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Abstract

For a sample of 9,799 subscribers to a single mobile operator, we observe switching between mobile handsets 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 brands. Our estimation results indicate the presence of significant inertia in the choice of operating systems and brands. 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 in such context.

Key Words: *Smartphones; Consumer Inertia; Switching Costs; Mixed Logit; iOS; Android*

JEL Classification: L13, L50, L96

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I Introduction

Within one decade, smartphones became almost indispensable in daily life of billions of people. By 2018, the total number of smartphones sold to consumers worldwide reached 1,555 million, which is an increase of more than 1100% from 122 million in 2007.[1] There are many smartphone manufacturers worldwide but as of today the industry is dominated by a handful of global companies including Samsung, Apple, Huawei, Xiaomi and Oppo. In particular, Apple and Samsung entered the market in 2008 and within three years achieved a joint market share of approximately 50% globally. Since then, their global market shares have been in decline, but they still remain the two largest global market players in this industry.[2]

The sales of smartphones determine the global market shares of pre-installed operating systems (OS). The operating systems are multi-sided platforms which match smartphone users and application developers. The value of the OS to users depends on the range and quality of available apps. There is an intense competition between app developers, who often provide apps for free or at very low prices. Essentially, there are two operating systems, iOS and Android, which have been competing with each other since the start of smartphone industry with different market strategies. iOS is a proprietary closed system belonging to Apple, which places relatively tight restrictions on third-party developers. The availability of high quality apps on iOS increases the value of the iPhone and allows Apple to extract high margins from its sales. At the same time, the iOS platform is more profitable for third-party developers than Android, which may be because iPhone's users are more loyal and tend to spend more on apps than Android users do (see Hagiu [2014]). Google's Android has a different strategy because it relies on revenues from advertising in connection to its search engine. Android is an open-source system: it can be adopted by any device manufacturer and modified to provide different functionality.[3] Google is also more liberal with respect to developers for its

[1]Source: Gartner

[2]Source: www.idc.com

[3]Google offers manufacturers an anti-fragmentation agreement (AFA) to ensure that pre-installed apps on the device work properly. Some additional agreements may also be signed between manufacturers and Google, such as the Mobile Application Distribution Agreement (MADA), which standardizes the device users' experience, and the Revenue Sharing Agreement (RSA), which ensures some form of exclusivity to Google's products. An overview of these agreements can be found in Etro and Caffarra [2017].

three-sided Android platform. Eventually, Android became the dominant OS, with a market share growing from zero in 2009 to approximately 85% of all smartphones sold to consumers globally by the end of 2018. iOS holds the second position with a market share of 14.9%. Other operating systems such as Windows Phone and BlackBerry have negligible market share.[4] The role of switching costs in the battle between iOS and Android is an important research question.

In this paper, we shed light on competition between smartphone manufacturers and operating systems by revealing some facts with respect to consumer behavior. We estimate consumers' choice of smartphone models using a database of subscribers from a single mobile operator in a European country; the data are on a monthly basis and collected between July 2011 and December 2014. We focus on the dynamics of the consumer decision problem and estimate consumer inertia with respect to choosing a smartphone brand and operating system. 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 choice of operating system and smartphone brand. In general, we observe that it is harder for consumers to switch from iOS to other operating systems. These higher switching costs may also be linked to the cost of moving away from the ecosystem built by Apple around the 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 the average to switch from BlackBerry to iOS, and there is no difference from the average switching costs when moving from Windows to different operating systems, except for iOS. Because smartphones manufactured by BlackBerry and Apple have proprietary operating systems, we cannot separate the inertia with respect to the choice of brand 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 conduct counterfactual simulations. First, we simulate market shares

[4] Source: www.idc.com

in the absence of OS-specific and brand-specific switching costs. This scenario is related to the increasing availability or ease of use of apps which allow to migrate users' data. We conclude that in such context, the market share of Android and smaller operating systems would increase at the expense of the market share of iOS. Our results confirm that there is tipping toward a single platform in the smartphone OS market. Apple managed to maintain market share due to presence of high switching costs to other brands and operating systems.

We also use our model to comment on whether a smartphone manufacturer can successfully launch its own operating system and stop using Android.[5] In particular, we simulate OS and brand market shares when Samsung develops its own OS. The market share of this new OS and hence Samsung depends on its value to consumers and the magnitude of switching costs. We show that if the value of the new OS were equal to Android, the market share of Samsung's Android smartphones would decrease from 20.4% to 17.6% due to switching costs. The overall Samsung share including feature phones and smartphones with other OS would decrease from 34.2% to 31.7%. At the same time, the market share of other manufacturers using Android would increase from 17.6% to 18.9%. The market share of iOS would also increase marginally from 28.4% to 29.2%. Thus, the vast majority of current Samsung users would continue with Samsung rather than switch to other manufacturers using Android or to other operating systems. We can conclude that for such value of new OS, switching costs from Android will not prevent consumers from adopting the new OS. Furthermore, if the joint value of the Samsung brand and its new OS would be equal to the value of iOS, the market share of Samsung would increase to 47.7% in the presence of switching costs. Thus, the valuation of the new OS by consumers has a critical impact on the market share of Samsung.

