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

Thanh Doan† Fabio M. Manenti‡ Franco Mariuzzo§

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Abstract

The tablet PC market is dominated by two platforms: iOS and Android. 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 whether the application quality affects tablet demand. We then run two counterfactuals. The first counterfactual suggests that an improvement in application quality benefits the tablet producers on that platform with a more pronounced effect on the demand for Android-based tablets. The second counterfactual discusses the policy of leveling the app quality of the two stores. It shows that such a policy favors the tablet producers adopting the lowest quality app store (Google) and stimulates the adoption of tablet PCs. This generates consumer surplus in tablet demand.

Keywords: app quality, Android, iOS, tablet demand.
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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 in 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 third quarter of 2022, more than 3.5 million apps were available in Google Play and nearly 1.7 million in Apple App Store (Statista.com), the two largest app stores by far. This astonishing app growth brought a new generation of hardware to the market – 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 platform, entirely controlled by Apple, which both produces the devices and manages the app marketplace (App Store), and the Android-based platform, with competitive and independent manufacturers producing the devices and Google managing the app store (Google Play).

We study how the quality of the apps distributed in each dedicated app store affects the outcome of the tablet market. In particular, we show how the quality of the apps in the two online stores has a differential impact on tablet producers due to the different levels of competition in the two platforms. 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).[1]

We construct an econometric model relying on the discrete choice literature for product differentiation to estimate the impact of app quality on tablet PC demand. More specifically, we choose the random coefficients nested logit model proposed by Grigolon and Verboven (2014) where, here, the nest captures the heterogeneity in operating systems. We account for observable and unobservable

[1] We also study what happens if we add app variety as an additional quality measure. Due to the large number of apps in the market, we have reasons to believe that the effect of app variety may be minimal, if not non-significant. We investigate this conjecture empirically.

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 information on income from a Eurostat dataset. We jointly estimate demand and pricing equations to investigate the role of app quality in the tablet market.

In the last part of the paper, we use the estimates of the random coefficient nested logit model to conduct two counterfactual analyses aimed at studying two alternative policies affecting app quality. First, we evaluate how tablet manufacturers' equilibrium prices, market shares, profits, and consumer surplus 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 onset, Apple has adopted a strict quality control system, and only developers meeting specific 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).[2] 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, one store at a time until the weighted average of the app quality increment grows approximately by one standard deviation, and then recompute the new equilibrium in the tablet market. Our findings confirm that improving app quality impacts 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; consumers surplus would grow by 1.42 €million when the quality of iOS apps increases, and by 2.44 €million when the quality of Google Play apps increases by the same amount. Our estimates reveal that due to the different levels of competition between the two platforms, Android tablets' demand expansion tends to be larger than

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

Apple's. We find that the increase in app quality in one store leads to a higher gain from the outside good than from demand from other competitors. Even though we do not model them explicitly, we interpret this evidence as due to switching costs in tablet PCs demand.

With the second counterfactual, we analyze how the demand for tablets, firms' profits, and consumer surplus change when the average quality of the apps is the same in the two stores. With this counterfactual, we can, at least partially and in the short run, replicate what could happen if the two platforms were interoperable.[3] In this case, an app developed for the Android system could also run in the iOS environment, and tablet users could access the apps of both stores, regardless of which tablet they choose. Consequently, app quality differences between platforms are leveled.[4]

The effect of imposing the same quality in the two stores depends on the level of the common quality in relation to the level of quality before the policy introduction. For this reason, we study various scenarios depending on where the common level of app quality is set (minimum quality, average quality, and maximum quality). Our data reveal that the average app quality in Google Play, measured in terms of weighted average users rating, is lower than in the App Store. We thus find that imposing the same app quality at the level of Google Play would benefit Android tablet producers. For example, to remain in the UK again, if the common weighted average app quality is set at the average quality of the two stores, the profits of Android tablet manufacturers grow by almost €2 million, while those of Apple are reduced by around €3.5 million. Hence, we claim that a policy that leans toward interoperability and reasonably increases the app quality for Android users tends to stimulate, in the short term, the demand for Android tablets and depress that of Apple tablets. We find that unless the policy lowers the average overall app quality, it stimulates tablet adoption and enhances consumer welfare.

To give an intuition for our empirical analysis, we describe, in the appendix, a stylized theoretical model of competition among tablet producers. We perform a two-stage game, where consumers first select the platform (operating system) and then, according to their choice, purchase their most preferred tablet model. Preferences for tablets are affected by the quality of the applications available for that platform. To reinforce our findings, we compare the simulations of the two counterfactuals obtained with our discrete random coefficient nested logit (RCNL) model with those calibrating the theoretical model. The conclusions reached by these calibrations are qualitatively in line with, and quantitatively close to, those of the RCNL model.

[3] Our analysis is short-run, as we do not evaluate the impact this policy has on the developers' and tablet manufacturers' incentives to market apps and tablets of a certain quality.

[4] In platform markets, interoperability often is seen as a way to deal with bottleneck positions, which 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).

The outline of this paper is the following. In the next section, we briefly review the relevant literature. We discuss the testable predictions in section 3. Section 4 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 and discusses limitations and extensions.

2 Relevant literature

Our paper first aims to contribute to the literature by analyzing the effect of complementary products on demand for high-tech goods on multi-sided markets/platforms. This literature has mainly focused on indirect network effects generated by product variety (often seen as a proxy for quality). 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 this additional effect. 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 by 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 applications that have 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 sources of externalities are 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 centralized control 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.[5] The literature has studied the increase of app quality through the disposal of low-quality apps. Teh (2022) highlights two effects that 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.[6] 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 being 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 app removal) on the user's demand for tablets.

Finally, though we do not model it, when we study the two stores having the same quality, we resonate with the idea of compatibility and interoperability. For this reason, we believe that our analysis can also add to the literature on technology compatibility and interoperability by studying the impact on firms and consumers when available technologies are interoperable (see, Katz and Shapiro, 1985; Farrell and Saloner, 1985; Matutes and Regibeau, 1988; Economides, 1989; Katz and

[5]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".

[6]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.

Shapiro, 1994, among others).

3 App quality: testable predictions

The aim of this section is to explain the role of app quality in the demand for tablet PCs and describe the market.

The tablet market is dominated by two platforms running incompatible operating systems (OS) and adopting different industrial organizations. Apple produces and sells iOS-based devices (iPads) and competes with several tablet manufacturers with installed Android, an OS developed by Google. Apple and Google run their online app stores, App Store and Google Play, respectively, where users can download software (mobile applications) for their devices. We claim that this different organizational structure is likely to have repercussions on the role played by the quality of the apps in the two dedicated stores.

In this section, we present a series of predictions on the differential role of app quality in the two platforms, which will then be studied empirically with the estimation of our tablet demand model. Using a simplified theoretical model of competition between tablet manufacturers, in Appendix A.1 we provide theoretical support to these predictions.

