CESifo WORKING PAPERS

7434
2018

December 2018

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Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
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Editors: Clemens Fuest, Oliver Falck, Jasmin Gröschl
www.cesifo-group.org/wp

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CESifo *Working Paper No. 7434*
Category 11: Industrial Organisation

Estimating Consumer Inertia in Repeated Choices of Smartphones

Abstract

In this paper, we use a unique dataset on switching between mobile handsets in a sample of about 8,623 subscribers using tariffs without handset subsidies from a single mobile operator on a monthly basis between July 2011 and December 2014. We estimate a discrete choice model in which we account for disutility from switching to different operating systems and handset brands and for unobserved time-persistent preferences for operating systems and brands. Our estimation results indicate the presence of significant inertia in the choices of operating systems and brands. We find that it is harder for consumers to switch from iOS to Android and other operating systems than from Android and other operating systems to iOS. Moreover, we find that there is significant time-persistent heterogeneity in preferences for different operating systems and brands, which also leads to state-dependent choices. We use our model to simulate market shares in the absence of switching costs and conclude that the market shares of Android and smaller operating systems would increase at the expense of the market share of iOS.

JEL-Codes: L130, L500, L960.

Keywords: smartphones, consumer inertia, switching costs, mixed logit, iOS, Android.

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We thank Marc Bourreau, Grazia Cecere, Toker Doganoglu, Tobias Kretschmer, Marc Lebourges, Thierry Pénard, Oleksandr Shcherbakov, Frank Verboven and participants at various seminars for helpful comments. All errors are our own.

1 Introduction

The total number of smartphones sold to consumers worldwide reached 1,536 millions by 2017, which is an increase of more than 1250% from 122 million in 2007.[1] During this period, the market for smartphones was inherently dynamic with new market players rapidly gaining global market shares and others being driven out of the market. In particular, Apple and Samsung entered the market in 2008 and within three years by 2011 reached a joint market share of about 50% globally. Since then their global market shares has been in decline, but they still remain the largest global market players in this industry.[2] At the same time, BlackBerry which was one of the most prominent smartphone vendors early on with sales peaking at 85 million worldwide in September 2013, lost its dominant position due to the success of the Android and iOS platforms. In March 2016, the number of BlackBerry subscribers fell to 23 million.[3] Since 2010, the global market shares of Asian manufacturers such as LG, Huawei, ZTE and Lenovo has been on the rise pushing manufacturers such as HTC and Motorola out of the market and eroding the position of Apple and Samsung.

Smartphones are sold with pre-installed operating systems (OS), thus the sales of smartphones determine the global market shares of operating systems. The big winner is Android with a market share growing from 0 in 2009 to about 85 percent of all smartphones sold to consumers globally in the first quarter of 2017. The second dominant operating system is iOS with market share of 14.7% as of the first quarter 2017. Other operating systems such as Microsoft, RIM, Bada and Symbian have a negligible total market share of 0.3%.[4] The success of smartphone manufacturers is intertwined with the success of operating system.

Due to the role which smartphones play in our daily lives and their increasing role as a platform for distribution of products and services, there is an immense interest in what drives their evolution and success. Fierce competition for the market between iPhone and Galaxy smartphones has already led to a series of ongoing lawsuits between Apple Inc. and Samsung Electronics with respect to the design of smartphones and tablet computers. Moreover, the

[1] Source: www.statista.com
[2] Source: www.businessinsider.com
[3] Source: Blackberry financial statement from April 2016.
[4] Source: www.idc.com

extremely high concentration in the operating systems market and the winner-takes-all feature of this market has drawn attention from policy makers. In 2017, the European Commission charged Google with unfairly using its search engine to promote its own comparison shopping services over those of its rivals. The Commission also looked into Google's relationships with some of the world's biggest manufacturers of mobile handsets, which have helped expand the reach of Android. A formal investigation of over three years ended in July 2018 with the announcement of the Commission imposing a fine of 4.34 billion euro to Google for breaching EU antitrust rules with agreements strengthening its dominant position.

In this paper, we shed light on competition between smartphone manufacturers and operating systems by revealing some facts with respect to consumer behaviour. We estimate consumer choices of smartphone models using a database of subscribers from a single mobile operator in a European country on a monthly basis between July 2011 and December 2014. We focus on the dynamics of the consumer decision problem and estimate consumer inertia with respect to the choice of smartphone brands and operating systems. Of particular interest for us is whether consumers face friction when switching between different brands of smartphones, especially Samsung and Apple, and between the two main operating systems: Android and iOS.

Our estimation results indicate that there is significant inertia in the choices of operating systems and smartphone brands. In general, we observe that it is harder for consumers to switch from iOS to other operating systems. These higher switching costs may be also linked to the cost of changing the ecosystem built by Apple around iPhone. Switching from Android to iOS is also costly but the switching costs in this direction are lower than average. It is also easier than average to switch from Blackberry to iOS. There is no difference from the average in switching from Windows to different operating systems, except to iOS. Since smartphones made by Blackberry and Apple have proprietary operating systems, we cannot separate the inertia with respect to the choices of brands and OS in the cases of these two brands. Moreover, we find that there is significant time-persistent heterogeneity in preferences for different smartphone brands and operating systems, which also leads to state-dependent choices. We use our model to simulate market shares in the absence of OS-specific and brand-specific switching costs and conclude that the market share of Android and smaller operating systems would increase at the expense of the market share of iOS.

The remainder of this paper is organized as follows. Section 2 discusses related literature. Section 3 presents the data used in the estimation. Section 4 introduces the econometric framework. Section 5 presents the estimation results. Finally, Section 6 concludes.

2 Literature review

The literature on the choice and use of smartphones is still very limited and recent, which is due to the fact that this industry came into existence 2007. The second reason is that data which is suitable for such modelling is hardly available. This paper is the first empirical analysis of repeated consumer choices of smartphones and the first attempt to estimate state-dependency in choices of operating systems and handset brands.

Our paper is related to the stream of empirical literature on consumer inertia and switching costs, which are a prominent feature of fixed and mobile telecommunication markets, as empirical evidence suggests. Among papers on switching costs between mobile providers, Cullen and Shcherbakov (2010) use U.S. survey data from 2005-2009 to estimate a model for myopic consumers who choose a service provider and a contract bundled with a handset. Accounting for the durability of the handset, they find that consumers have significant switching costs associated with a change of provider, which amounted to approximately $230 USD. They acknowledge however they are not able to disentangle switching costs from persistent unobserved consumer heterogeneity in their data. In another paper at the provider level, Weiergraeber (2017) uses survey data of U.S. consumers for the years 2006-2010 to estimate a dynamic demand model with both switching costs and network effects. He estimates switching costs in the range of US $40 to US $88. He suggests that he is able to disentangle sources of consumer inertia, which are switching costs and network effects related to the tariff structure with different on-net and off-net pricing. Switching costs are also found to lead to inertia in the choices of tariffs. Grzybowski and Liang (2015) use consumer-level information on a monthly basis for 2013 from a single mobile provider in an European country to estimate switching costs between tariffs. They find significant switching costs which reduce consumer surplus on average by 48-55 Euros per month.

They capture unobserved persistent consumer preferences by estimating random coefficients.

The challenges in the identification of sources of consumer inertia are well established. Heckman (1981) distinguishes true state-dependency, where past experience has a genuine effect on the consumer's decision, from spurious state dependency, where persistent unobserved heterogeneity is correlated with the probability of repeating the same decision. More recently, Dube et al (2010) disentangle different sources of consumer inertia in modeling demand for margarine and refrigerated orange juice, namely loyalty, search and learning. They show that consumer inertia is associated with brand loyalty in their case, but not with search or learning costs.