The remainder of this paper is organized as follows. Section II discusses related literature. Section III presents the data used in the estimation. Section IV introduces the econometric framework. Section V presents the estimation results and Section VI discusses counterfactual simulations. Finally, Section VII concludes.

[5]In May 2019, the US Commerce Department designated Huawei to Entity List, thus preventing it from buying products or services from US companies or using their technologies. In response to this decision, in August 2019, Huawei launched its own operating system, HarmonyOS, planning to switch to it in case it could not use Android in the future.

II Related literature

The literature on the choice and use of smartphones is still very limited and recent because this industry only came into existence in 2007. Moreover, data suitable for modeling smartphone choice are hard to find. This paper is the first empirical analysis of repeated consumer choices of smartphones and the first attempt to estimate state dependency in the 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 two prominent features of fixed and mobile telecommunication markets. 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. They acknowledge, however, that they are unable to disentangle switching costs from persistent unobserved consumer heterogeneity in their data. In another paper at the provider level, Weiergräber [2018] 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 $40 to $88. The main contribution of this paper is to disentangle sources of consumer inertia, namely, the switching costs and the network effects arising from the tariff structure, which differentiates on-net and off-net usage. Switching costs are also found to lead to inertia in the choice of tariffs. In another paper, Grzybowski and Liang [2015] use consumer-level information from a single mobile provider in a European country on a monthly basis for 2013 to estimate switching costs between tariffs. They find significant switching costs that reduce consumer surplus by 48-55€ per month on average. They capture unobserved persistent consumer preferences by estimating random coefficients.

The challenges to identifying 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, Dubé, Hitsch and Rossi [2010] disentangle different sources of consumer inertia in modeling demand for margarine and refrigerated orange juice, namely loyalty, search cost and learning cost. They show that, in their case, consumer inertia is associated with brand loyalty but not with search or learning costs.

To the best of our knowledge, only five recent papers estimate demand for smartphones in a structural framework, but they do not account for switching costs. In the first paper, Sun [2012] uses monthly data on sales of smartphones in the U.S. in the years 2007-2009. He estimates an equilibrium model of aggregate smartphone demand and application supply to analyze the impact of the app stores on the brand value of three smartphone operating systems: iOs, BlackBerry, and Android. He finds that the app stores contributed to the growth in the value of the three platforms. Moreover, he highlights that platform openness to developers participation was a critical factor for achieving brand value growth in the market transition to two-sided platforms.

In the second paper, Sinkinson [2014] estimates a structural model of demand for smartphones and carriers simultaneously. He uses a monthly market-level dataset of US consumer decisions between the years 2008-2010 and estimates price elasticities for smartphones and carriers. Next, he 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 entry incentives.

In the third 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 the 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.

In the fourth paper, Fan and Yang [2018] also use data on the sales and prices of smartphones in the U.S. in the years 2009-2013 to estimate a random coefficients demand model. They use the model to study whether, from a welfare perspective, oligopolistic competition leads to too few or too many products in a market and how a change in competition affects the number and composition of product offerings. They find that the smartphone market contains too few products and that a reduction in competition decreases both the number and the variety of products.

Finally, Luo [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 she approximates 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 two-year contracts were eliminated, consumer surplus and smartphone penetration would decrease.

In addition, there is one paper by Park and Koo [2016] that attempts to estimate switching costs between smartphones. Nevertheless, the analysis relies on cross-sectional survey data from Korea in which individuals declare their willingness to switch their handset given their current device and a restricted choice set of new handsets selected by the researchers. Our study, based on observations of handsets used by consumers over time and structural demand estimation, allows for a more reliable and detailed approach.

III Data

This analysis is based on two data sets that we combine together. The first data set initially consists of approximately 84,843 mobile subscribers to a single carrier in a European country; they 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. Some consumers do join or leave the operator during this period. From this database, we focus on observations of consumers using handsets that are not subsidized by the operator, i.e., consumers who 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 at least one month during our study period. We focus on these consumers and observations to avoid modeling choices of handsets and tariffs with subsidies together.

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 different levels of subsidy. Thus, the consumers in our sample must pay the full price for the handset that they switch to, unless they already had it before, received it from someone or purchased it second-hand at a lower price.

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 the 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. For comparison, in the full database, we observe 197,876 instances of handset switching by 84,843 customers. Figure B.6 in the Appendix 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 (who are on a SIM-only tariff). We acknowledge that there is less switching in our sample, although the seasonal increases are similar in both samples, particularly around Christmas.

The second database consists of names and prices of handsets that were advertised by the operator in its catalogs and published on a quarterly basis between April 2011 and December 2014. Subscribers can purchase these handsets at listed prices without a subsidy. This database is complemented by a list of prices from a database purchased from IDC, which contains quarterly information on the revenues and quantities of a representative set of feature phones and smartphones shipped to the country.[6] We also collected a long list of handset characteristics from online sources, including the release date in the country considered. In 28% of cases, consumers with SIM-only tariffs switched to handsets that are not listed in the catalogues. We drop these observations because we do not have information on prices

[6] Source: www.idc.com

and other characteristics for these devices.[7] Our final sample used in the estimation includes 14,268 instances of handset switching by 9,799 customers.