Tablets differ along two dimensions: hardware (e.g., memory, screen size, etc.) and software, i.e., characteristics and quality of the available apps. It is worth noticing that these two dimensions act at different levels: the hardware characteristics differentiate a device from another and, as such, they are a typical form of differentiation between products, while the characteristics of the software and the quality of apps available in each dedicated app store differentiate iOS and Android platforms and, as such, they are a form of differentiation between groups of products. In particular, we are interested in this second layer of product differentiation. In our empirical analysis, app quality is measured using the weighted average of app ratings, where each app quality is weighted by its downloads.[7] This measure allows us to account for a 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 jointly estimate the demand and the pricing equations for tablets. Then we use our estimates to conduct two counterfactual analyses aimed at simulating the impact on market equilibrium (quantity, prices, and profits) of strategies affecting the quality of the apps on the two platforms. More specifically, we analyze what happens to the market equilibrium when: 1) the average quality

[7] We provide robustness checks of this measure in Appendix A.2.

of the apps available in a store increases while holding the quality of apps in the competing store fixed, and 2) the average quality of the apps is imposed to be the same in the two stores. Our analysis is short-run. Unfortunately, our data do not lend themselves to assessing the medium/long-term effects of these interventions, as those depend on developers, and/or on firms' strategies.

With counterfactual 1), we wish to evaluate the platforms' incentives to implement app quality control strategies aimed at increasing the average quality of the apps in their store. As the intrinsic quality of a tablet running with a given operating system depends on the quality of the apps available for that operating system, it is natural to expect that growth in the quality of the apps in a platform's store stimulates tablets' sales in that platform, as well as manufacturers' profits and consumer surplus. Cross-effects are expected to move in the opposite direction and be of a smaller magnitude. Due to the presence of competition on the Android platform, where tablets are produced by several independent manufacturers, the impact on tablet demand of an increase in the average quality of the apps on the dedicated store is expected to be greater for Android tablets than Apple's. While Apple can exploit the greater quality by increasing the prices of its devices, Android manufacturers have a lower ability to do so due to the competitive pressure they exert on each other. Hence, to a large extent, the increase in app quality on the Android platform translates into higher quantity demanded.

Summing up, we can postulate the following testable prediction.

Prediction 1 (Effects of a rise in a store's app quality) *When the weighted average of users' app rating for apps distributed in the store increases we have that, i) the demand for tablets on the same platform increases and, hence, also manufacturers' profits and consumer surplus, ii) the impact of application quality on tablet demand tends to be higher on the Android platform, and iii) in absolute values, own-effects are greater than cross-effects; finally, iv) Apple tablet prices are expected to increase.*

Both Apple and Android tablet manufacturers have the incentive to stimulate the quality of the apps available in their stores. However, the question of who has greater incentives remains open and can be answered only empirically.

Counterfactual 2) analyzes how the demand for tablets and, in general, the market equilibrium would change if the average quality of the apps in the two stores were the same. With this analysis, we mimic one of the main effects, at least in the short term, of imposing interoperability between the two platforms. With interoperable platforms, tablet users can access all the apps in the two stores, regardless of which platform the apps are designed for, and hence the average quality is the same. We expect the effects on Apple and Android tablet demands to be different and to depend on where the common bar relating to the quality of the apps is set. Before the introduction of this policy, the two platforms hold different levels of app quality. As we do not model the effect on developers of this policy, we prefer to be agnostic on the possible outcomes of quality change. Hence, we study three possible scenarios: (a) the bar is set at the minimum level between the app quality levels of the two stores, (b) at the intermediate level, and (c) at the maximum level.

Specifically, our data reveals that iOS apps are, on average, of higher quality than Androids. Hence in scenarios (a) and (b), the perceived quality of Apple tablets decreases —on top of this, in scenario (b) this goes in hand with an increase in the quality of Android tablets —; in scenario (c), the quality of Android tablets increases significantly, while that of Apple tablets does not vary. Therefore, in all three scenarios, compared to that of the Apple platform, the quality of the Android platform improves. For this reason, we expect the demand for Android tablets to grow in all three scenarios, while that for Apple tablets to shrink. As far as the overall quantity of tablets sold is concerned, we expected this to increase if the common level at which the quality of the apps is set is not lower than the average quality of the app in the two stores before the policy. Finally, as in all three scenarios the quality of Android tablets improves compared with that of Apple, we expect an increase in the profits enjoyed by Android manufacturers and a decrease in those of Apple.

Prediction 2 (Leveling app quality) *When a policy aimed at leveling the app quality in the two platforms is imposed, we have that, i) the demand for Android tablets increases, and that of Apple tablets decreases; ii) the overall demand for tablets increases (if the common level at which the quality of the apps is set is not lower than the average qualities of the app in the two stores before the policy), and iii) the profits of Android tablet manufacturers increase, while those of Apple from the tablet market decrease.*

As mentioned, we can use this counterfactual to assess the potential effects of what resonates as interoperability between the two platforms. We do not know in advance the impact of interoperability on developers' incentives towards quality, nor is our setting appropriate to evaluate it. Nonetheless, distinguishing between three alternative scenarios is an attempt to take into account for heterogeneous effects of interoperability on developers' incentives.[8]

[8]Note that interoperability can be seen as an increase in competition among developers; hence, it would be a matter of understanding how greater competition affects quality incentives. The economic literature - theoretical and empirical - studying the relationship between competition and quality is inconclusive. Some authors find a positive relationship (Schmalensee, 1974), others a negative relationship (Gal-Or, 1983), no relationship (Swan, 1970) or a relationship which depends on the modeling assumptions (Banker et al., 1998).

4 Econometric model

We devote this section to illustrating our empirical model. 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 of that consumer associated with buying tablet j in the market t is expressed as:

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

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. Note that we model hardware and software quality as an additive, bearing in mind that only products with a minimum level of hardware and software quality will be marketed.[9] In this respect, there is less of a need to interact with these terms, as we do in the theoretical model in Appendix A.1. The list of tablet characteristics includes storage capacity, screen resolution, screen size, and 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 the case of expected (weighted) average mobile application quality. Groups are created based on the operating system; g=0 is the outside option, g=1 is iOS, and g=2 is Android.[10] As often is the case, not all product characteristics are observed by the researcher. Those unobserved characteristics are captured by the variable ξ_{jt}. The coefficients βs are constant, while the coefficient on prices, α_i, is random —this is to account for heterogeneous price sensitivity.[11] 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

[9]Note that in equation (1) we specify $\underbrace{\beta_s x_{sjt}}_{E(\alpha_i)E(z_{sjt})}$, and similarly for the hardware characteristics, to account for the fact that in the theoretical model shown in Appendix A.1, the price has coefficient one, and therefore $E(z_{hjt})$ and z_{hjt} are expressed as a willingness to pay in monetary value.

[10]One alternative was to choose the group based on brands. Consumers choose first the brand and then the product within the brand. A nest of potential interest is Apple, Samsung, and other tablets, because Samsung may be a valid alternative to Apple. However, the descriptive statistics in Table A.1 suggest that Samsung's tablets are better than other Android tablets, but they are still very far from Apple's. There does not seem to be enough scope to nest the brands. We thus maintain the focus on the operating system.

[11]Only the price variable has a random coefficient. We experimented by adding a random coefficient to app quality, but the estimated standard deviation of the random coefficient 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.

