\tilde{x}_{20}$ join platform 2;[18] the total demand for platform 1 is therefore $q_{h1} = \tilde{x}_{12} - \tilde{x}_{10}$, while that for platform 2 is $q_{h2} = \tilde{x}_{20} - \tilde{x}_{12}$. Using expressions (A.1) and (A.2), we can rewrite these first period demands as follows:

$$q_{h1}(p_{h1}, p^*_{h2}) = \frac{l_2 - l_1}{2} + \frac{2v + 3z_{h1}\bar{z}_{s1} - z_{h2}\bar{z}_{s2} - (3\,p_{h1} - p^*_{h2})}{2k}$$

$$q_{h2}(p_{h1}, p^*_{h2}) = \frac{l_2 - l_1}{2} + \frac{2v + 3z_{h2}\bar{z}_{s2} - z_{h1}\bar{z}_{s1} - (3\,p^*_{h2} - p_{h1})}{2k}.$$

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

$$\Pi_{h1}(p_{h1}, p^*_{h2}) = (p_{h1} - c_1)\left(\frac{l_2 - l_1}{2} + \frac{2v + 3\bar{z}_{s1}z_{h1} - \bar{z}_{s2}z_{h2} - (3\,p_{h1} - p^*_{h2})}{2k}\right), \tag{A.3}$$

where c_1 is the firm marginal cost of production.

With regard to platform 2, it is useful to report the first-stage overall profits enjoyed by the n

[17] Under very mild conditions on model parameters, it is possible to show that at the equilibrium these marginal customers, and therefore also the non-marginal ones, do not find optimal to purchase from the distant firm. The proof is available upon request from the authors.

[18] All through this section, we assume that at the equilibrium the model admits an internal solution: $0 < \tilde{x}_{10} < \tilde{x}_{12} < \tilde{x}_{20} < 1$.

tablet manufacturers, given prices, $\Pi_{h2} = \sum_n \pi_{h2,i}$:

$$\Pi_{h2}(p_{h1}, p^*_{h2}) = (p^*_{h2} - c_2)\left(\frac{l_2 - l_1}{2} + \frac{2v + 3\bar{z}_{s2}z_{h2} - \bar{z}_{s1}z_{h1} - (3\,p^*_{h2} - p_{h1})}{2k}\right). \tag{A.4}$$

Solving the first-order condition of platform 1 tablet producer, and given that the price of platform 2 tablets is as in expression (1), it is possible to derive the equilibrium price of platform 1 tablets given in expression (2).[19] Using p^*_{h1} and p^*_{h2}, equilibrium quantities, given the average quality of the apps available in the two platforms, are as in expressions (3).

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

A.2 Additional tables and figures

Table A.1: Instrument strength of demand side-First stage regression results

Variables	Price		$\text{Ln}(s_j \in g)$		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_4	0.035**	0.015	-0.002**	0.000	-4E-05**	9E-06
h_6	19.677	18.726	0.182	0.499	-0.153**	0.011
h_7	-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: The 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.