Table A.3 shows the shares of smartphones and iPhones among 84,843 consumers in the original data set and in our sample of 9,799 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 for less popular handsets. Moreover, subscribers who opt for handsets without subsidies have a different profile from those using subsidized handsets. As shown in Table A.2, even though both groups are comparable in terms of average age and gender distribution, the consumers in our sample use, on average, more data and voice. Thus, our sample is not fully representative of the customer base of our operator or for the country population as a whole: we end up with a higher share of iOS and Apple users. Figure A.1 shows the market share of smartphones with different operating systems in our sample and in the population.

The handset characteristics that we use in the estimation include (i) list price from the catalogs; (ii) brand; (iii) operating system; (iv) screen size; (v) dimensions: height, thickness and weight; (vi) battery life; (vii) camera dummy; (viii) number of CPU cores; and (ix) speed of CPU in GHz. The characteristics of handsets do not change over time, but the catalog price may change from one quarter to another.[8] Table A.3 shows summary statistics for the attributes of handsets used in the estimation, and Table A.4 shows changes over time in the 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 that we use in the estimation are the most important handset attributes considered by consumers when getting a handset.

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 A.5 illustrates switching between feature phones and smartphones

[7] The average age of handsets in the choice set is 11.1 months versus 11.7 months for handsets that are dropped.

[8] Because prices are from catalogs that are published quarterly, we assume that the offer and prices are valid for three months after publication.

with different operating systems, where feature phones are broadly defined as handsets without OS, i.e., not smartphones. We observe that among Android users, 56.5% switch to Android, and among iOS users, 66.1% switch to iOS. There is therefore substantial inertia towards using iOS, in particular. This inertia is not present in the case of Windows Phone users, among whom only 17.8% switch to another smartphone running on Windows. Similarly, only 14.4% of BlackBerry users switch to another BlackBerry device. Users of Windows tend to switch more to Android (40.4%) than to iOS (26.6%), whereas users of BlackBerry tend to switch more to iOS (32.2%) than to Android (29.9%). Users of other operating systems switch more to Android (40.4%) than to iOS (22.2%). Only 3.8% of them switch to a device that relies on another OS. Finally, 43.6% of users of feature phones switch to another feature phone, which is still a high number.

Among the 56.4% of feature phone users who switch to a smartphone, 60.1% choose Android versus 20% who opt for iOS. The higher popularity of Android among users of feature phones may be due to the greater range of offers of Android smartphones both in terms of brands and specific models. Moreover, iPhones are generally 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 (7% of observations). The smallest share of switchers to feature phones are users of Windows Phone (3.3%), followed by BlackBerry (13.7%) and other operating systems (19.1%). The highest share of smartphone users who switch to feature phones is among users of devices running on iOS (21.9%) and Android (42%). 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 share.

Table A.6 illustrates switching between different handset brands. As above, we observe that 66.1% of iPhone users switch to iPhone. Furthermore, 32.2% of BlackBerry users and between 14.1% and 18.5% of users of the other brands switch to iPhone. We also observe that 33.8% of Samsung users switch to Samsung, where the percentage of users of other Android brands who switch to Samsung ranges between 27.7% for Sony-Ericsson to 44.5% for Sony. At the same time, 17.3% of iPhone users and 26.8% of BlackBerry users switch to Samsung. The percentage of consumers who switch within the same brand relative to switching to another brand 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 any previously used applications need to be installed again, and (iii) there may be OS-specific network effects, for instance, friends may be using certain apps that are not available on all operating systems. However, consumers may also simply like the brand and operating system, and thus, when switching handsets, they prefer to stay with that brand.

IV Model

We estimate a discrete choice model to analyze consumer choice of handsets and operating systems. We construct a consumer choice set in a given month that includes all handsets that were chosen by at least one consumer who switched in that month. The choice set ranges between 74 and 197 unique handsets that belong to 16 different brands.[9] We do not consider that consumers purchase second-hand handsets.[10]

We use a standard linear utility specification that depends on handset characteristics and price.[11] We also account for the heterogeneity in preferences for operating systems and brands

[9] In an alternative model specification, we include in the choice set all handsets offered at full price in the operator's catalog in a given month. This broader choice set ranges between 150 and 246 unique handsets and includes many that are not used by any consumers in the sample, but the estimation results are comparable. In particular, expanding the choice set in such a way does not have an impact on our estimates of switching costs.

[10] This assumption is supported by the 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. Moreover, according to Technology, Media and Telecommunications (TMT) Predictions from consultancy firm Deloitte, in 2015, only approximately 10% of customers from our focal country considered purchasing a second hand handset.

[11] In the previous version of this paper, the choice set was defined as a combination of handsets and tariff plans without commitment and the utility included tariff characteristics and tariff price. The estimation results

by means of random coefficients. The utility that individuals $i = 1, ..., N$ derive from handset $j = 1, ..., J_t$, which are available in month t, is given by:

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

where p_{jt} denotes the price of a handset with individual-specific valuation α_i, and X_j is a row vector of main handset characteristics with valuations β_i: (i) brand; (ii) operating system; (iii) screen size; (iv) dimensions: height, thickness and weight; (v) battery life; (vi) camera dummy; (vii) number of CPU cores; and (viii) speed of CPU in Ghz. The valuations of these characteristics are the same for all individuals, except for the individual-specific preferences for brands and operating systems as well as price. We also include in the estimation a large number of fixed effects for the handsets that are most frequently chosen in our sample denoted by ξ_j, which control for the unobserved quality of handsets. As we discuss below, we do not let them vary by time due to data constraints. 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.