To the best of our knowledge, only three recent papers estimate demand for smartphones in a structural equilibrium framework, but they do not account for switching costs. In the first paper, Sinkinson (2014) estimates a structural model of demand for smartphones and carriers at the same time. He uses monthly market-level dataset of US consumer decisions between the years 2008-2010 and estimates price elasticities for smartphones and carriers and studies the implications of exclusive contracts for smartphones. Based on counterfactual simulations he concludes that AT&T had the highest willingness to pay for exclusivity with Apple and that this exclusivity increased rival's entry incentives. In the second paper, Hiller, Savage and Waldman (2018) use data on sales of smartphone brands and models in the U.S. in the years 2010-2015 on a quarterly basis to estimate random coefficients demand model. They use demand estimates and a Nash-Bertrand equilibrium framework to simulate the impact of different hypothetical patent infringements on equilibrium outcomes. Fan and Yang (2018) also use data on sales and prices of smartphones in the U.S. in the years 2009-2013 to estimate random coefficients demand model. They use the model to study whether, from a welfare point of view, oligopolistic competition leads to too few or too many products in a market, and how a change in competition affects the number and the composition of product offerings. They find that smartphones market contains too few products and that a reduction in competition decreases both the number and variety of products. Finally, Lou (2018) uses product level data from August 2011 to July 2013 in the U.S. to estimate a structural model of consumer demand and telecom carriers' dynamic pricing game for two-year contract smartphones. She finds that there are significant and positive OS-specific network effects, which are approximated using OS market shares in the estimation.

Furthermore, she finds that telecom carriers internalize OS network effects when pricing their products. Based on counterfactual simulations she concludes that if the two-year contracts were eliminated, consumer surplus and smartphone penetration would decrease.

Finally, there is only one paper by Park and Koo (2016) which attempts to estimate switching costs between smartphones. But the analysis is based on a cross-sectional survey data from Korea and declarations of consumers about switching smartphones in the past. Our study, based on observations of handsets used by consumers over time and structural demand estimation, allows for a more reliable and detailed approach.

3 Data

This analysis is based on two data sets which we combine together. The first data set at the starting point consists of about 113,488 mobile subscribers to a single carrier in a European country who are observed on a monthly basis between June 2011 and December 2014. This data set includes only residential consumers with contracts, i.e., there are no prepaid users and no business customers. There are some consumers who are joining or leaving the operator during this period. From this database, we focus on observations of consumers using handsets which are not subsidized by the operator, i.e., consumers have so called SIM-only tariffs without commitment or with a commitment of 12 or 24 months. There are 27,974 consumers in our database who used these tariffs in at least one month during our period. We focus on these consumers and observations to avoid modeling choices of handsets and tariffs at the same time. The modeling of the consumer decision problem can be greatly complicated when in addition to the choice of handset we would need to consider a large number of tariffs with a different level of subsidy. Thus, consumers in our sample must pay the full price for a handset to which they switch, unless they already had this handset before, received it from someone or purchased with a discount from elsewhere.

From this reduced data set, we select months in which a consumer used a different mobile handset than in the previous month. Such information is recorded in our database because the SIM card used by a consumer automatically detects and registers the model of a handset based on a unique international code called IMEI (International Mobile Equipment Identity). The handset information is registered twice a week on Monday and Thursday. We have information about the handset used by a consumer at the end of each month. We observe 19,873 instances of handset switching by 11,795 customers using SIM-only tariffs. In the full database, we observe 197,876 instances of handset switching by 84,843 customers. Figure 1 shows the percentage of consumers who switched handsets in each month among all consumers observed in the month and among consumers who use a handset without a subsidy (are on a SIM-only tariff). There is less switching in our sample. There are seasonal increases in switching handsets around Christmas.

The second database consists of names and prices of handsets which were advertised by the operator in its catalogues and published on quarterly basis between April 2011 and December 2014. Subscribers can purchase these handsets at listed prices without a subsidy. We collected a long list of handset characteristics from online sources including the release date in the country considered. In 38% of cases, consumers with SIM-only tariffs switched to older handsets which are not listed in the catalogues. We drop these observations because we do not have information on prices and other characteristics for older handsets. Our final sample used in the estimation includes 12,290 instances of handset switching by 8,623 customers.

Table 3 shows the shares of smartphones and iPhones among 113,488 consumers in the original data set and in our sample of 8,623 consumers. The adoption of smartphones grew rapidly in both data sets but the number of iPhone users increased much more in our sample. This is a result of dropping observations with older handsets. Subscribers who opt for handsets without subsidies have a different profile to those using subsidized handsets. As shown in Table 2, even though both groups are comparable in terms of average age and gender distribution, they consume on average more data and voice. Thus, our sample is not fully representative for the customer base of our operator and for the population as a whole. We end up with a higher share of iOS and Apple products. Figure 2 shows the market shares of smartphones with different operating systems in our sample and in the population.

The handset characteristics which we use in the estimation include: (i) list price from the catalogue (ii) brand; (iii) operating system; (iv) screen size; (v) measures: height, thickness and weight; (vi) battery life; (vii) camera resolution; (viii) number of CPU cores; and (ix) speed of

CPU in GHz. The characteristics of handsets do not change over time but the catalogue price may change from one quarter to another.[5] Table 3 shows summary statistics of attributes of handsets used in the estimation and Table 4 shows changes over time of average characteristics of handsets used by consumers. The average price of handsets is comparable but all characteristics improved, thus the quality-adjusted price declined. The characteristics which we use in the estimation are the most important handset attributes considered by consumers when getting a handset.[6]

3.1 Switching between smartphone brands and operating systems

Before moving to econometric estimation we first compute some statistics to illustrate how consumers switch between different handset brands and operating systems using all observations in our sample. Table 5 illustrates switching between feature phones and smartphones with different operating systems, where feature phones are broadly defined as handsets without an operating system, i.e., not smartphones. We observe that 47.7% of switching takes place from Android to Android and 71.8% from iOS to iOS. There is therefore substantial inertia towards using iOS especially. This inertia is not present among users of Windows among whom only 18.6% switch to another smartphone running on Windows. Similarly, only 15.4% of Blackberry users switch to another Blackberry device. Users of Windows tend to switch slightly more to Android (33.7%) than to iOS (31.3%) whereas users of Blackberry clearly switch more to iOS (36.1%) than to Android (22.9%). Users of 'other' operating systems switch more to Android (32.7%) than to iOS (26.4%). Only 4.3% of them switch to a device which also relies on an 'other' operating system.

Finally, 43.9% of users of feature phones switch to another feature phone, which is still a high number. Among 56.1% of feature phone users who switch to a smartphone, 53.8% choose Android versus 23.3% opt for iOS. The higher popularity of Android among users of feature

[5]Since prices come from the catalogues which are published quarterly, we assume that the offer and prices are valid for three months after publication.

[6]According to a 2017 report by consultancy Kantar "An Incredible Decade for Smartphones", in the US, UK and China in 2016, the top 3 purchase drivers among smartphone buyers were (1) screen size, (2) camera quality and (3) phone reliability (US and UK) or screen resolution (China). Phone reliability is related to battery life. The report also indicates that price is the main purchase driver in these three countries.

phones may be due to a greater range of offers of Android smartphones both in terms of brands and specific models. Moreover, iPhones are in general more expensive and first time smartphone users may opt for cheaper brands for their first experience.

The adoption of smartphones is on the rise but there are still some smartphone users who switch back to feature phones (about 7.3% of observations). The smallest share of switchers to feature phones are users of Windows OS (3.4%), followed by BlackberryOS (14.8%) and other OS (18.9%). The highest share of smartphone users who switch to feature phones are among users of devices running on iOS (21.4%) and Android (41.5%). The observed switching patterns indicate that the operating system market is evolving rapidly towards a duopoly of Android and iOS with the remaining operating systems and feature phones losing market shares.

Table 6 illustrates switching between different handset brands. As above, we observe that 71.8% of iPhone users switch to iPhone. Furthermore, 36.1% of Blackberry users and between 1.3% to 26.5% of users of the other brands switch to iPhone. We also observe that 46.3% of Samsung users switch to Samsung, where the percentage of users of other Android brands who switch to Samsung ranges between 28.3% for Sony to 41.5% for LG. At the same time 15.4% of iPhone users and 26.5% of Blackberry users switch to Samsung. The percentage of consumers who switch within the same brand relative to switching to the other brands is also high for the remaining brands. This indicates that there is consumer inertia when switching between smartphone brands, which varies depending on brand.