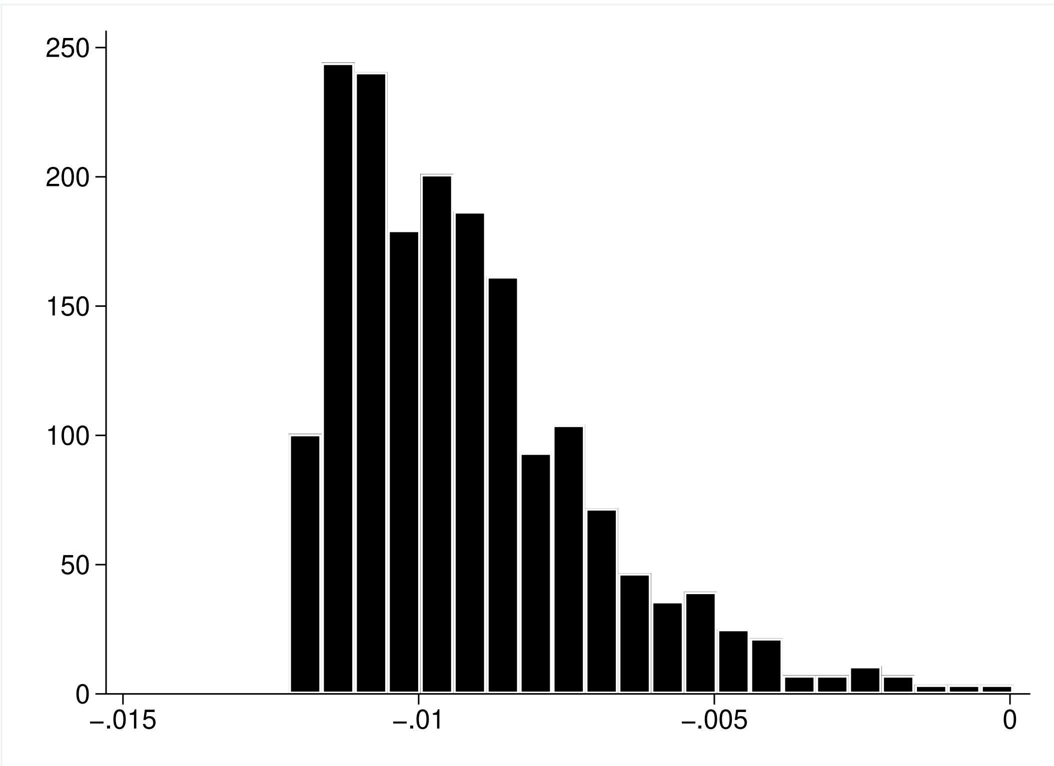

Figure A.1: Frequency distribution of price sensitivity

Table A.2: Summary of market statistics in 2014Q1

		France	Germany	Italy	Spain	UK
Apple	Number of producers	1	1	1	1	1
	Number of products	26	26	26	26	26
	(z_h) surplus weighted avg tablet quality (€)	1051.30	1062.20	1056.20	1055.80	1058.90
	(z_s) surplus weighted avg app quality (€)	196.53	199.56	202.21	199.75	201.78
	Weighted average prices (€)	421.36	437.74	420.85	420.10	422.68
	Weighted average marginal cost (€)	278.24	245.14	263.73	229.48	250.62
	Weighted average price-cost margin	0.35	0.44	0.38	0.46	0.41
	Total market share (%)	1.76	2.74	1.29	1.37	4.57
	Total profit (€ million)	29.01	105.40	30.39	29.95	124.25
Android	Number of producers	19	21	20	17	23
	Number of products	217	222	235	220	245
	(z_h) surplus weighted avg tablet quality (€)	906.20	905.20	836.90	907.00	801.10
	(z_s) surplus weighted avg app quality (€)	195.73	197.71	196.25	190.81	196.11
	Weighted average prices (€)	209.17	198.33	196.10	194.29	193.85
	Weighted average marginal cost	160.51	143.29	146.02	129.40	141.91
	Weighted average price-cost margin	0.28	0.30	0.30	0.35	0.29
	Total market share (%)	5.97	5.62	4.73	4.73	8.26
	Total profit (€ million)	34.16	61.88	35.55	35.29	68.69
All	Market size (million)	16.5	20.15	15	11.75	16
	Estimated consumer welfare (€ thousand)	114435.13	218181.82	110461.22	169527.44	175979.23

Notes: z_h is calculated as the ratio between the multiplication of the hardware characteristics with the coefficients displayed in column (5) of Table (2) and the average α. The constant is not included in the calculation. Similarly, z_s is the ratio between the product of app quality with values given in Table (A.3) with the corresponding coefficient, and the average α. The value of average α, $E(\alpha_i)$, is set to 0.01 because $-\alpha$ is -0.009 (see column (5) of Table (2)) and the effect of the parameters σ and π are negligible since the coefficient σ is multiplied to a mean zero variable, and π is multiplied to a variable whose mean is close to zero, 0.27 (see Table 1), and therefore contributes little the value of α.

Table A.3: Changes in weighted average app rating when imposing interoperability

Country	OS	Before	After	Change
France	iOS	4.155	4.155	0.000
	Android	4.138	4.155	0.017
Germany	iOS	4.219	4.219	0.000
	Android	4.180	4.219	0.039
Italy	iOS	4.275	4.275	0.000
	Android	4.149	4.275	0.126
Spain	iOS	4.223	4.223	0.000
	Android	4.034	4.223	0.189
UK	iOS	4.266	4.266	0.000
	Android	4.146	4.266	0.120