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

were identical.

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. Apart from switching costs, state-dependent choices of smartphone brands and operating systems may be due to persistent heterogeneity in consumer preferences. Consumers may continue buying the same brand and OS because it better fits their individual taste. We discuss the identification of switching costs in Section IV(ii).

We allow for consumer-specific switching costs as follows. Consumers who have switched operating systems previously are already familiar with the process. They know how much time it takes to install apps, copy their contact list, etc. Thus, their switching costs between operating systems should be lower. We create a dummy variable that in a given month takes the value one for consumers who have 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.

The following decomposition of utility function (1) covers all possible switching situations in period t conditional on the last choice of brand (br) and operating system (os) in period $t-1$:

$$V_{ijt} = \begin{cases} X_j\beta_i - \alpha_i p_{jt} + \xi_j & \text{if } br_t = br_{t-1} \text{ and } os_t = os_{t-1} \\ X_j\beta_i - \alpha_i p_{jt} + \xi_j + \gamma_1 S^1_{ijt} & \text{if } br_t = br_{t-1} \text{ and } os_{t-1} = 0 \text{ and } os_t \neq 0 \\ X_j\beta_i - \alpha_i p_{jt} + \xi_j + \gamma_2 S^2_{ijt} & \text{if } br_t = br_{t-1} \text{ and } os_{t-1} \neq 0 \text{ and } os_t = 0 \\ X_j\beta_i - \alpha_i p_{jt} + \xi_j + \gamma_3 S^3_{ijt} & \text{if } br_t \neq br_{t-1} \text{ and } os_t = os_{t-1} \text{ and } os_{t-1} \in \{\text{Android, Windows, other, 0}\} \\ X_j\beta_i - \alpha_i p_{jt} + \xi_j + \gamma_1 S^1_{ijt} + \gamma_3 S^3_{ijt} & \text{if } br_t \neq br_{t-1} \text{ and } os_{t-1} = 0 \text{ and } os_t \in \{\text{Android, Windows, other}\} \\ X_j\beta_i - \alpha_i p_{jt} + \xi_j + \gamma_2 S^2_{ijt} + \gamma_3 S^3_{ijt} & \text{if } br_t \neq br_{t-1} \text{ and } os_t = 0 \text{ and } os_{t-1} \in \{\text{Android, Windows, other}\} \\ X_j\beta_i - \alpha_i p_{jt} + \xi_j + \gamma_{4i} S^4_{ijt} & \text{if } br_t = br_{t-1} \text{ and } os_t \neq os_{t-1} \text{ and } os_{t-1} \neq 0 \text{ and } os_t \neq 0 \\ X_j\beta_i - \alpha_i p_{jt} + \xi_j + \gamma_{4i} S^4_{ijt} + \gamma_3 S^3_{ijt} & \text{if } br_t \neq br_{t-1} \text{ and } os_t \neq os_{t-1} \text{ and } os_{t-1}, os_t \in \{\text{Android, Windows, other}\} \end{cases}$$

where $os_t \neq 0$ denotes a handset with operating system and $os_t = 0$ without. The coefficient γ_1 captures the switching cost from a feature phone to a smartphone; γ_2 the switching cost from a smartphone to a feature phone and γ_3 captures the average switching cost between brands, excluding Apple and BlackBerry which have their own operating systems. Next, γ_{4i} is a vector of switching costs between operating systems. We allow the coefficients included in γ_{4i} to vary across pairs of operating systems and across individuals depending on whether they switched OS before.

For example, if a consumer switches from a Samsung smartphone to another Samsung smartphone, she will face none of the switching costs described above. If she downgrades to a Samsung feature phone, she will face the switching cost γ_2. Instead, if a consumer previously used a feature phone from Samsung and switches to a smartphone from Samsung, she will face the switching cost γ_1. If a consumer switches from a Samsung smartphone to a HTC smartphone, both functioning on Android, she will only face the switching cost for brand γ_3. Finally, if a consumer who used a smartphone from Samsung switches to an iPhone, she will face the switching cost for operating system γ_{4i}. But if the same consumer switches to a Nokia smartphone operating on Windows, she will face both the switching cost for operating system γ_{4i} and for brand γ_3. Switching costs between brands are estimated in three cases when consumers: (i) switch brand on the same OS; (ii) switch brand and upgrade from a feature phone and a smartphone; (iii) switch brand and downgrade from a smartphone to a feature phone.

We estimate the following vector of coefficients:

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

where $\theta = (\beta, \alpha, \gamma)'$ refers to a $(K + 1 + L) \times 1$ vector of mean valuations for K handset characteristics and L switching cost dummies, D_i is a $d \times 1$ vector of observable individual characteristics, and Π is a $(K + 1 + L) \times d$ matrix of parameters capturing the impact of individual characteristics on the valuations. We only use a dummy variable for previous switching between operating systems. The randomly drawn vector from the standard-normal distribution ν_i captures unobserved individual heterogeneity with respect to price, brand and operating system. The scaling matrix Σ has zeros off the diagonal and the standard deviations around the mean valuations on the diagonal. The random coefficients account for unobserved individual time-persistent preferences for particular brands and operating systems, which may result in state-dependent choices.