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 distribution. In the random coefficient specification, the price coefficient is the additive value $\alpha_i = \alpha + \sigma\nu_i + \pi y_i$, 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). In the nested logit specification, the price coefficient does not have the random components, thus it simplifies to $\alpha_i = \alpha$, with $\sigma = \pi = 0$.

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,

$$\phi_{ijt}(x_t, p_t, \xi_t, y_i, v_i, \theta) = \frac{exp\left(\left(x_{jt}\beta - \alpha_i p_{jt} + \xi_{jt}\right) / \left(1-\rho\right)\right)}{exp\left(I_{ig} / \left(1-\rho\right)\right)} \frac{exp\left(I_{ig}\right)}{exp\left(I_i\right)}, \tag{2}$$

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

$$\begin{aligned} I_{igt} &= (1-\rho)\ln\sum_{l=1}^{J_{gt}} exp\left(\left(x_{lt}\beta - \alpha_i p_{lt} + \xi_{lt}\right) / \left(1-\rho\right)\right), \\ I_{it} &= \ln\left(1 + \sum_{g=1}^{G_t} exp\left(I_{igt}\right)\right). \end{aligned} \tag{3}$$

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 (2) with respect to the income distribution and the distribution of individual unobserved heterogeneity, 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. Multiproduct tablet producers observe the demand for tablets and choose their products' prices to maximize profit, given the prices and characteristics of the other products in the market. The marginal cost of producing the tablet j in the market t, c_{jt}, is assumed to be constant in output. The manufacturer m in market t produces and distributes the set $\mathcal{J}_{mt}$ of J_t new tablets to be marketed to I_t consumers. Given the demand (share) function for the product j, s_{jt}, and output $s_{jt}I_t$ the pricing equation for the product j is the one that solves the first-order condition of the profit maximization:

$$p_{jt}(\cdot) = \arg\max_{p_{jt}\geq 0} \pi_{mt} = \sum_{r\in\mathcal{J}_{mt}} (p_{rt} - c_{rt}) s_{rt} I_t \quad \text{with} \quad j, r \in \mathcal{J}_{mt}. \tag{4}$$

The first-order conditions $\forall j \in \mathcal{J}_{mt}$ and $\forall m$ are:

$$s_{jt} + \sum_{r\in\mathcal{J}_{mt}} (p_{rt} - c_{rt}) \frac{\partial s_{rt}}{\partial p_{jt}} = 0. \tag{5}$$

Upon defining Δ_t a $J_m \times J_t$ matrix whose (j, r) element is $\Delta_{jr} = -\frac{\partial s_{rt}}{\partial p_{jt}}$ if $r \neq j \in \mathcal{J}_{mt}$ and zero otherwise, the first order conditions given above can be written in matrix notation as the system of pricing equations, where the right-hand side can be decomposed in markup, m_t, and marginal cost, c_t:

$$p_t = \underbrace{\Delta_t^{-1} s_t}_{m_t} + c_t. \tag{6}$$

We assume the marginal cost to be a linear function of observable product characteristics w_t and the random component ω_t, yielding the J_t marginal cost equations:

$$p_t - m_t = \underbrace{w_t\gamma + \omega_t}_{c_t}. \tag{7}$$

As we estimate jointly the demand and pricing equations, as in Berry et al. (1995), we account for the correlation between the demand-side unobservable product characteristics, ξ_{jt}, and the cost-side unobservable product characteristics, ω_{jt}.

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 tablet quality. Consequently, the markups derived from the pricing equations will be overestimated and lead to several negative marginal costs.[12] 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 with 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 (Breiman et al., 1984) to capture any non-linear effects of tablet characteristics on prices and within market shares. This process enables us to generate a set of instruments for both 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),[14] h_3 (sum of the screen resolution (log) of other products by the same firm), h_4 (sum of

[12] Equation (6) shows that a too high markup can lead to negative marginal costs. The literature has developed transformations to avoid negative marginal costs. For example, Bellemare and Wichman (2020) suggest an inverse hyperbolic sine transformation. This functional form has the advantage of having zero part of its domain and associating negative values with real numbers.

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

[14] The idea is that prices of products by a firm in a country reflect the underlying firm's costs (productivity and marketing) and country-specific factors varying over time, as retailers in different countries run promotions of firms' products at various stages. To the extent that the country-specific unobservables are independent of each other, prices of products of firms from other countries can serve as instruments for the price of a firm in a country.

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>12GB and zero otherwise), h_9 (a dummy taking value one if Storage>48GB and Screen size>7.9" and zero otherwise), and h_{10} (a dummy taking value one if Storage≥24GB and zero otherwise). The first stage of the regressions and selected instruments for the RCNL model are presented in Table A.2 in the annex. Combinations of the above instruments are used in the various types of regressions.

5 Data

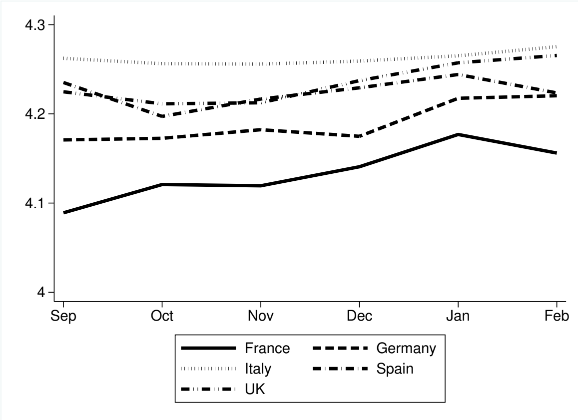
In our empirical work, we combine three datasets. The first dataset is on the new tablet market, maintained by IDC. The dataset contains product-level information on tablet characteristics such as model name, model ID, producer name, operating system (OS), CPU type, connectivity, screen size, screen 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 quarters 2013Q3, 2013Q4, and 2014Q1.[15]

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 microdata on labor, education, health, income, poverty, social exclusion, and living conditions in all EU countries.[16] 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.

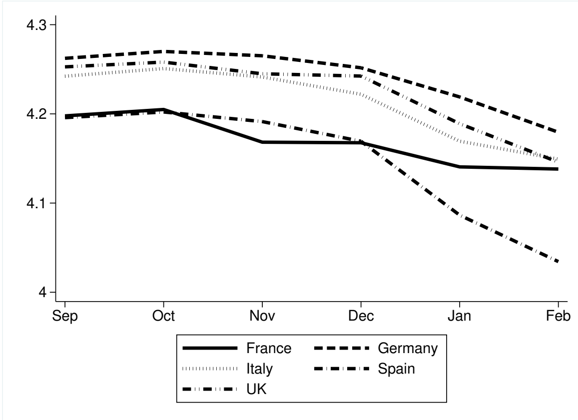
The third dataset that we use is made of mobile application data. This dataset, assembled by Priori Consulting Analytics, is made of six-monthly panels of the top 1,000 ranked (based on downloads) apps in Google Play and Apple Store in each of the five European countries mentioned

[15]The IDC data usage referenced in the article was extracted from IDC's Quarterly Tablet Tracker program at the time in 2014 covering the sales of Tablet products in Europe and across the World. IDC continues to track Tablets in its Worldwide Quarterly Personal Computing Device Tracker. For any information on IDC's Tracker programs, you can contact IDC or visit www.idc.com.