Table A.4: Different measures of application quality

	Top 100		Top 200		Bottom 100		Bottom 200	
	Parameter (1)	SE (1)	Parameter (2)	SE (2)	Parameter (3)	SE (3)	Parameter (4)	SE (4)
Demand side								
Constant	-13.532**	0.032	-11.417**	0.007	-10.134**	1.870	-11.734**	4.931
Storage	0.006**	0.001	0.005**	0.001	0.002	0.005	0.005	0.004
Screen resol.	0.582**	0.046	0.434**	0.011	0.337**	0.118	0.412 *	0.210
Screen size	0.109**	0.015	0.078**	0.013	0.044	0.032	0.069	0.041
Connection	0.306**	0.040	0.226**	0.035	0.134	0.121	0.207	0.132
App quality	0.480**	0.132	0.529**	0.026	0.528	0.401	0.669	0.469
Price (βp)	-0.010**	0.000	-0.007**	0.000	-0.005**	0.001	-0.006**	0.003
Price (σp)	0.007**	0.000	0.006**	0.001	0.004	0.018	0.005	0.028
Price (πp)	0.013**	0.000	0.010**	0.000	0.007	0.005	0.009**	0.003
Correlation ρ	0.715**	0.015	0.785**	0.006	0.792**	0.060	0.796**	0.104
Pricing equation								
Constant	0.608**	0.019	0.725**	0.006	-0.496	0.308	0.376	0.446
Storage	0.004	0.003	0.005**	0.002	0.008	0.014	0.005	0.013
Screen resol.	0.234**	0.014	0.224**	0.010	0.283 *	0.125	0.245**	0.086
Screen size	0.115**	0.019	0.114**	0.013	0.135	0.171	0.117 *	0.052
Connection	0.261**	0.037	0.255**	0.039	0.343	0.370	0.277	0.682
Model Statistics								
N	3753		3753		3753		3753	
Pseudo R^2_D	0.714		0.732		0.701		0.705	
Pseudo R^2_S	0.657		0.648		0.652		0.685	
J-stat	13.034		11.039		4.178		25.871	
N mc<0	9		9		12		8	
Average pcm	0.250		0.268		0.354		0.268	

Notes: The table presents the results of the random coefficients nested logit estimation when we use different measures for application quality. 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: $h_1, h_2, h_4, h_6, h_7, h_8$. pcm=price-cost margin.

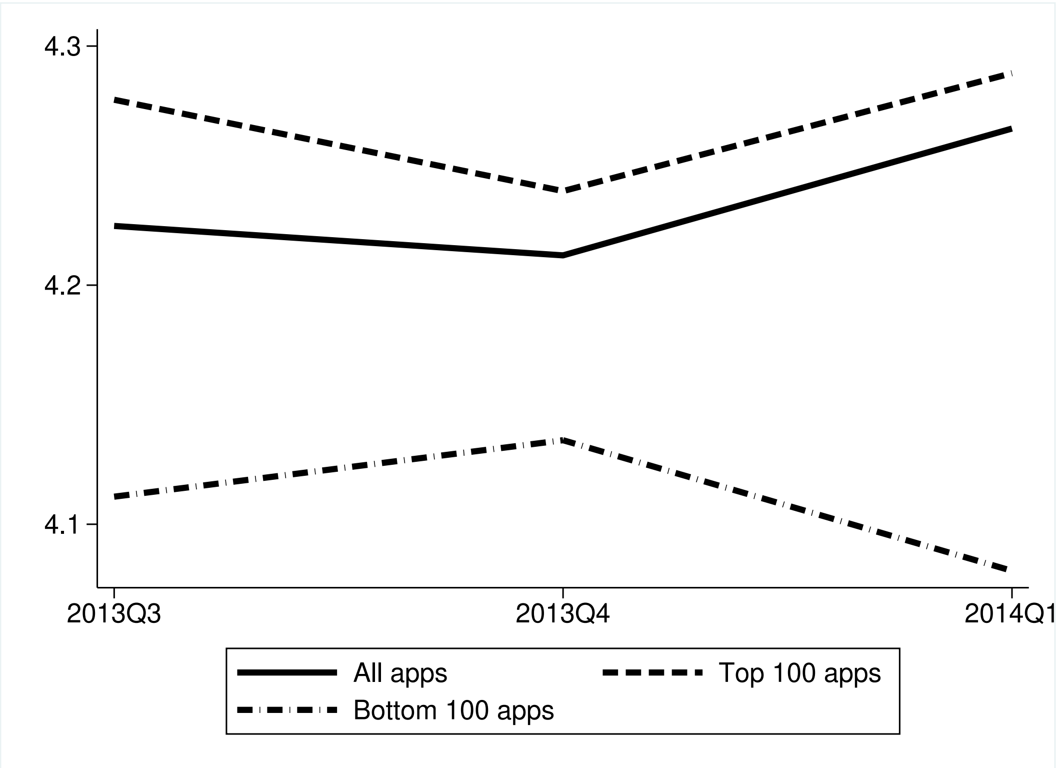

Figure A.2: The weighted average of application rating of all apps, top 100, and bottom 100 applications (based on total downloads) of the 1000 most downloaded applications. Example based on the UK Apple App Store