In the special case when Σ is a matrix of zeros, there is no unobserved individual heterogeneity and we obtain the multinomial 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.

IV(i) *Choice Probabilities and Estimation*

The consumer chooses a handset that maximizes his utility in a single month. In reality, handsets are durable goods, and consumers may be forward looking, i.e., they may form expectations about the future range of products, their quality and prices.[12] In Section (V), we use information on consumer switching to argue that consumers do not postpone their switching decision before the launch of flagship models by Apple and Samsung. An individual i switches to handset m_t in period t if this handset gives him the highest utility among all the available alternatives, i.e., $U_{im_tt} = \max_{j\in C_t} U_{ijt}$, where C_t is the choice set in month t, which is the same for all consumers.

Our data are an unbalanced panel, where we have multiple observations for consumers who switch. As shown in Table A.7, 72.5% of consumers in our sample switch handsets only once, and the remaining 27.5% switch more than once. Hence, the probability that individual i makes a sequence of one or more handset switches is given by:

$$\begin{aligned} l_i(\theta, \Pi, \Sigma) &= \prod_{t=1}^{T_i} \Pr\left(U_{im_tt} = \max_{j\in C_t} U_{ijt}\right) \\ &= \prod_{t=1}^{T_i} \frac{\exp(V_{im_tt})}{\sum_{j\in C_t} \exp(V_{ijt})} \end{aligned}$$

where the second line follows from the distributional assumptions of the logit error term ϵ_{ijt}.

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

We need to integrate the conditional choice probability $l_i(\theta, \Pi, \Sigma)$ over the joint distribution of ν_i:

$$(3) \quad s_i(\theta, \Pi, \Sigma) = \int_{\nu} l_i(\theta, \Pi, \Sigma) f(\nu) d\nu.$$

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

$$(4) \quad \mathcal{L}(\theta, \Pi, \Sigma) = \sum_{i=1}^{N} \log(s_i(\theta, \Pi, \Sigma))$$

To approximate the integral entering the choice probabilities $s_i(\theta, \Pi, \Sigma)$ 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:

$$(5) \quad \widehat{s}_i(\theta, \Pi, \Sigma) = \frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T_i} \frac{\exp\left(V^r_{im_t t}\right)}{\sum_{j \in C_t} \exp\left(V^r_{ijt}\right)}$$

The maximum simulated likelihood estimator gives the values of parameters θ, Π and Σ, which maximizes the likelihood function $\mathcal{L}$ given by equation (4) after substituting the probability function (5) into it.[13]

IV(ii) *Identification*

We can identify switching costs from the data as follows. First, we can identify switching costs between OS by comparing the choice of smartphone made by consumers who switch from a feature phone with those made by consumers who switch from a smartphone. Assuming that users of feature phones and smartphones have similar preferences for operating systems, the observed inertia towards using the same OS can be attributed to switching costs. In Table A.5 we observe that the share of iOS users who switch to iOS is 66.1%, compared to the 11.3% share of users of feature phones who switch to iOS. Among Android users, 56.5% switch to

[13]The algorithm for estimating a mixed logit model is explained in detail in Train (2009). We estimate the mixed logit model for 200 Halton draws.

Android versus 33.9% among feature phone users. The respective numbers for BlackBerry are 14.4% versus 4.1%, and for Windows, 17.8% versus 4.1%.

Second, the identification of switching costs is aided by monthly variation in the choice set due to the introduction and withdrawal of handsets from the catalogues. As mentioned above, the choice set ranges between 74 and 197 unique handsets on monthly basis that belong to 16 different brands. For example, when a new iPhone is launched by Apple, there are some Android users who switch to iOS. For those who switch, the utility of this new iPhone is greater than the utility of any other Android smartphone in the choice set by at least the magnitude of switching costs. On the other hand, switching costs are too high for those who do not switch. The observations of switching and non-switching individuals between OS, brand and handset type help identifying switching costs.

Third, price changes of the same handset over time also help identifying switching costs. Consumers may switch to another brand and handset type when the price differential becomes sufficiently low. The same concerns changes in the quality of handsets. Table A.4 shows changes over time in the average characteristics of handsets used by consumers. The average price of handsets is comparable, but all characteristics improved.

As discussed above, consumers may also simply like the brand and operating system, and thus, when switching handsets, they prefer to stay with that brand. In our sample, 27.5% of consumers switch handsets two times and more. Many of them repeatedly choose the same brand and operating system even though new high-valued brands and models are introduced on the market. The panel data of consumer choices enable us to identify persistent consumer preferences. However, separating true and spurious state dependency is challenging, as acknowledged in the previous studies (see Dubé, Hitsch and Rossi [2010]; Cullen and Shcherbakov [2010]). It is also demanding for our data to separate in the estimation switching costs from persistent unobserved consumer heterogeneity.