The statistics discussed above suggest that when consumers purchase smartphones, they are more likely to stick to the same brand and operating system they used previously. There may be different reasons for this including: (i) learning costs, i.e., consumers do not switch because they find it easier to operate a familiar OS, (ii) transaction costs, i.e., it takes time and effort to find a new suitable smartphone and the applications used previously need to be installed; and (iii) there may be OS-specific network effects, for instance, friends may be using the same apps which are not available on all operating systems. But consumers may also simply like the brand and operating system, and thus when switching handsets prefer using the same as before.

4 Model

We estimate a discrete choice model to analyze consumer choices of handsets and operating systems. We construct a consumer choice set in a given month which includes all handsets that were chosen by at least one consumer who switched in this month. The choice set ranges between 74 to 197 unique handsets, which belong to 16 different brands.[7] We do not consider that consumers purchase second hand handsets.[8]

We use a standard linear utility specification which depends on handset characteristics and price.[9] We also account for the heterogeneity in preferences for operating systems and brands by means of random coefficients. The utility of individuals $i = 1, ..., N$ derived from handset $j = 1, ..., J_t$ which are available in month t is given by:

$$U_{ijt} = X_j \beta_i - \alpha_i p_{jt} + S_{ijt} \gamma_i + \epsilon_{ijt} = V_{ijt} + \epsilon_{ijt}. \tag{1}$$

where p_{jt} denotes the price of a handset with individual-specific valuation α_i, and X_j includes the main handset characteristics with valuations β_i: (i) brand; (ii) operating system; (iii) screen size; (iv) measures: height, thickness and weight; (v) battery life; (vi) camera resolution; (vii) number of CPU cores; and (viii) speed of CPU in Ghz. The valuations of these characteristics are the same for all individuals, except individual-specific preferences for brands and operating systems. We also include in the estimation a large number of fixed effects for handsets which are most frequently chosen in our sample. These fixed effects control for unobserved quality of handsets. The individual-specific valuation for handset j at time t, i.e., the "logit error term"is represented by ϵ_{ijt}. It is assumed to be identically and independently distributed over handsets and individuals according to the type I extreme value distribution.

[7] In an alternative model specification, we include all handsets offered at a full price in the catalogue of the operator in a given month in the choice set. This broader choice set includes many handsets which are not used by consumers in the sample but the estimation results are comparable.

[8] This assumption is supported by available market research information. According to Technical Market Index (TEMAX) from the market research firm GfK, only 15% of handsets sold in 2012 were second hand handsets. Moreover, according to Technology, Media and Telecommunications (TMT) Predictions from consultancy firm Deloitte, in 2015 only about 10% of customers from our country considered purchasing a second hand handset.

[9] In the previous version of this paper, the choice set was defined as a combination of handsets and tariffs without commitment and the estimation included tariff characteristics and tariff price. The estimation results for handsets were almost identical.

The vector of switching dummies is denoted by S_{ijt}, which take the value zero when the current choice is the same as the previous one, and the value one otherwise. By construction the coefficients on these variables can be interpreted as the disutility from switching, which is denoted by γ_i. We consider four types of switching dummies. First, we use a dummy variable for switching from a feature phone to smartphone. Second, we use a dummy variable for switching from a smartphone to a feature phone. Third, we estimate average switching costs between operating systems and a set of dummy variables which are specific switching costs between pairs of operating systems. In this way, we allow the disutility from switching to vary depending on the OS from which consumers switch and the OS to which they go. In the case of iPhone and Blackberry, which have proprietary operating systems, switching costs between operating systems and brands are equivalent. For smartphones that operate on Android, Windows and other smaller operating systems, we also estimate the average switching costs between brands.

We allow for consumer-specific switching costs. First, consumers who switched handsets previously are likely familiar with the process. They know how much time it takes to install apps, copy contact list, etc. Thus, their switching costs between operating systems should be lower. We create a dummy variable which in a given month takes a value one if a consumer switched OS before in our data, and zero otherwise. This dummy variable is interacted with a dummy variable for switching OS and it is expected to have a positive coefficient. Second, we consider that the longer consumers use a particular OS, the higher the 'investment' they make in terms of the number of apps installed, familiarity with the system, etc. They should therefore be less willing to switch to an alternative OS. We create four variables which in a given month represent the share of time a consumer previously used each operating system: iOS, Android, Windows and other operating systems. We use shares of time because consumers in our database are observed for a different period of time and the number of observations prior to a handset switch differs. These variables are interacted with our switching dummies from different operating systems and they are expected have negative coefficients. For instance, a consumer who used iOS for a longer period of time relative to other OS, should have higher switching costs to Android, Windows and other OS, than a consumer who used iOS for a shorter period of time.

Apart from switching costs, state-dependent choices of smartphone brands and operating systems may be due to persistent heterogeneity in consumer preferences denoted by β_i. Consumers may continue buying the same brand and OS because it better fits their individual tastes. Separating true state-dependency, which may be caused by switching costs, from spurious state-dependency is challenging. In addition, the observed choices of the first period depend on the choices made in the earlier period, which we do not observe in our data. Moreover, the initial choices also depend on unobserved heterogeneity and are endogenous. Sinkinson (2014) proposes a solution to this problem by simulating choices of individual consumers prior to the start of the data.[10] In our setting, the initial conditions problem is mitigated by the fact that we observe many consumers switching from feature phones to smartphones, and so we observe their first choices of operating system. In 43% of our observations, consumers switch from a feature phone to another feature phone or smartphone. We test for the impact of initial conditions as follows. For all the other consumers in our sample who used smartphones before their first switch, we randomly draw a feature phone from the list of handsets which were advertised in the last catalogue before the start of our data in April 2011. For these consumers we then add in the estimation one more switching observation from randomly assigned feature phones to observed smartphone. By doing this we assume that all users of smartphones had a feature phone before and we model the first choice of OS made by all consumers.

We estimate the following vector of coefficients:

$$\theta_i \equiv \begin{pmatrix} \beta_i \\ \alpha_i \\ \gamma_i \end{pmatrix} = \begin{pmatrix} \beta \\ \alpha \\ \gamma \end{pmatrix} + \Pi D_i + \begin{pmatrix} \sigma_\beta \\ \sigma_\alpha \\ 0 \end{pmatrix} \nu_i \quad , \qquad \nu_i \sim N(0,1) \tag{2}$$

where (β, α, γ) refers to a $(K+1+L) \times 1$ vector of mean valuations for K handset characteristics and L switching costs dummies, D_i is a $d \times 1$ vector of observable individual characteristics, and Π a $(K+1+L) \times d$ matrix of parameters capturing the impact of individual characteristics on the

[10] Other solutions to the problem of endogenous initial conditions for the dynamic probit model are discussed in Heckman (1981) and Wooldridge (2005). Heckman (1981) proposes approximating the conditional distribution of the initial condition. Wooldridge (2005) suggests modelling the distribution of the unobserved effect conditional on the initial value and any exogenous explanatory variables.

valuations, which we only use for selected switching dummy variables S_{ijt}. The randomly-drawn vector from the standard-normal distribution ν_i captures unobserved individual heterogeneity with respect to brands, operating systems and price. The vector of standard deviations around the mean valuations is denoted by $\Sigma = (\sigma_\beta, \sigma_\alpha, 0)$. The random coefficients account for unobserved individual time-persistent preferences for particular brands and operating systems, which may result in state-dependent choices. In this analysis, we do not use any other observable individual characteristics which influence valuations of handset attributes because such information is confidential and not available.

In the special case, where $\sigma_\beta = \sigma_\alpha = 0$, there is no unobserved individual heterogeneity and we obtain the conditional logit model. In a more general framework, we estimate a mixed or random coefficients logit model. The utility function specified above with observed and unobserved heterogeneity and switching costs allows for flexible substitution patterns between handsets. In this way we can capture which handsets are closer substitutes from the consumer's perspective.