[16]Information on the availability of the data to the public can be found at https://tinyurl.com/5xjvstr4.



(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

earlier. The period covered by the data is 2013M9-2014M2. Our interest in this dataset is, in this work, limited to having 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, 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). Note that 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, and equally important, there are apps that are local, i.e., apps distributed only in that country.[17] Third, had the top 1,000 apps been the same in 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 in in-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

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

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.[18] 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
Screen resol.	3753	13.835	0.658	12.858	15.226
Connectivity	3753	1.344	0.475	1.000	2.000
App quality	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 it 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 (Screen resol.). 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 demand and supply without controlling for the endogeneity of price, the 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

[18] We have run a sensitivity check that readjusts the market size to be 34.5% and 19.6% of the country's population, which is the highest and lowest tablet PC penetration rate among the five countries in our data according to Statista (See `https://tinyurl.com/53bs6bba`). The only significant change is in the intercept. The table of results is available upon request.

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
Connectivity	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	-0.002**	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
Connectivity	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.2, where it is shown that the instruments that we have chosen are valid and strong. PCM=price-cost margin.

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; on top of that, 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 effects on the utilities (βs). Both estimations show similar estimated coefficients on the tablet characteristics such as 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 the RCNL. We choose the RCNL model with application quality treated as endogenous as our preferred specification.[19] 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 effects 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.[20] 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 such as 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 the pair of columns (5) to quantify consumer valuation for hardware and software, as well as the marginal cost and other relevant statistics. We document, in Table A.4 in the appendix, the relevant information for each country and the last period. The surplus generated by the average Apple tablet quality (z_h) is estimated to be just over €1,000, whereas app quality (z_s) is predicted just below or borderline above €200.[21] The weighted marginal

[19] App variety is another measure of app quality. We follow Nair et al. (2004) to measure app variety within our data. Due to the large number of apps in the market, we believe that app variety is no longer a key factor for tablet demand. We repeat the estimates of the RCNL model in Table A.3. The results confirm our belief. The coefficient of app variety is not significant, app rating is, and all other parameter values are similar to the case without app variety. For this reason, we do not include this variable in our main regressions.

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

[21] Indeed, these values benchmark a tablet with zero characteristics and zero app quality rather than a tablet with minimal product characteristics and minimal app quality (the minimum average rating is one). Yet, they are

cost ranges between €229.48 in Spain and €278.24 in France; 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 between €800 and €900, and the corresponding willingness to pay for 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 market shares and on the number of products. The larger market share of Android-based tablets is sufficient to generate greater profits for Android than for Apple.

We document the own- and cross-price elasticities averaged over products and segments in Table 3. We separate the average cross-price elasticities into, within the same and across other segments. The average own-price elasticities of Apple's products using iOS is, in absolute value, higher than that of Android-based tablets. This evidence seems to be at odds with the fact that the production of Android-based tablets occurs competitively. The lower elasticity for Android tablets is therefore due to the difference in production costs, which are on average much lower than for Apple tablets.[22]

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 of Table 3. 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 across 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.

indicative of monetary values. This benchmark does not affect the counterfactuals, as it appears both in the factual and counterfactual, and therefore, cancel out.

[22] As documented in Table A.4, the average marginal cost of producing an iOS-based tablet is between 40% and 80% higher than that of Android-based tablets. Higher marginal costs translate into higher prices and, consequently, higher elasticity at the equilibrium.

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%.

6.1.1 Counterfactual 1: Increasing apps quality

Earlier, we showed that the average application quality in the app store impacts tablet demand positively. As discussed above, platforms increasingly play a regulatory role, deciding what third 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 this 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 approximately 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 rather 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; we do so 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), largely 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

Table 4: Counterfactual 1 - Increasing the weighted average rating of each store (2014Q1)

	France	Germany	Italy	Spain	UK
Increase in Apple app store quality					
Apple market share changes (bps)	3.98	5.95	2.98	3.13	9.44
Android market share changes (bps)	-0.43	-0.44	-0.24	-0.22	-1.22
Apple avg price change (€)	0.09	-0.15	-0.03	-1.08	0.13
Android avg price change (€)	-0.00	-0.12	-0.04	-0.00	-0.08
Apple profit changes (€ thousand)	668.94	2206.49	691.32	676.03	2518.38
Android profit changes (€ thousand)	-28.21	-182.26	-29.95	-45.98	-292.78
Change in consumer welfare (€ thousand)†	642.12	1966.44	664.69	1151.11	1421.76
Increase in Google Play app store quality					
Android market share changes (bps)	13.23	12.43	10.63	10.57	17.81
Apple market share changes (bps)	-0.31	-0.10	-0.13	-0.08	-0.96
Android avg price change (€)	-0.00	-0.05	-0.03	-0.00	-0.04
Apple avg price change (€)	-0.07	-0.79	-0.26	-2.35	-0.09
Android profit changes (€ thousand)	732.77	1294.24	772.46	760.15	1386.61
Apple profit changes (€ thousand)	-62.30	-306.02	-69.58	-72.98	-433.47
Change in consumer welfare (€ thousand)††	1909.57	2630.61	1772.69	2461.23	2440.65

Notes: Basis points (bps): 100 bps = 1%. For example, given the original market share of 1.76% of Apple in France (see Table A.4), 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%, 0.90%, 0.60%, 0.68% and 0.81%. †† In percentages, the changes are: 1.67%, 1.21%, 1.60%, 1.45%, and 1.39%. The percentage change for profits is around 2% in all countries and stores.

on manufacturers' profits (own-effect), and a negative impact on tablet demand and profits of the manufacturers of the other platform (cross-effect). As predicted, the absolute values of the own effects are much larger than those of the cross effects. Indeed, competition between tablet producers across platforms is weak, as shown by 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. Although we do not explicitly model switching costs, it is interesting to notice how this result signals the presence of considerable friction in users' switching from one platform to another.[23] As predicted, the effects on market shares are large and higher for Android. On the other hand, contrary to what was expected, price changes are negligible also for Apple.[24]

[23] Grzybowski and Nicolle (2021), using a dataset covering a similar period, empirically verify the existence of friction in this market. They studied switching between mobile handsets between July 2011 and December 2014. They find evidence of inertia in the choice of operating systems and brands and simulate that, from the various operating systems, iOS is the one that has the most to gain from switching costs. To model switching costs, our static demand model would need to be modified to allow for repeated choices. Nevertheless, though we do not model switching costs, we come across the result of inertia.

[24] There are instances of negative price changes which are quite unexpected given that an increase in the quality of apps leads to an outward shift in demand. Indeed, the econometric model assumes a logistic distribution and the demand is a sigmoid shape. It is now possible that the outward demand shift is associated with a flatter inverse demand function. Hence, 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.

Prediction 1 left open the question of which platform has the most to gain from an increase in app quality. The results of our counterfactual are unable to give a definite answer. According to Table 4, in France, Italy, and Spain, it is for 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 vary greatly, especially on the Android platform, we find that an app quality improvement boosts consumer surplus, particularly on the Android tablet market.