The observed choices of handsets in the first period of our data depend on choices made in the earlier period, which we do not observe. These initial choices also depend on unobserved heterogeneity and are endogenous.[14] In an alternative specification, we account for

[14]Sinkinson [2014] suggests a solution to this problem by simulating the choices of individual consumers prior

endogenous initial conditions as follows. There is a significant number of consumers in our sample (29% of all) who switch from a feature phone to a smartphone and hence are making their first selection of an operating system. For consumers for whom the first observation in our data is a switch between smartphones, we generate additional observations on switching from a feature phone to a smartphone to model their first choice of OS. The sample that we use in the estimation is smaller because price information is missing for some smartphones. We estimate the model for 7,434 individuals for whom we observe 13,128 instances of handset switching (out of which 2915 observations are generated). The estimation results for the multinomial logit are shown in Table B.1 in the Appendix. The estimates of switching costs between operating systems decrease, which suggests that switching costs are overestimated when the initial smartphone and operating system choices are not taken into account.[15]

V Results

V(i) *Estimation results*

The estimation results for the multinomial and mixed logit models are shown in Table A.9. In Model I, we estimate average switching costs between brands and operating systems. In Model II, we account for the endogeneity of price by means of a control function approach. In Model III, switching costs are allowed to vary between pairs of operating systems. In Model IV, we introduce random coefficients on price, handset brand and operating system, which account for unobserved time-persistent preferences. The estimates in all four regressions are comparable. The log-likelihood values indicate that Model III with OS-specific switching costs

to the start of the data. 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 modeling the distribution of the unobserved effect conditional on the initial value and any exogenous explanatory variables.

[15] We consider that the average replacement cycle of handsets in our country is 24 months. The feature phone is randomly drawn from IDC catalogs 24 months before the generated additional switching from a feature phone to a smartphone (i.e., 48 months before the first switching between smartphones observed in the data). Thus, consumers are assigned feature phones from different periods depending on the month in which we observe them for the first time in our data. Consequently, we draw feature phones from IDC catalogs between January 2009 and December 2010. The number of feature phone models per catalog ranges between 63 and 110. We also take into account market shares of handsets in each catalog, so that our random draws are based on their popularity. The estimates are sensitive to the way in which feature phones are assigned.

is preferred to Model II with average switching costs between operating systems and brands. Model IV with unobserved preferences for brands and operating systems is preferred to the other models. The discussion below is based on the results from this model.

We account for the endogeneity of price due to possible correlation with unobserved quality of handsets by means of a control function approach, which involves a two-stage estimation (see Petrin and Train [2010]). Usually, handsets which are more advertised and of higher quality are more expensive because they have higher costs and may be more demanded. When advertising and some handset attributes are not observed, the estimated price elasticities will be biased in the positive direction. The idea behind the control function correction for endogeneity is to derive a proxy variable that conditions on the part of price that depends on the error term, so that the remaining variation in the endogenous variable is independent of the error. We consider that only the key handset attributes enter the utility function directly, such as screen size, camera quality, battery life and few others, which is supported by market research.[16] There are other handset attributes which consumers do not necessarily consider when making their choice, but they impact the cost of manufacturing and, hence, also the price. These handset attributes are our excluded instruments.

The results of the first stage OLS regression are shown in Table A.8 in the Appendix. We use observations on all handsets in the choice set in each month between July 2011 and December 2014, totaling 8,382 observations. The regression shows that Apple is on average 267€ more expensive than handsets from other manufacturers, while BlackBerry smartphones are 137€ more expensive. Smartphones that are LTE compatible are on average 30€ more expensive. A higher CPU speed and a greater number of CPU cores as well as greater height, width and weight imply higher prices. Thicker handsets are on average cheaper. A longer battery talk time and greater quality of the camera positively impact the final price of the device. We also interacted selected features: screen size, thickness and battery life with time trend to account for how their quality changed over time. In the time period considered,

[16] According to the 2017 report by the consultancy firm Kantar 'An Incredible Decade for Smartphones', in 2016 in the US, UK and China, 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.

the average prices of handsets dropped drastically as indicated by declining coefficients on monthly dummy variables. The pricing regression is used to predict the error term, which incorporates factors that affect price but are not captured by handset attributes, including the average value of the unobserved handset attributes.[17]

In the second stage, we estimate a series of discrete choice models, in which the error term (control variable) is added to the observed portion of utility as an additional variable. The estimated coefficient on the control variable is positive and significant, which indicates a positive correlation between the unobserved handset attributes and price. The price coefficient is estimated at -0.002 when control variable is included. Without correcting for endogeneity, in Model I, the price coefficient is biased toward zero and estimated at -0.001. The standard deviation of the random coefficient on price is significant, which indicates that there is heterogeneity with respect to price sensitivity.

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 battery life is 0.01, which gives a willingness to pay of 5€ per hour of talk time. Screen size is positively valuated with a coefficient of 0.27, which implies that on average, consumers are willing to pay 135€ per inch. The coefficient on weight is significant and negative at -0.005, which implies that consumers are willing to pay 25€ to reduce weight by 1 gram. Handsets with cameras are, on average, more valued with a willingness to pay for the camera of 95€. The number of CPU cores is significant and positive as well as the speed of CPU in GHz.[18] The coefficients on height and thickness are not significant.

We also include 50 fixed effects for handsets that are most frequently chosen by consumers in our sample in the estimation. Altogether, they represent over 66% of handsets selected by individuals in our sample. The estimates of fixed effects are highly significant. After inclusion of fixed effects, some handset characteristics become insignificant.[19] There are significant

[17]We also estimated model specification with a broader range of handset attributes, which turn out to be insignificant.