4.1 Choice Probabilities and Estimation

Consumers choose a handset that maximizes their utility in a single month. In reality, handsets are durable goods and consumers are forward-looking, i.e., they form expectations about the future range of products, their quality and prices.[11] An individual i switches to a handset m in period t if this handset gives him the highest utility among all the available alternatives, i.e., $U_{imt} = \max_{j \in C_t} U_{ijt}$, where C_t is a choice set in month t, which is the same for all consumers.

Our data is an unbalanced panel, where for consumers who switch more than once in the time period considered we have multiple observations. As shown in Table 7, 74% of consumers in our sample switch handsets only once and the remaining 26% more than once. Hence, the

[11]Gowrisankaran and Rysman (2012) emphasize the importance of dynamic modeling of demand for durable goods, which experience rapid prices declines and quality improvements. They estimate a dynamic structural model using data on the digital camcorder industry.

probability that individual i makes a sequence of one or more handset switches is given by:

$$\begin{aligned} l_{im}(\theta_i) &= \prod_{t=1}^{T_i} \Pr\left(U_{imt} = \max_{j \in C_t} U_{ijt}\right) \\ &= \prod_{t=1}^{T_i} \frac{\exp(V_{imt})}{\sum_{j \in C_t} \exp(V_{ijt})} \end{aligned}$$

where the second line follows from the distributional assumptions of the logit error term ϵ_{ijt}. We need to integrate the conditional choice probability $l_{im}(\theta_i)$ over the joint distribution of θ_i:

$$s_{im}(\theta, \Sigma) = \int_\theta l_{im}(\theta) f(\theta) d\theta. \tag{3}$$

where θ and Σ are the vectors of parameters to be estimated.

The probability that each individual in the sample selects the sequence of alternatives as observed can be written as the log-likelihood function:

$$\mathcal{L}(\theta, \Sigma) = \sum_{i=1}^{N} \log(s_{im}(\theta, \Sigma)) \tag{4}$$

To approximate the integral entering the choice probabilities $s_{im}(\theta, \Sigma)$ in (3), we use a simulation method taking R draws for vector ν from the joint normal distribution to obtain the average choice probability per individual:

$$\widehat{s}_{im}(\theta, \Sigma) = \frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T_i} \frac{\exp(V_{imt}^r)}{\sum_{j \in C_t} \exp\left(V_{ijt}^r\right)} \tag{5}$$

The maximum simulated likelihood estimators are the values of parameters θ and Σ which maximizes the likelihood function $\mathcal{L}$ given by equation (4) after substituting the probability function (5) into it.[12]

[12]The algorithm for estimating a mixed logit model is explained in detail in Train (2003). We estimate the mixed logit model using the Stata procedure mixlogit with 200 Halton draws.

5 Estimation results

The estimation results for the conditional and mixed logit models are shown in Table 8. In Model I, we estimate average switching costs between brands and operating systems. In Model II switching costs are allowed to vary between pairs of operating systems. In Model III, we introduce individual-specific interaction terms with switching costs, i.e., variables which approximate learning about how to switch between operating systems and 'investments' made into an OS in terms of time. Model IV introduces random coefficients on price, handset brands and operating systems, which account for unobserved time-persistent preferences of consumers. We discuss the construction of these variables in Section 4. The estimates in all four regressions are comparable. The log-likelihood values indicate that the model with OS-specific switching costs is preferred to the model with average switching costs between OS and brands. Moreover, the model with unobserved brand and OS preferences and the additional individual-specific variables is preferred to the other three models. Below we discuss the estimates of Model IV.

The coefficient estimates can be divided into handset characteristics, switching costs and unobserved heterogeneity. The coefficient for handset price is highly significant at -0.0015. We include in the estimation 28 fixed effects for handsets which are most frequently chosen in our sample. These 28 products altogether represent 65% of handsets selected in our sample. The estimates of fixed effects are highly significant but we do not show them in the paper to save space. After inclusion of product fixed effects, some product characteristics become insignificant.[13] We can interpret significant handset characteristics in terms of willingness to pay, i.e., by dividing their estimated coefficients by the coefficient on handset price. The coefficient on weight is significant and negative at -0.0026, which implies that consumers are willing to pay 1.7€ to reduce weight by 1 gram. Thickness appears to be positively valuated, which is counterintuitive and caused by inclusion of product fixed effects. Battery life is positively valuated with a coefficient of 0.0447, which implies that in average, consumers are willing to pay 29.8€ per additional hour of battery life in talk time. Handsets with camera are in average more appreciated, with a willingness to pay of 251€ for the camera. The number of CPU cores

[13] We estimated models with a different number of fixed effects. The inclusion of a greater number of fixed effects absorbs variation in product attributes but the estimates of switching costs remain unchanged.

is significant and positive but the speed of CPU in GHz is insignificant.

We find that there are significant switching costs between operating systems and brands, which vary across OS pairs. The average switching costs between different operating systems are estimated at -0.336. The disutility from switching between brands on the same operating system is estimated on average to be -0.172. In terms of willingness to pay, these numbers translate to approximately 224€(=-0.336/-0.0015) and 115€, which are substantial monetary switching costs between OS and brands. Switching costs from feature phones to smartphones and from smartphones to feature phones are both significant and negative, with comparable coefficients of -0.653 and -0.690 respectively. The cost of switching varies greatly between operating systems and brands. In particular, switching from iOS to other operating systems and brands is much harder. The highest cost of switching is estimated from iOS to other operating systems such as Symbian and Bada followed by the cost of switching from iOS to Windows. It is also harder to switch from Android to other OS including Symbian and Bada compared to switching from Android to Windows and Blackberry, with a cost close to the average. On the other hand, the cost of switching from Android to iOS is below average. For Windows and Blackberry, the cost of switching to other operating systems is close to the average, except that it is easier to switch from Blackberry and Windows to iOS, as reflected by the significant and positive coefficients.

Overall, we find asymmetry in the cost of switching from iOS to Android and from Android to iOS. The much higher cost of switching from iOS may be due to the fact that iPhone users tend to have other devices from Apple, such as iPad or Mac, which have limited compatibility with other brands. Thus, what we estimate may be the cost of switching the whole ecosystem of iPhone. Figure 3 compares switching costs between pairs of operating systems in monetary terms based on the willingness to pay calculation, which also account for individual-specific switching costs discussed next.

The additional individual-specific interaction terms introduced in Model III are highly significant with anticipated signs. Consumers who switched OS before have on average lower switching costs between operating systems. When consumers do not know whether they will be able to use easily installed apps and services, they may be reluctant to switch to a smartphone with a different OS. But after they went through OS switching once, they have lower disutility from doing it again. This suggests that switching costs between operating systems arises partly from transactional costs such as learning how to switch, time needed to install apps, etc. Furthermore, the interaction terms of switching cost dummies with the ratios of time spent using different operating systems are positive. Consumers who have been using a particular OS for a long period of time have higher disutility from switching to other operating systems. These switching costs may be linked to 'investment' which consumers make in using an OS, such as a greater number of installed apps.[14] We find the OS-specific 'investment' are the highest for iOS, followed by Windows and Blackberry. The coefficient estimated for Android is insignificant, which implies no cost arising from 'investment'.[15]

Model IV accounts for heterogeneity in consumer preferences for brands and operating systems. We estimate a significant heterogeneity of tastes as reflected by significant standard deviations on all brand coefficients, except Apple. The estimates of heterogeneity vary across brands with the highest estimates of standard deviations for Sony and HTC, and the lowest for Sony Ericsson and Blackberry. There is also significant unobserved heterogeneity for Android, as reflected by the statistically significant estimate of standard deviation on the dummy variable for Android.[16]

We use the estimates to compute aggregate own and cross price elasticities for selected models, for which we use the formulas shown in the Appendix. The computation is done for a single month (January 2014) because different models are available in different months. Because of a large number of models in the data we cannot show the full matrix of estimates and report only the ten top-selling products, which are mainly smartphones manufactured by Apple and

[14] As of 2017 there were approximately 3.2 million Android-exclusive apps, 1.6 million iOS-exclusive apps and 450,000 multi-platform apps. Source: Mobile Trends for 2018.