6.1.2 Counterfactual 2: Leveling apps quality

In this counterfactual, we analyze how the demand for tablets and the market equilibrium would change if the average quality of the apps in the two stores were the same. We model three scenarios: (a) the common level of app quality is set at the minimum between the quality levels of the two stores, (b) at the intermediate level, or (c) at the maximum level. This analysis is interesting as it allows us to mimic one of the main effects, at least in the short term, of platform interoperability, which is an often suggested potential remedy to reduce/eliminate the negative effects of bottleneck positions in platform markets. Useful for our scopes, with interoperable platforms, tablet users can access all the apps in the two stores, regardless of which platform apps are designed for.

Similar to the first counterfactual, we restrict the analysis to the last quarter. As shown in Table A.5 in the appendix, the average (weighted) application quality in the Apple App Store is higher than in Google Play in all countries. Hence, in scenario (a) the quality of the apps in the Apple store is lowered to the level of the Android apps, in scenario (b) the quality of the Android apps is increased while that of the iOS apps is reduced, although less than in the previous scenario, and in scenario (c) the quality of Android apps is raised to the level of iOS apps.

The results of this second counterfactual are shown in Table 5. They support our second prediction. In all three scenarios, Apple's market share is depressed while that of Android manufacturers increases —leveling app quality means increasing the average quality of the apps available for Android tablets comparatively to those of Apple, hence Android tablets become more attractive relative to Apple iPads. Naturally, moving from scenario (a) to (c) the impact of the policy becomes more and more advantageous for Android manufacturers. Our findings confirm also point *ii*) of the prediction: in scenarios (b) and (c) the drop in Apple's market shares is more than compensated by the increase in Android's market shares. Interpreting this in terms of interoperability, this finding reveals that a policy that mandates platform interoperability in a way such that the average overall

Table 5: Counterfactual 2 - Leveling apps quality (2014Q1)

	Scenario	France	Germany	Italy	Spain	UK
Apple						
Total market share changes (bps)	(a)	-1.36	-4.61	-7.09	-11.21	-21.87
	(b)	-0.73	-2.35	-3.77	-5.89	-12.21
	(c)	-0.10	-0.07	-0.36	-0.37	-2.28
Avg price changes (€)	(a)	-0.03	0.11	-0.05	1.67	0.07
	(b)	-0.03	-0.26	-0.33	-2.83	-0.26
	(c)	-0.02	-0.63	-0.61	-4.76	-0.09
Total profit changes (€ thousand)	(a)	-328.61	-1722.34	-1677.91	-2483.87	-5835.24
	(b)	-179.97	-984.51	-935.00	-1404.63	-3468.36
	(c)	-30.87	-242.49	-175.34	-258.22	-1101.68
Android						
Total market share changes (bps)	(a)	0.11	0.40	0.50	0.84	2.76
	(b)	2.34	5.07	13.66	20.52	22.78
	(c)	4.57	9.77	27.16	41.16	43.22
Avg price changes (€)	(a)	0.00	0.11	0.09	0.13	0.19
	(b)	0.00	0.03	0.01	0.00	0.05
	(c)	-0.00	-0.04	-0.07	-0.07	-0.07
Total profit changes (€ thousand)	(a)	13.91	143.23	96.67	160.98	684.08
	(b)	188.16	582.94	1023.70	1540.17	1998.26
	(c)	362.97	1025.15	1972.00	2948.12	3530.97
Change in consumer welfare (€ thousand)	(a)*	-219.92	-1522.16	-1591.22	-4121.94	-3270.18
	(b)**	218.69	266.71	1426.76	2612.09	1266.15
	(c)***	658.87	2068.03	4521.99	9505.01	5938.34

Notes: The table shows the effect of leveling app quality on the outcome variable of each product in each store. (a): leveling app quality to the minimum of the average quality of the two stores. (b): leveling app quality to the average of the two store's average quality values. (c): leveling app quality to the maximum of the average quality of the two stores. In percentages, change in consumer welfare are: * -0.19%, -0.70%, -1.44%, -2.43%, -1.86% ;** 0.19%, 0.12%, 1.29%, 1.54%, and 0.72%; *** 0.58%, 0.95%, 4.09%, 5.61%, and 3.37%

app quality is not reduced, promotes the adoption of tablet technologies.

The simulations in Table 5 quantify the profit gains from the policy for Android tablet producers and the losses for Apple; in scenarios (b) and (c), i.e. when the common quality level is not below the ex-ante average quality, the policy of leveling app quality benefits consumers.

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 for 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 App Store (but similar patterns hold for the other countries and the other platform), 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.6 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 for the impact of app quality for lower ranking 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 is 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 and discussion

This paper examines the role of the quality of applications on tablet demand, focusing on the case of iOS versus Android. 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 average quality of the apps to be the same in the two stores as if the two platforms were interoperable. 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. Balancing app quality implies an increase in the quality of Android-based versus iOS-based apps. The effect of this rearrangement is that Android tablet producers would gain more market shares and profits at the expense of Apple. We show that when this policy implies an increase in the overall average quality of the apps, it stimulates the overall adoption of tablet PCs and enhances consumer surplus; hence, if the regulator cares only about consumers, it should go ahead with this policy.

Due to the lack of data, our analysis has some limitations. A first limitation concerns the quality of apps and tablets, which we take for exogenously given. This represents a limitation, especially in reference to counterfactual 2 where we study the effect of imposing the same app quality in the two stores and which, quite broadly, we interpret as the imposition of interoperability between platforms. By taking the quality of the apps as exogenously given, our investigation can be considered as a short-term analysis of interoperability; in the medium/long term, in fact, this policy is likely to have an impact on developers as well as device manufacturers which is to some extent ignored by our analysis. A very interesting extension of our work is therefore to fully characterize 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.

Another limitation of our work concerns switching costs. Even though our results confirm that the market is characterized by a certain degree of inertia, the two counterfactuals are analyzed without explicitly considering the costs, monetary and non-monetary, that an individual may incur when changing platforms. In order to account for the presence of switching costs, our static demand model would need to be modified to allow for repeated choices. Having access to more detailed information about consumer preferences and switching rates between platforms may allow future research to complement our analysis.

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A Appendixes

A.1 A stylized model of platform competition

To illustrate our testable predictions, in this appendix we develop a stylized theoretical framework of competition between tablet producers. Being based on different functional forms than the structural estimation, this theory also represents a useful robustness analysis for the empirical findings.

We model the tablet market as characterized by two alternative platforms based on incompatible operating systems: iOS and Android OS. Apple, which controls iOS, produces and sells an iOS-based device, iPad, and competes with n tablet manufacturers producing Android OS-based devices. Apple runs the iOS app store, while the Android apps are distributed through Google Play which is run by Google. In line with our structural estimation, we assume a two-stage competitive process:[25]

1. In the first stage, consumers decide which operating system (platform) to adopt, and if they prefer iOS, they eventually buy an iPad; we refer to this as inter-platform competition.

2. In the second stage, those who have chosen Android will decide which tablet to purchase among the n alternatives; we refer to this as within-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. Tablets of the two platforms are assumed to differ in two dimensions: hardware (screen size, storage, etc.) and software. As software is concerned, differentiation originates from the fact that to a large extent, the two dedicated app stores contain different applications. Formally, we represent inter-platform competition using a Hotelling framework with qualitatively different products. 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 ratings, where each app quality is weighted by its downloads.