[18]Apple is known to deliver superior CPU performance with fewer cores and lower frequencies on the A series processors compared with the Android phones. This effect is captured in our estimation by the dummy variable for Apple as well as in the 50 models fixed effects that include all iPhones.

[19]We estimated models with different numbers 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.

differences in the valuation of the main brands, which are interpreted relative to the less popular brands not included in the model.[20] These valuations can be computed using a combination of coefficients on brand dummy variables and product fixed effects.

We estimate a significant heterogeneity of taste as reflected by significant standard deviations for all brand coefficients except Apple. The estimates of heterogeneity vary across brands, with the highest estimates of standard deviations being for Sony and HTC and the lowest being for Sony Ericsson and BlackBerry. There is also significant unobserved heterogeneity for Android, as reflected by the statistically significant estimate of the standard deviation on the dummy variable for Android.

In alternative approach, we follow Goolsbee and Petrin [2004] and Berry, Levinson and Pakes [2004] and estimate a multinomial logit model including a set of 400 product fixed effects to control for the quality differences between handsets.[21] In this regression, we drop product attributes, including price, due to collinearity. While the product characteristics of the handsets do not change over time, there is some variation in prices, which decline for some models. However, this variation is not sufficient to identify the price coefficient when a large number of product fixed effects is included in the estimation. The estimates of switching costs, shown in the second column of Table B.2 in the Appendix change only marginally compared to Model III shown in the first column. In the second stage, we regress estimated product fixed effects on a set of product characteristics and price using instrumental variables regression. As instruments we use the same set of product attributes as in the control function approach. The estimation results are shown in the third column of Table B.2 in the Appendix. The price coefficient remains almost unchanged compared to the estimate based on the control function approach. In another specification, we estimate a multinomial logit model with 400 product fixed effects and brand and OS dummies interacted with months. In this way, we account for differences in product quality and for changes in brand quality over time. The estimates of switching costs change only marginally. We show the results from this estimation in Table

[20] The other brands include Acer, Huawei, Icephone, Motorola, Sagem and some country-specific brands.

[21] There are a total of 444 unique handsets in our data. The 400 handsets for which we use fixed effects represent 99.7% of total sales in our sample. We cannot estimate fixed effects for all handsets because there are very few observations for the remaining models, which results in convergence issues during estimation.

B.3 in Appendix.[22]

V(ii) *Switching costs*

We find that there are significant switching costs between operating systems and brands, which vary across OS pairs. Switching costs from feature phones to smartphones (γ_1) and from smartphones to feature phones (γ_2) are both significant and negative, with coefficients of -0.41 and -1.48, respectively. The disutility from switching between brands (γ_3) is estimated on average at -0.51. The average switching costs between different operating systems (γ_4) is estimated at -1.04. In terms of willingness to pay, these numbers translate to approximately 255€ (=-0.51/-0.002) for switching brand and 520€ for switching OS, which are substantial monetary switching costs.

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 and from iOS to Android. On the other hand, the cost of switching from Android to iOS, as well as from BlackBerry to iOS, is below average, as reflected by the significant and positive coefficients. Figure A.2 compares switching costs between pairs of operating systems in monetary terms based on the willingness to pay calculation. 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 because iPhone users tend to have other devices manufactured by Apple, such as an iPad or Mac, which have limited compatibility with other brands. Thus, what we estimate may be the cost of switching away from the whole ecosystem of the iPhone. We also find that consumers who have switched operating systems before have, on average, lower switching costs between operating systems. This suggests that switching costs between operating systems arise partly from transactional costs such as learning how to switch, the time needed to install apps, etc.[23]

[22] We also estimate a model with fixed effects for the 15 most popular handsets interacted with months. Due to a large number of parameters and convergence issues, we cannot estimate a model with a greater number of individual product effects interacted with month.

[23] 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. At the same time, as suggested by Lam [2017], an increase in the

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

V(iii) *Elasticities*

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 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 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.

VI Counterfactual simulations

We use the Model IV in Table A.9 to simulate the market shares of brands and operating systems for a stepwise decline in switching costs. This scenario is related to the increasing

number of apps and their availability on different platforms may reduce switching costs between operating systems. In alternative model specification, we used the number of apps interacted with OS dummy variables to approximate the role of network effects. When doing so, we allow for different functional forms of network effects: linear, logarithmic and s-shaped. We find that the number of apps is nonsignificant in the case of Android and iOS, significant and negative in the case of BlackBerry and significant and positive in the case of Windows. The other estimates are not affected by the inclusion of interaction terms. However, this approach to estimating network effects is imprecise and similar to the inclusion of OS-specific time trends. We do not report these results in the paper.

availability or ease of use of apps which allow to migrate users' data. These apps have evolved significantly in the last years, in terms of quality, speed of transfer and completeness. The early apps were mostly enabling to copy contacts and texts, leaving the transfer of pictures and music to other apps, if existing. Now, the range of apps available to consumers is broad and most smartphone manufacturers develop their own: MovetoiOS (Apple) Samsung Smart Switch (Samsung), OnePlus Switch (OnePlus), Phone Clone (Huawei and Honor), Xperia Transfer Mobile (Sony) and LG Mobile Switch (LG). There are also apps offered by mobile operators and third party developers such as SHAREit or File Transfer. A recent trend is the use of cloud-based services such as Google Drive and Dropbox to migrate data between devices. For example, the use of Google Drive is promoted by Android. Although the variety and quality of apps which enable switching between smartphones and OS have been increasing over the last years, these solutions can be slow, limited in terms of supported files and do not work with all devices. They should improve over time and further reduce switching costs. This scenario may also correspond to the situation studied by Lam [2017]. She considers that if one OS invests in its library, so that its available apps are similar to those offered by a larger library, this increases the utility of consumers through the network externality, but also decreases switching costs between OS.