[15] The value of a smartphone to a consumer depends on the availability and quality of apps on its OS and indirectly on the number of other users. For instance, Luo (2018) estimates OS network effects which are approximated by their market shares. In an alternative model specification, we also tried to approximate the role of network effects in OS choices and interacted country-level OS market shares with OS dummy variables. A higher market share of OS should increase its value to consumers. This approach towards estimating network effects is however imprecise and does not produce interesting results.

[16] As discussed in Section 4, in alternative specification we tried to account for endogenous initial conditions by simulating previously used feature phones and modeling the first choice of OS by all consumers in our sample. The model is estimated using a smaller sample of 7,013 consumers for whom we observe 13,205 instances of handset switching (10,207 without simulated switching from feature phone to smartphone). The sample is smaller because we model choices of different handsets and price information is missing for some of them. The estimates of switching costs between OS decrease substantially, which indicates that our switching costs may be overestimated when initial choices of smartphones are not considered.

Samsung, as shown in Table B.1. Smartphones produced by the same manufacturer are closer substitutes to each other, which is driven by both switching costs and unobserved preferences. In Table B.2 we also show a matrix of aggregate own and cross price elasticities on the brand level. There is asymmetry in substitution between different brands, which is again driven by switching costs, unobserved heterogeneity and the number of products which belong to different manufacturers in the choice set.

Next, we use the model to simulate the market shares of brands and operating systems in the absence of switching costs. To do this we set the estimates of switching costs between brands and OS to zero, including individual-specific switching costs. Since we estimated the highest disutility from switching from iOS to other operating systems, in the absence of switching costs iOS loses market share, while Android's market share increases. As of January 2014, in the absence of switching costs the market share of iOS in our sample would drop from 32.6% to 22.7%. At the same time, the market share of Android would increase from 30.7% to 35.2%, with the smaller operating systems gaining market share as well (see Figure 4). Our sample is skewed towards iOS, but we can expect that market shares change in a similar direction in the wider population. We can therefore conclude that the market position of Android in the absence of switching costs between operating systems and brands would be closer to monopoly.

Our model is estimated using data from a single mobile operator, and for consumers using SIM-only tariffs and non-subsidized handsets. We also excluded consumers who switch to older and thus cheaper handsets, which are not listed in our catalogues. As a result, our sample consists of consumers who use mobile phones more intensively and have stronger preferences for Apple products (see Table 3). They may have lower switching costs between operating systems and brands. Moreover, we use only observations for consumers who switch handsets and must have lower switching costs than the others.

6 Conclusions

This is the first paper which relies on detailed consumer-level data on choices of handsets over time to shed light on consumer inertia in choices of smartphone brands and operating systems.

Our analysis contributes to the understanding of the role which inertia plays in the evolution of shares of market players and competition between iOS and Android.

We estimate consumer choices of smartphones using a database of subscribers to a single mobile operator in a European country on a monthly basis between June 2011 and December 2014. We find that there is significant inertia in the choices of operating systems and smartphone brands. We observe that it is harder for consumers to switch from iOS to other operating systems, while switching to iOS is easier than average. There is no difference from the average in switching from Windows to different operating systems, except to iOS. Smartphones made by Blackberry and Apple have proprietary operating systems and the state-dependency between operating systems and brands cannot be separated. Moreover, we find that there is significant time-persistent heterogeneity in preferences for different smartphone brands and operating systems, which also leads to state-dependency of choices. However, due to endogenous initial conditions problem our switching costs may be overestimated.

The observed and estimated state-dependency may have different reasons including: learning costs, transaction costs and OS-specific network effects. In one model specification, we account for different sources of switching costs. First, we find that consumers who switched operating systems before have lower switching costs and thus it is easier for them to switch again. This suggests that switching costs between operating systems arise partly from transactional costs such as learning how to switch, time needed to install apps, copy contact list, etc. Second, we find that consumers who have been using a particular OS for a long period of time have higher disutility from switching to other OS. This suggests that switching costs may be linked to 'investment' which consumers make in using an OS, such as a greater number of installed apps.

We use our model to simulate the market shares of brands and operating systems in the absence of switching costs. Since we estimated the highest disutility from switching from iOS to other operating systems, in the absence of switching costs iOS and Apple lose market share, while Android's market share increases. We conclude that in the absence of switching costs between operating systems and brands the market position of Android would be closer to monopoly.

Our estimates suggest that smartphone manufacturers and owners of operating systems have substantial market power over consumers. Apple in particular is able to exploit presence of large switching costs and charges prices which are higher than the prices of comparable products from other manufacturers. The key component of Apple's strategy is to create an ecosystem around the iPhone including other products such as the iPad and Mac, which increases consumer switching costs. However, as our simulation suggests, these large switching costs might have prevented the industry from tipping towards Android, in which case the antitrust concerns would be even bigger.

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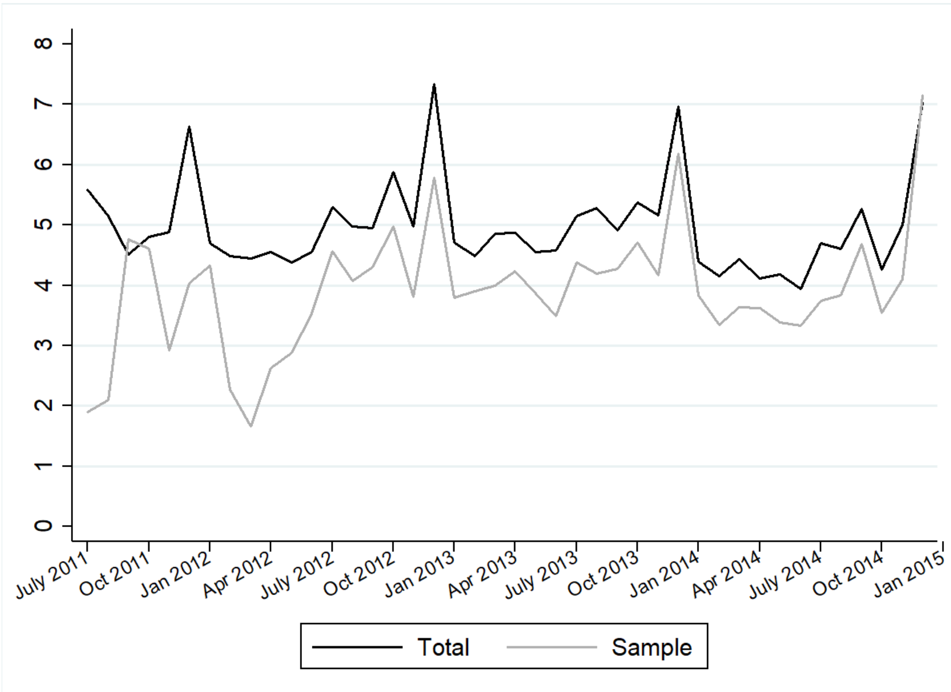
Appendix A

Figure 1: Share of subscribers who switch handsets (%)



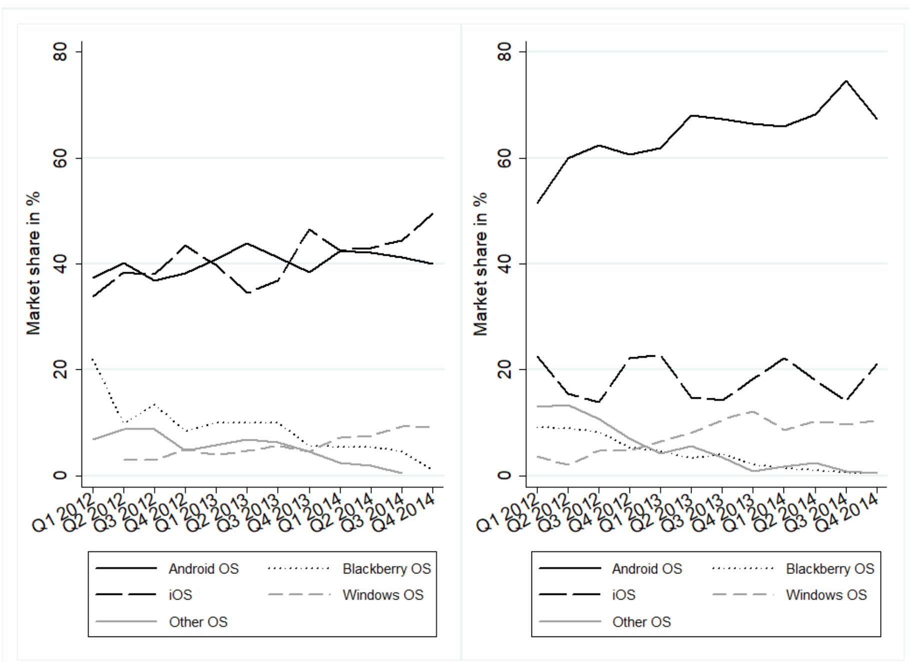
Total: 113,448 individuals; Sample: 27,974 individuals using SIM-only tariffs.