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 within-platform competition as a Salop

[25]Like the empirical model, our theoretical setting produces an asymmetric within-platform competition. In both types of models, consumers choose tablets sequentially. First, they choose the operating system and then the product. The difference between the empirical and theoretical models is that in the empirical model, the firms choose prices simultaneously (Bertrand differentiated products); in the theoretical model, the platform choice is sequential.

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.[26] 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 $p^*_{h2} = c_2 + t/n$, 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.

The second stage equilibrium price of Android tablets is p^*_{h2}. Going backward, the indifferent customer between platforms 1 and 2 is identified by:

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

To allow for market expansion, the market is not fully covered. 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

[26] This assumption is not taken without loss, though, and it results in the prediction that the price of Android-based tablets is entirely driven by the competition between Android manufacturers. In essence, we represent the Android manufacturers as a competitive fringe enjoying positive margins from their Salop-style differentiation.

between adopting platform 1/resp. platform 2 or not adopting are located at:[27]

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

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;[28] 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 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 $p^*_{h2} = c + t/n$, the equilibrium price of platform 1 tablets is:[29]

$$p^*_{h1} = \frac{2v + 3c_1 + c_2}{6} + \frac{t + n\,(3\bar{z}_{s1}z_{h1} - \bar{z}_{s2}z_{h2}) + kn\,(l_2 - l_1)}{6n}, \tag{A.5}$$

Using p^*_{h1} and p^*_{h2}, equilibrium quantities, given the average quality of the apps available in the two platforms, are:

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

[27] We assume that, at the equilibrium, these marginal customers, and therefore also the non-marginal ones, do not find optimal to purchase from the distant firm.

[28] We assume that at the equilibrium the model admits an internal solution: $0 < \tilde{x}_{10} < \tilde{x}_{12} < \tilde{x}_{20} < 1$. Consumers in $[0, \tilde{x}_{10})$ and in $(\tilde{x}_{20}, 1]$ do not purchase.

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

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

We can use these expressions to illustrate our testable predictions. The first prediction regards the effect of a change in the average quality of the apps available on platform j. 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).[30] Formally:

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

and

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

Note that, in absolute values, own-quality effects exceed the cross-quality effects. Expressions (A.6) reveal another interesting observation. If the platform hardware qualities are not too different, formally if $z_{h1}/z_{h2} < 17/9$,[31] our model confirms that the impact on demand for an increase in the quality of applications is higher for platform 2's tablets than for platform 1.

As regards the impact on profits, it can be shown that the equilibrium profits of the manufacturers on the two platforms are equal to $\Pi^*_{h1} = 2(q^*_{h1})^2 k/3$, and $\Pi^*_{h2} = jq^*_{h2}/n$, respectively. As $dq^*_{hi}/d\bar{z}_{si} > 0$ and $dq^*_{hi}/d\bar{z}_{sj} < 0$, $i, j = 1, 2$, it follows immediately that both platforms benefit from an increase in the quality of the apps in their own store while being hurt by an increase in the quality of the apps in the rival store. Unfortunately, the model is unable to tell us which platform benefits most; hence, this remains a question that can only be answered empirically. As regards prices, our model predicts that an increase in the quality of the apps implies an increase in the price on platform 1, while due to competition between Android manufacturers, the price on platform 2 does not change. Finally, it is possible to check that consumers benefit from higher quality.

Consider now Prediction 2. We can use our simple framework to explore this counterfactual by imposing the condition $\bar{z}_{s1} = \bar{z}_{s2} = \bar{z}_s$, where $\bar{z}_s$ is the common average quality of the apps. We study three scenarios: (a) the common quality level is set at the minimum level between the quality levels of the two stores, (b) the common quality level is set at the average level, and (c) the common quality level is set at the maximum level between the quality levels of the two stores. In the period under consideration, our data reveal that before the policy, the average quality of the apps in platform 1 is higher than in platform 2: $\bar{z}_{s1} > \bar{z}_{s2}$. The three scenarios are therefore: (a) $\bar{z}_s = \bar{z}_{s2}$, (b) $\bar{z}_s = (\bar{z}_{s1} + \bar{z}_{s2})/2$, and (c) $\bar{z}_s = \bar{z}_{s1}$.

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

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

Imposing $\bar{z}_{s1} = \bar{z}_{s2} = \bar{z}_s$ in the above expressions q^*_{h1} and q^*_{h2}, where $\bar{z}_s$ takes the values imposed in the three scenarios, we obtain the equilibrium quantities when the policy of imposing the same app quality is introduced. As for the effect on the quantity of platform 1 tablets, the difference between the total quantity of tablets with the policy $\bar{z}_s$ and before the policy is $(3\, z_{h1}\,(\bar{z}_s - \bar{z}_{s1}) - z_{h2}\,(\bar{z}_s - \bar{z}_{s2}))\,/4k$: it follows that in all three scenarios, the impact of the policy on quantities is negative. As for the effect on the quantity of platform 2 tablets, the difference is $(3\, z_{h1}(\bar{z}_{s1} - \bar{z}_s) - 17 z_{h2}\,(\bar{z}_{s2} - \bar{z}_s))/12k$, and the impact of the policy is always positive. We also find that p^*_{h1} decreases when the quality of the apps in the two stores is leveled, while the price of Android-based tablets does not change due to within-platform competition; hence, it follows that in all three scenarios, the overall profits obtained by platform 2 tablet manufacturers grow with the policy, while those of the platform 1 tablet manufacturer decrease.

Finally, if we add up the two differences in the number of tablets demanded on the two platforms, we can obtain the impact of the policy on the overall quantity of tablets. Formally, it can be easily seen that the difference between the total amount of tablets demanded with and without the policy is $(3\, z_{h1}(\bar{z}_s - \bar{z}_{s1}) + 7 z_{h2}\,(\bar{z}_s - \bar{z}_{s2}))/6k$; this last expression is negative in scenario (a) and it is positive in scenarios (b) and (c).[32] Hence, our model predicts that unless the policy leads to a reduction in the average quality of the apps on the two platforms, imposing a common quality stimulates tablet sales. Prediction 2 is also confirmed by our theoretical model.

Model's calibration. We use 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.4 to calibrate our theoretical model and check what it would have suggested about sign and magnitude of the changes in the two counterfactuals. By inserting the values of Table A.4 in the expressions q^*_{h1} and q^*_{h2}, we calibrate the model to back out the equilibrium market shares, the overall profits of tablet manufacturers on the two platforms, and the consumers surplus.[33] As the first counterfactual is concerned, we impose an increase in $\bar{z}_s$ by 0.05 and calculate how prices, markets share (in base points), profits, and consumer surplus change. As regards the second counterfactual, we impose the condition $\bar{z}_{s2} = \bar{z}_{s2}$ and then compute the simulated values. Table A.7 shows the outcomes of these

[32]It should be noted that in scenario (b) for which $\bar{z}_s = (\bar{z}_{s1} + \bar{z}_{s1})/2$, the total quantity of tablets grows with the introduction of the policy if $3z_{h1} < 7z_{h2}$. Based on our estimates reported in Table A.4, this condition is empirically verified.