Table 1: Average prices of handsets and shares of smartphones and iPhones

	Total			Sample		
Quarter	Price (€)	Smartphone (%)	iPhone (%)	Price (€)	Smartphone (%)	iPhone (%)
Q3 2011	273	39	9	318	55	9
Q4 2011	300	49	15	337	48	18
Q1 2012	297	52	14	304	45	15
Q2 2012	287	52	12	320	52	20
Q3 2012	294	57	14	354	63	24
Q4 2012	329	67	20	392	72	31
Q1 2013	303	65	15	356	65	26
Q2 2013	302	64	15	335	64	22
Q3 2013	300	66	15	306	66	24
Q4 2013	333	75	22	351	76	35
Q1 2014	313	73	17	329	75	32
Q2 2014	313	74	18	325	76	33
Q3 2014	322	77	21	334	81	36
Q4 2014	362	83	27	366	89	44
Total	309	63	17	344	74	32

Total: 84,843 individuals; Sample: 8,623 individuals. Only switching consumers are considered.

Figure 2: Smartphone OS market shares in the sample and for the whole population



Sample: 8,623 individuals; Source for population data: Kantar Worldwide Panel

Table 2: Consumer demographics and phone usage in the sample

	Total				Sample			
	Female	Age	Data use	Minutes use	Female	Age	Data use	Minutes use
2011	53%	47.8	0.09	172.6	52%	46.4	0.09	157.9
2012	52%	47.3	0.16	171.6	44%	44.6	0.29	230.1
2013	51%	49.4	0.22	163.7	51%	47.4	0.33	230.6
2014	51%	50.9	0.34	170.4	50%	48.5	0.58	213.9
Total	52%	48.3	0.17	169.9	50%	47.4	0.43	222.6

Total: 84,843 individuals; Sample: 8,623 individuals. Only switching consumers are considered.

Table 3: Characteristics of available handsets

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Handset price (in €)	301.6	172.1	34.9	799.9
Height (mm)	115.2	15.5	67	172
Width (mm)	58.5	8.7	26	85.9
Thickness (mm)	12.2	3.3	6.7	40
Screen size (inches)	3.3	1.1	1	10.1
Battery life: talk time (hours)	8.1	4.3	2.8	24
Speed of CPU (GHz)	0.7	0.7	0	2.7
Number of CPU cores	1.2	1.3	0	8

Sample of 278 unique handsets

Table 4: Characteristics of available handsets by year

	2011	2012	2013	2014
Handset price (in €)	294.7	283.1	280.0	283.6
Height (mm)	108.2	109.8	112.2	120.2
Width (mm)	54.6	55.8	56.9	61.4
Thickness (mm)	13.4	13.1	12.7	11.4
Screen size (inches)	2.8	2.9	3.1	3.7
Battery life: talk time (hours)	6.3	6.7	7.3	9.6
Camera quality (mpixels)	3.5	3.8	4.2	6.1
Speed of CPU (GHz)	0.4	0.4	0.5	0.9
Number of CPU cores	0.5	0.7	0.8	1.6
Number of handsets	165	207	236	162

Table 5: Operating system before and after switching handset (% of observations)

		OS after switching						
		Android	Blackberry	Windows	iOS	Other OS	Feature phone	Total
Before switching	Android	47.7	3.5	5.8	26.2	1.5	15.4	100
	Blackberry	22.9	15.4	5.2	36.1	2.7	17.7	100
	Windows	33.7	3.1	18.6	31.3	3.1	10.3	100
	iOS	15.4	3.0	2.3	71.8	0.9	6.7	100
	Other OS	32.7	4.3	7.9	26.4	4.3	24.4	100
	Feature phone	30.2	4.7	4.6	13.1	3.6	43.9	100
	Total	30.0	4.7	4.8	31.9	2.5	26.1	100

12,290 observations of switching

Table 6: Brand before and after switching handset (% of observations)

		Brand after switching									
		Apple	BBerry	HTC	LG	Nokia	Samsung	Sony	Son.Eric.	Others	Total
Before switching	Apple	71.8	3.0	1.3	1.0	3.6	15.4	2.2	0.7	1.0	100
	BlackBerry	36.1	15.4	1.3	3.4	9.1	26.5	3.8	1.5	3.0	100
	HTC	23.0	3.2	11.2	2.9	10.2	39.9	5.1	1.3	3.2	100
	LG	18.2	3.9	2.7	5.3	13.5	41.5	4.3	1.8	8.8	100
	Nokia	16.9	4.2	2.2	3.7	23.0	36.8	3.4	1.3	8.5	100
	Samsung	19.5	4.1	1.4	4.1	11.3	46.3	5.1	1.2	7.0	100
	Sony	23.0	1.3	2.0	3.3	9.9	28.3	29.0	0.7	2.6	100
	Sony-Ericsson	16.4	5.2	2.2	4.3	11.1	36.5	10.9	6.9	6.4	100
	Other brands	16.1	5.6	1.4	4.8	13.7	36.2	4.9	1.0	16.4	100
	Total	31.9	4.7	1.8	3.4	11.4	34.4	4.7	1.4	6.3	100

12,290 observations of switching

Table 7: Switching per individual

	Freq.	Percent
1	6,384	74.03
2	1,467	17.01
3	464	5.4
4	173	2.0
5	62	0.72
6	32	0.37
7	14	0.16
8	9	0.1
> 8	18	0.21
Total	8,623	100

Table 8: Estimation results

	Model I	Model II	Model III	Model IV
Mean				
Handset characteristics				
Handset price	-0.0015***	-0.0015***	-0.0015***	-0.0015***
	(0.00)	(0.00)	(0.00)	(0.00)
Apple	1.8132***	1.4296***	1.1522***	0.9458***
	(0.20)	(0.20)	(0.20)	(0.21)
BlackBerry	0.5807***	0.4766***	0.3685***	-0.2291
	(0.10)	(0.11)	(0.11)	(0.17)
HTC	-0.5250***	-0.5217***	-0.5125***	-1.4829***
	(0.09)	(0.09)	(0.09)	(0.25)
LG	-0.1203	-0.1160	-0.1116	-0.9031***
	(0.07)	(0.07)	(0.07)	(0.19)
Nokia	0.3101***	0.3210***	0.3405***	-0.1148
	(0.06)	(0.06)	(0.06)	(0.10)
Samsung	0.3005***	0.3164***	0.3416***	0.3780***
	(0.05)	(0.05)	(0.05)	(0.06)
Sony	0.2034**	0.2088**	0.2162***	-0.8292***
	(0.06)	(0.06)	(0.06)	(0.23)
Sony Ericsson	-0.3482***	-0.3436***	-0.3381***	-1.0397***
	(0.09)	(0.09)	(0.09)	(0.30)
Battery life: Talk time	0.0436***	0.0438***	0.0440***	0.0447***
	(0.01)	(0.01)	(0.01)	(0.01)
Screen size	0.0020	0.0029	0.0029	0.0223
	(0.05)	(0.05)	(0.05)	(0.05)
Height	0.0011	0.0011	0.0010	0.0008
	(0.00)	(0.00)	(0.00)	(0.00)
Weight	-0.0023***	-0.0023***	-0.0023***	-0.0026***
	(0.00)	(0.00)	(0.00)	(0.00)
Thickness	0.0292***	0.0291***	0.0289***	0.0282***
	(0.01)	(0.01)	(0.01)	(0.01)
Camera	0.3788***	0.3794***	0.3791***	0.3762***
	(0.07)	(0.07)	(0.07)	(0.07)
Number of CPU cores	0.2999***	0.3065***	0.3076***	0.3088***
	(0.02)	(0.02)	(0.02)	(0.02)
Speed of CPU in Ghz	-0.0096	-0.0050	-0.0065	-0.0239
	(0.06)	(0.06)	(0.06)	(0.06)
Android Os	0.0084	-0.0328	-0.1351	-0.3102**
	(0.08)	(0.09)	(0.09)	(0.10)
Windows Os	0.0867	-0.0041	-0.1698	-0.5177**
	(0.09)	(0.11)	(0.11)	(0.16)
Handset FE for 28 most popular models	Yes	Yes	Yes	Yes
Switching costs				
Switching from feature phone to smartphone	-1.2867***	-1.1083***	-0.9007***	-0.6533***
	(0.08)	(0.09)	(0.09)	(0.09)
Switching from smartphone to feature phone	-1.4708***	-1.6274***	-1.0021***	-0.6898***
	(0.08)	(0.09)	(0.10)	(0.11)
Switching cost for changing o.s.	-1.4574***	-1.3554***	-0.7195***	-0.3358**
	(0.03)	(0.10)	(0.11)	(0.13)
Switching cost for changing o.s. * Dummy for already switched o.s. before	1.2850***	1.2567***	1.0309***	1.4409***
	(0.07)	(0.07)	(0.08)	(0.09)
Switching cost for changing brand	-0.5565***	-0.5070***	-0.4166***	-0.1722***