[33]Calibrations have 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 price p^*_{h2}; knowing the price, the number of tablet producers and the marginal costs of production (see Table A.4), 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.

calibrations. 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, largely confirming the empirical simulation reported in Tables 4 and 5.

A.2 Additional figures and tables

Table A.1: Summary statistics of relevant variables by producers

	N	Mean	Std.dev	Min	Max
Apple					
Market share (s)	360	6.73E-04	8.37E-04	1.09E-05	0.007
Price (p)	360	486.513	120.083	256.302	885.000
Screen size	360	8.850	0.900	7.900	9.700
Storage	360	47.556	37.287	16.000	128.000
Screen resol.	360	14.499	0.654	13.575	14.962
Connectivity	360	1.500	0.501	1.000	2.000
App quality	360	4.208	0.051	4.089	4.275
Samsung					
Market share (s)	741	2.79E-04	3.98E-04	6.67E-07	2.43E-03
Price (p)	741	333.914	126.593	78.155	748.000
Screen size	741	8.813	1.438	7.000	12.200
Storage	741	24.702	13.449	8.000	64.000
Screen resol.	741	13.968	0.672	13.328	15.226
Connectivity	741	1.513	0.500	1.000	2.000
App quality	741	4.196	0.059	4.034	4.265
Other Android Producers					
Market share	2,652	1.33E-04	3.69E-04	7.41E-08	0.011
Price	2,652	209.767	149.788	37.740	1050.000
Screen size	2,652	8.574	1.391	7.000	13.300
Storage	2,652	16.144	13.069	0.512	64.000
Screen resol.	2,652	13.707	0.590	12.858	15.226
Connectivity	2,652	1.276	0.447	1.000	2.000
App quality	2,652	4.194	0.060	4.034	4.265
Income (in 100K)	500	0.272	0.177	0.052	0.995

Notes: Connectivity is one if it 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 (Screen resol.). 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.

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

Variables	Price		$\mathrm{Ln}(s_j \in g)$		Application quality	
	Parameters	SE	Parameters	SE	Parameters	SE
Constant	-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
Screen resol.	82.808**	2.247	0.306**	0.060	4E-04	0.001
Screen size	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.

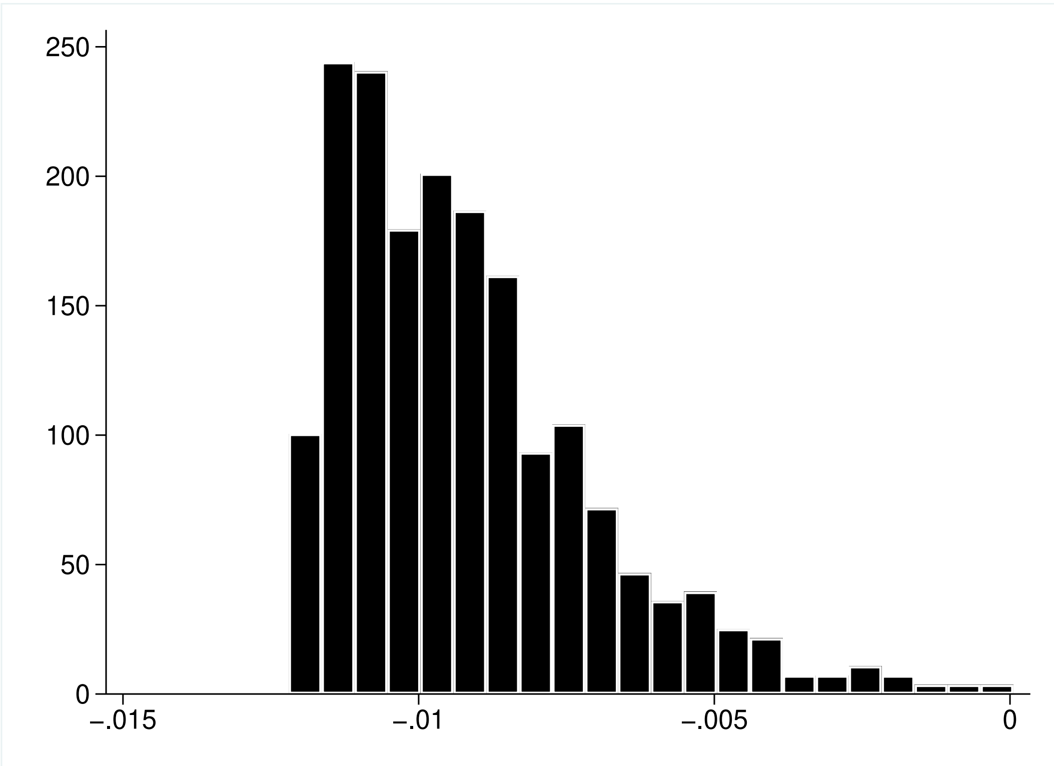

Figure A.1: Frequency distribution of price sensitivity

Table A.3: Inclusion of application variety results

	(1)		(2)	
	Parameter (1)	SE (1)	Parameter (2)	SE (2)
Demand side				
Constant	-12.903**	0.000	-13.407**	0.090
Storage	0.006**	0.001	0.005**	0.001
Screen resol.	0.581**	0.003	0.605**	0.052
Screen size	0.105**	0.001	0.105**	0.017
Connectivity	0.294**	0.000	0.296**	0.045
App variety	-0.071**	0.001	0.270	0.336
App quality	0.418**	0.001	0.480**	0.156
Price (βp)	-0.010**	0.000	-0.010**	0.000
Price (σp)	0.006**	0.001	0.006**	0.002
Price (πp)	0.013**	0.000	0.014**	0.001
Correlation ρ	0.704**	0.006	0.675**	0.021
Pricing equation				
Constant	0.699**	0.000	0.713**	0.044
Storage	0.543**	0.000	0.286**	0.061
Screen resol.	0.004**	0.001	0.004 *	0.002
Screen size	0.239**	0.001	0.248**	0.014
Connectivity	0.113**	0.001	0.121**	0.017
Model Statistics				
N	3753		3753	
Pseudo R^2_D	0.705		0.689	
Pseudo R^2_S	0.641		0.624	
J-stat	13.262		22.474	
N mc<0	9		13	
Average PCM	0.259		0.270	

Notes: The table presents the results of the random coefficients nested logit estimation when we include application variety as the number of apps have monthly downloads greater than the mean monthly download of top 1000 apps in the store. Significance level: $^*p < 0.05$, $^{**}p < 0.01$. Application quality is treated as endogenous. (1): App variety is treated as exogenous, (2): App variety is treated as endogenous. Time, country, and firm fixed effects are included both in the demand and pricing equations but not reported. Instruments: (1): $h_1, h_2, h_4, h_6, h_7, h_8$, (2): $h_1, h_2, h_4, h_5, h_6, h_7, h_8$. PCM=price-cost margin.

Table A.4: 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.5 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 $-\alpha$.

Table A.5: Leveling apps quality - the three scenarios

Country	OS	Pre-policy	(a)	(b)	(c)
France	iOS	4.155	4.138	4.146	4.155
	Android	4.138			
Germany	iOS	4.219	4.180	4.199	4.219
	Android	4.180			
Italy	iOS	4.275	4.149	4.212	4.275
	Android	4.149			
Spain	iOS	4.223	4.034	4.128	4.223
	Android	4.034			
UK	iOS	4.266	4.146	4.186	4.266
	Android	4.146			

Table A.6: 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
Connectivity	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
Connectivity	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: $^{*}p < 0.05$, $^{**}p < 0.01$. 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.

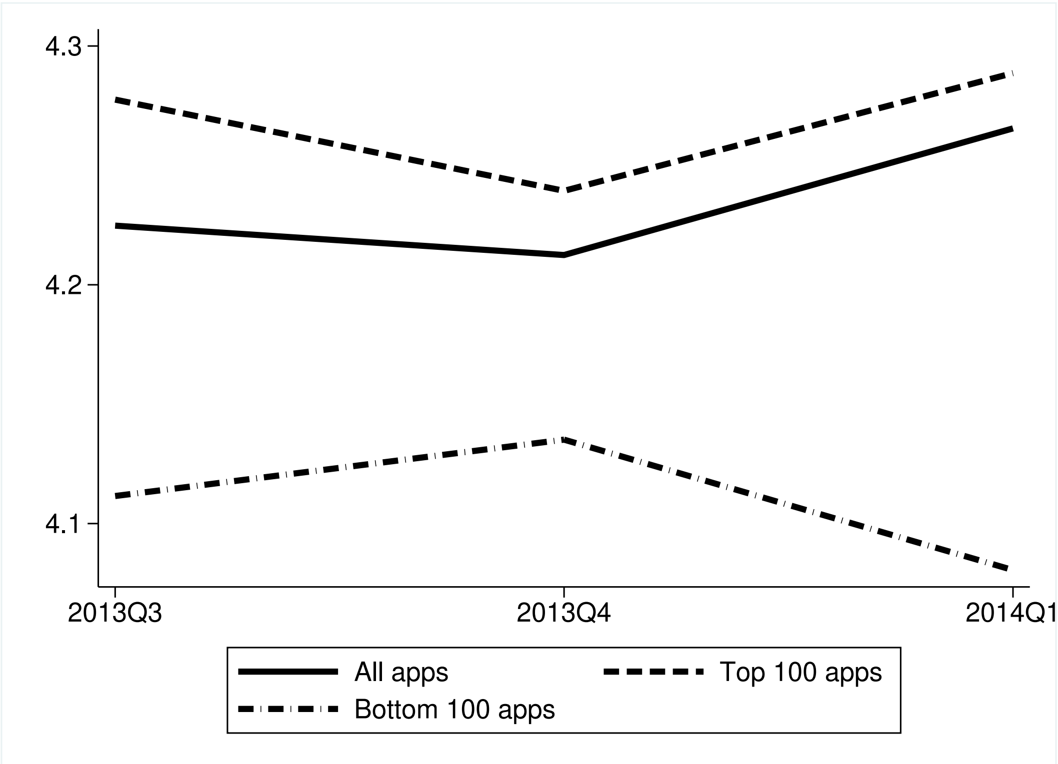

Figure A.2: The weighted average of application rating of all apps, top 100, and bottom 100 applications (based on total downloads) of the 1000 most downloaded applications. Example based on the UK Apple App Store

Table A.7: Calibrating counterfactuals

		France	Germany	Italy	Spain	UK
Counterfactual 1 - Increasing the weighted average rating of each store						
Increase in Apple app store quality						
Apple market share changes (bps)		12.43	12.56	12.49	12.48	12.52
Android market share changes (bps)		-4.14	-4.19	-4.16	-4.16	-4.17
Apple avg price change (€)		1.24	1.26	1.25	1.25	1.25
Android avg price change (€)		0	0	0	0	0
Apple profit changes (€ thousand)		1163.63	2308.46	1468.28	1560.95	1867.45
Android profit changes (€ thousand)		-332.70	-464.34	-312.74	-317.31	-346.86
Change in consumer welfare (€ thousand)†		581.81	1154.23	734.19	780.47	933.73
Increase in Google Play app store quality						
Android market share changes (bps)		20.24	20.22	18.69	20.26	17.89
Apple market share changes (bps)		-3.57	-3.57	-3.30	-3.58	-3.16
Android avg price change (€)		0	0	0	0	0
Apple avg price change (€)		-0.36	-0.36	-0.33	-0.36	-0.32
Android profit changes (€ thousand)		1625.13	2242.36	1404.22	1504.65	1487.02
Apple profit changes (€ thousand)		-324.90	-644.14	-380.02	-440.24	-463.01
Change in consumer welfare (€ thousand)††		4386.88	5686.72	3613.65	3249.06	3519.33
Counterfactual 2 - Leveling apps quality						
Apple	Sc					
Total market share changes (bps)	(a)	-4.21	-9.82	-31.48	-41.47	-30.02
	(b)	-2.71	-6.31	-19.89	-30.35	-18.78
	(c)	-1.21	-2.79	-8.31	-13.51	-7.57
Avg price changes (€)	(a)	-0.42	-0.98	-3.15	-4.72	-3.00
	(b)	-0.27	-0.63	-1.99	-3.04	-1.88
	(c)	-0.12	-0.28	-0.83	-1.35	-0.76
Total profit changes (€ thousand)	(a)	-382.07	-1761.46	-3492.89	-5569.64	-4272.82
	(b)	-246.59	-1135.38	-2242.28	-3642.00	-2708.92
	(c)	-110.38	-504.32	-951.43	-1648.37	-1104.71
Android						
Total market share changes (bps)	(a)	1.40	3.27	10.49	15.73	10.00
	(b)	4.12	9.54	28.89	46.16	26.45
	(c)	6.85	15.82	47.11	76.58	42.90
Avg price changes (€)	(a)	0	0	0	0	0
	(b)	0	0	0	0	0
	(c)	0	0	0	0	0
Total profit changes (€ thousand)	(a)	112.54	363.23	788.13	1199.45	831.59
	(b)	331.13	1058.65	2163.45	3519.22	2198.33
	(c)	549.73	1754.07	3538.77	5838.98	3565.07
Change in consumer welfare (€ thousand)	(a)*	-191.94	-880.73	-1746.44	-2784.82	-2136.40
	(b)**	641.41	1772.70	3680.19	4776.23	3147.86
	(c)***	1576.16	4441.18	9209.82	12542.29	8525.65

Notes: Basis points (bps): 100 bps = 1%. For example, given the original market share of 1.76% of Apple in France (see Table A.4), 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: 1.71%, 1.34%, 2.08%, 1.51% and 2.84%. ††In percentages, the changes are: 12.92%, 6.60%, 10.25%, 6.30%, 10.72%. *In percentages, the changes are: -0.56%, -1.02%, -4.95%, -5.39% and -6.51%. **In percentages, the changes are: 1.89%, 2.06%, 10.44%, 9.25%, and 9.59%. The percentage change for profits is around 2% in all countries and stores. ***In percentages, the changes are: 4.35%, 5.15%, 26.12%, 24.30% and 25.96%.