	(0.04)	(0.04)	(0.04)	(0.05)
Switching from Android to iOS		0.5276***	0.4770***	0.3834**
		(0.11)	(0.11)	(0.13)
Switching from Android to Blackberry OS		0.0398	-0.1568	-0.2391
		(0.16)	(0.16)	(0.18)
Switching from Android to Windows OS		0.2477	0.0802	0.0683
		(0.14)	(0.14)	(0.16)
Switching from Android to other os		-0.2815	-0.5998**	-0.6854**
		(0.22)	(0.22)	(0.22)
Switching from iOs to Android		-0.6940***	-0.1766	-0.3112*
		(0.11)	(0.12)	(0.13)
Switching from iOs to Blackberry OS		-0.3440*	0.1699	0.0852
		(0.16)	(0.16)	(0.18)
Switching from iOs to Windows OS		-0.9564***	-0.3642*	-0.4132*
		(0.17)	(0.17)	(0.19)
Switching from iOs to other os		-1.0231***	-0.6625**	-0.7440**
		(0.24)	(0.24)	(0.24)
Switching from Blackberry OS to Android		-0.3355*	-0.2885	-0.3232
		(0.14)	(0.15)	(0.17)
Switching from Blackberry OS to iOs		0.5735***	0.7986***	0.7868***
		(0.14)	(0.14)	(0.16)
Switching from Blackberry OS to Windows OS		-0.1083	0.0018	0.0478
		(0.21)	(0.21)	(0.24)
Switching from Blackberry OS to other		-0.2558	-0.3139	-0.3080
		(0.27)	(0.27)	(0.28)
Switching from Windows OS to Android		-0.0477	0.1388	0.2854
		(0.18)	(0.21)	(0.24)
Switching from Windows OS to iOs		0.3087	0.6747**	0.7653**
		(0.19)	(0.21)	(0.25)
Switching from Windows OS to Blackberry OS		-0.4272	-0.2184	-0.0766
		(0.37)	(0.38)	(0.42)
Switching from Windows OS to other		0.1036	0.1820	0.0575
		(0.38)	(0.39)	(0.41)
Previous experience				
Switching from Android* Previous experience Android			-0.3141**	-0.4218***
			(0.10)	(0.12)
Switching from iOS * Previous experience iOS			-1.6227***	-2.1462***
			(0.10)	(0.12)
Switching from BB* Previous experience BB			-0.7501***	-0.7406***
			(0.17)	(0.21)
Switching from Windows* Previous experience Windows			-1.1279***	-1.3484***
			(0.26)	(0.33)
Standard Deviation				
Handset price				-0.0020***
				(0.00)
Apple				-0.2249
				(0.16)
BlackBerry				1.2559***
				(0.13)
HTC				1.4952***
				(0.19)
LG				1.4270***
				(0.16)
Nokia				1.2794***
				(0.11)
Samsung				0.7769***
				(0.09)
Sony				1.8083***

				(0.20)
Sony Ericsson				1.3388***
				(0.27)
Android Os				1.0265***
				(0.08)
Windows Os				0.8674***
				(0.19)
Observations	1,559,919	1,559,919	1,559,919	1,559,919
Unique choices	12,290	12,290	12,290	12,290
Unique consumers	8,623	8,623	8,623	8,623
Log likelihood	-49,490	-49,366	-49,216	-48,880

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 3: Estimated switching costs between operating systems (in terms of WTP)

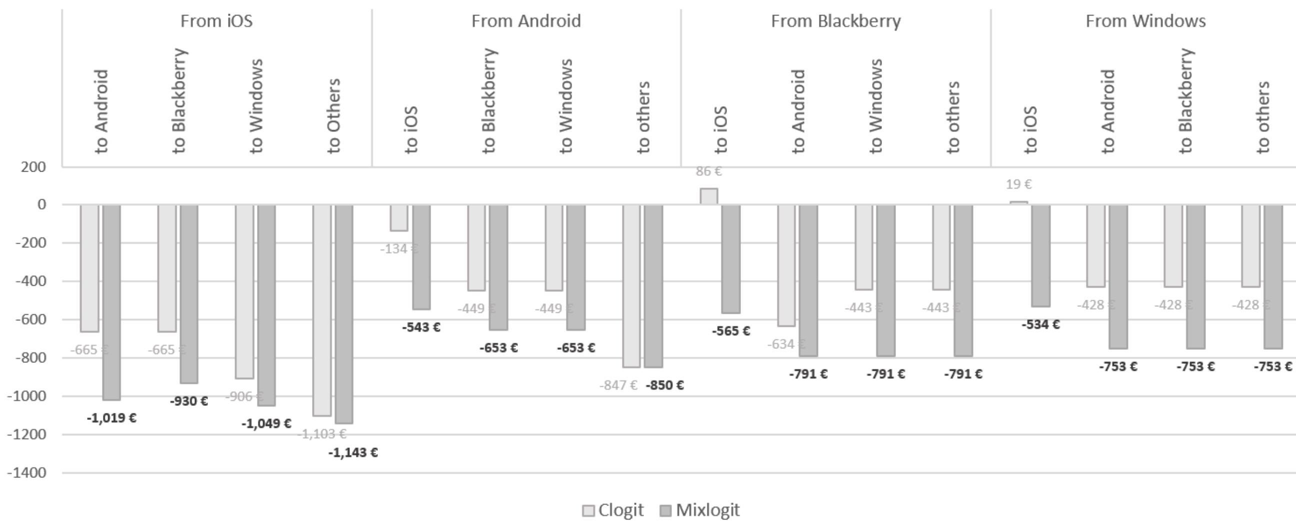
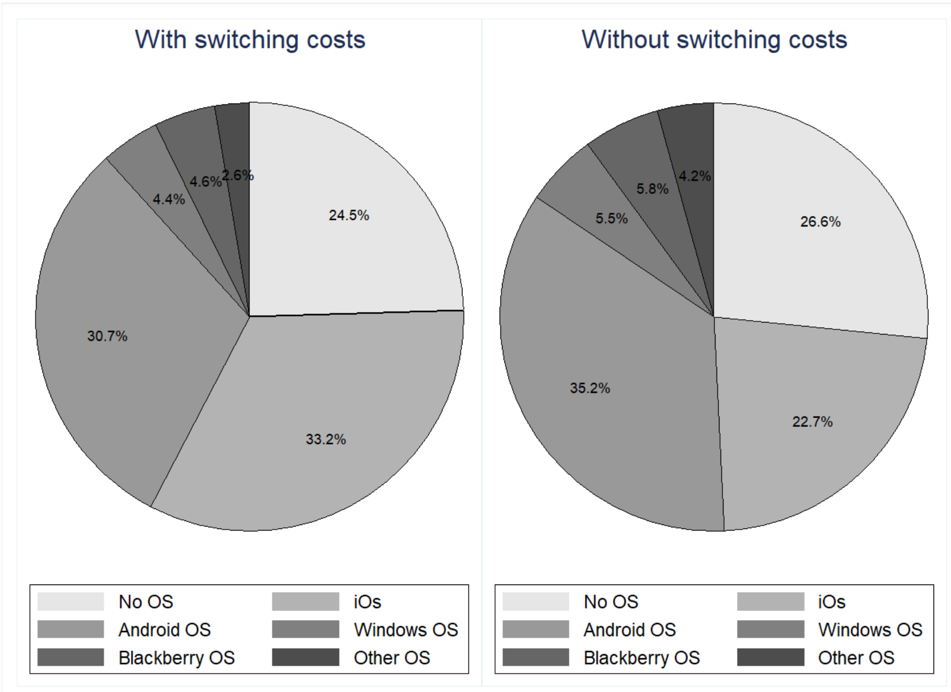


Figure 4: Simulation results for January 2014



Appendix B: Price elasticities

The model can be used to calculate price elasticities of demand. In particular, we report a matrix of own- and cross- price elasticities for selected products (smartphone models), and a matrix of elasticities for the main brands in our sample. In the derivation below we skip the time subscript t for ease of notation.

Product-level elasticities To calculate the own- and cross-price elasticities at the level of the individual products we proceed as follows. Let the aggregate market share for product j be given by $s_j \equiv \sum_i s_{ij}/N$, where N is the number of consumers. The effect of a *percentage* price increase of product k on the *level* of individual i's probability of choosing product j is:

$$\frac{\partial s_{ij}}{\partial p_k} p_k = \begin{cases} -\alpha_i s_{ij}(1-s_{ij})p_j & \text{if k=j} \\ \alpha_i s_{ij} s_{ik} p_k & \text{otherwise} \end{cases}.$$

This could also be called individual i's semi-elasticity of demand for j with respect to the price of k. Using $s_j \equiv \sum_i s_{ij}/N$, the aggregate product-level semi-elasticity is defined as the sum:

$$\frac{1}{N}\sum_i \frac{\partial s_{ij}}{\partial p_k} p_k = \begin{cases} \frac{1}{N}\sum_i(-\alpha_i) s_{ij}(1-s_{ij})p_j & \text{if k=j} \\ \frac{1}{N}\sum_i \alpha_i s_{ij} s_{ik} p_k & \text{otherwise} \end{cases}.$$

This is the effect of a percentage price increase on the level of aggregate demand for product j. The aggregate product-level elasticity of demand for product j with respect to the price of k is defined as:

$$\varepsilon_{jk} = \frac{1}{N}\left(\sum_i \frac{\partial s_{ij}}{\partial p_{ik}} p_{ik}\right)\frac{1}{s_j} = \begin{cases} \sum_i(-\alpha_i) s_{ij}(1-s_{ij})p_j/\sum_i s_{ij} & \text{if k=j} \\ \sum_i \alpha_i s_{ij} s_{ik} p_k/\sum_i s_{ij} & \text{otherwise} \end{cases}.$$

Brand-level elasticities Brand-level elasticity is a percentage change in demand for a group of products belonging to a given brand in response to a 1% change in the price of all products in this brand. To calculate the price elasticity at the level of a brand $j \in \delta$ (e.g. Apple, Samsung, Nokia) we proceed as follows. Let the aggregate market share for products $j \in \delta$ be given by $s_\delta \equiv \sum_i \sum_{j\in\delta} s_{ij}/N$. The effect of a *percentage* price increase of products belonging to δ on the *level* of the individual choice probability of choosing from the brand δ is:

$$\sum_{j\in\delta}\sum_{k\in\delta} \frac{\partial s_{ij}}{\partial p_k} p_k = -\alpha_i \sum_{k\in\delta} s_{ik} p_k (1 - \sum_{j\in\delta} s_{ij}).$$

Using $s_\delta \equiv \sum_i \sum_{j\in\delta} s_{ij}/N$, the aggregate brand-level semi-elasticity is defined as the sum:

$$\frac{1}{N}\sum_i \left[\sum_{j\in\delta}\sum_{k\in\delta} \frac{\partial s_{ij}}{\partial p_k} p_k\right] = \frac{1}{N}\sum_i (-\alpha_i)\Big[\sum_{j\in\delta} s_{ik} p_k (1 - \sum_{j\in\delta} s_{ij})\Big].$$

This is the effect of a joint percentage price increase of all products in brand δ on the level of aggregate demand for products from brand δ. The aggregate brand-level elasticity of demand for the brand δ with respect to a joint percentage price increase is then defined as:

$$\varepsilon_\delta = \frac{1}{N}\sum_i \left[\sum_{j\in\delta}\sum_{k\in\delta}\frac{\partial s_{ij}}{\partial p_k}p_k\right]\frac{1}{s_\delta} = \sum_i(-\alpha_i)\Big[\sum_{k\in\delta}s_{ik}p_k(1-\sum_{j\in\delta}s_{ij})\Big]/\sum_i\sum_{j\in\delta}s_{ij}.$$

Table B.1: Elasticities at product-level for selected top-selling handsets in January 2014

	Apple iPhone 3GS	Apple iPhone 4	Apple iPhone 4S	Apple iPhone 5	Apple iPhone 5S	Nokia Lu. 520	Samsung E1190	Samsung Galaxy S3	Samsung Gal. Trend	Samsung Galaxy Y
iPhone 3G S	-0.731	0.040	0.032	0.037	0.043	0.009	0.002	0.022	0.009	0.005
iPhone 4	0.069	-0.766	0.061	0.070	0.080	0.017	0.003	0.042	0.017	0.010
iPhone 4S	0.060	0.065	-0.618	0.061	0.070	0.015	0.003	0.036	0.014	0.009
iPhone 5	0.045	0.049	0.040	-0.737	0.053	0.011	0.002	0.028	0.011	0.007
iPhone 5S	0.061	0.066	0.054	0.062	-0.841	0.016	0.003	0.038	0.015	0.009
Lumia 520	0.017	0.018	0.015	0.017	0.020	-0.273	0.001	0.018	0.007	0.004
E1190	0.015	0.016	0.013	0.015	0.018	0.007	-0.059	0.018	0.007	0.004
Galaxy S3	0.021	0.023	0.018	0.021	0.025	0.009	0.002	-0.709	0.010	0.006
Galaxy Trend	0.016	0.018	0.014	0.017	0.020	0.007	0.001	0.019	-0.277	0.005
Galaxy Y	0.018	0.020	0.016	0.019	0.022	0.008	0.002	0.021	0.008	-0.169

Table B.2: Elasticities at brand-level in January 2014

	Apple	Blackberry	HTC	LG	Nokia	Other	Samsung	Sony	Sony-Ericsson
Apple	-0.740	0.159	0.216	0.193	0.233	0.115	0.685	0.280	0.126
Blackberry	0.029	-0.388	0.034	0.031	0.038	0.020	0.111	0.043	0.020
HTC	0.009	0.007	-0.607	0.010	0.012	0.006	0.037	0.015	0.007
LG	0.013	0.012	0.018	-0.380	0.020	0.011	0.061	0.023	0.011
Nokia	0.025	0.022	0.033	0.031	-0.250	0.020	0.111	0.042	0.020
Other	0.015	0.014	0.021	0.021	0.025	-0.188	0.074	0.027	0.013
Samsung	0.039	0.035	0.052	0.050	0.060	0.032	-0.389	0.068	0.032
Sony	0.018	0.015	0.024	0.022	0.026	0.013	0.078	-0.567	0.014
Sony-Ericsson	0.007	0.007	0.010	0.009	0.011	0.006	0.033	0.013	-0.469