We implement this counterfactual by multiplying all coefficients related to switching costs by 0.75, 0.5, 0.25 and zero, and illustrate the impact on market shares using 504 consumers in our sample who switch handset in January 2014. Because we estimate the highest disutility for switching from iOS to other operating systems, in the absence of switching costs, iOS loses market share, while Android's market share increases. In the absence of switching costs, the market share of iOS in our sample would drop from 28.4% to 22.4%. At the same time, the market share of Android would increase from 38.0% to 43.8%, with the smaller operating systems gaining market share as well (see Figure A.3). We conclude that the market position of Android, in the absence of switching costs between operating systems and brands, would be closer to a monopoly. Our results confirm that there is tipping towards a single platform in the smartphone OS market. Apple managed to maintain market share due to presence of high switching costs to other brands and operating systems.

Next, we use our model to comment on whether a smartphone manufacturer can successfully launch its own operating system and stop using Android. We motivate this scenario by the fact that in May 2019, the US Commerce Department placed Huawei on the Entity List, thus preventing it from buying products or services from US companies or using their technologies.[24] In response to this decision, in August 2019, Huawei launched its own operating system, HarmonyOS, planning to switch to it in case it could not use Android in the future. We do not observe Huawei in our data because it was not distributed at that time. Instead, we simulate OS and brand market shares when Samsung develops its own OS. We consider that the choice of Samsung is now associated with a new OS of the same value to consumers as Android, i.e., we use the same coefficient estimate. But when the new OS is launched, current Samsung users incur switching costs from Android, which we set to be the same as to 'other OS' that we estimate in Model IV in Table A.9. This cost now discourages Samsung users to continue with Samsung and encourages them to switch to other brands on Android. On the other hand, there are also switching costs between brands, which encourage them to continue with Samsung. As in the previous scenario, we illustrate the impact on market shares using sample of consumers who switch in January 2014. We predict individual choice probabilities, which after averaging yield predicted market shares in the first period after introducing the new OS.

The market share of this new OS and hence Samsung depends on its value to consumers and the magnitude of switching costs. Figures A.4 and A.5 show market shares of operating systems and main manufacturers after launch of the new OS by Samsung for two scenarios: (i) the value of new OS is equal to Android's value; and (ii) the joint value of the Samsung brand and its new OS is equal to the value of iOS. The initial share of Android is 38.0%, where 21.4% are Samsung smartphones. If the value of new OS were equal to Android, the market share of Samsung's Android smartphones would decrease to 17.6% due to switching costs. The overall Samsung share including feature phones and smartphones with other OS would

[24]Based on the definition given by the US Federal Register, the 'Entity List identifies entities for which there is reasonable cause to believe, based on specific and articulable facts, that have been involved, are involved, or pose a significant risk of being or becoming involved in activities contrary to the national security or foreign policy interests of the United States.'

decrease from 34.2% to 31.7%. At the same time, the market share of other manufacturers using Android would increase from 17.6% to 18.9%. The market share of iOS would also increase marginally from 28.4% to 29.2%. Thus, the vast majority of current Samsung users would continue with Samsung rather than switch to other manufacturers using Android, or to other operating systems. We can conclude that for such value of new OS, switching costs from Android will not prevent consumers from adopting the new OS. Furthermore, if the joint value of the Samsung brand and its new OS would be equal to the value of iOS, the market share of Samsung would increase to 47.7% in the presence of switching costs. Thus, the valuation of the new OS by consumers has a critical impact on the market share of Samsung.

VII Conclusions

This is the first paper that relies on detailed consumer-level data on choices of handsets over time to shed light on consumer inertia when choosing smartphone brands and operating systems. Our analysis contributes to the understanding of the role that inertia plays in the evolution of the market shares and competition between iOS and Android. The extremely high concentration in the operating systems market and the winner-takes-all tendency has drawn the attention of policy makers.[25]

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 July 2011 and December 2014. We find that there is significant inertia in the choice of operating system and smartphone brand. We observe 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 smartphone brands and operating systems, which also leads to the state-dependency of choices.

The observed and estimated state-dependency may have different causes, including learn-

[25] 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 taking over three years ended in July 2018 with the announcement that the Commission was imposing a fine of 4.34 billion Euros on Google for breaching EU antitrust rules with agreements that strengthened its dominant position.

ing costs, transaction costs and OS-specific network effects. We find that consumers who have 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 the time needed to learn how to switch, install apps, and copy the contact list.

We use our model to simulate the market shares of brands and operating systems in the absence of switching costs. Because 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 results confirm that there is tipping towards a single platform in the smartphone OS market. Apple managed to maintain market share due to presence of high switching costs to other brands and operating systems. 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.

We also use our model to comment on whether a smartphone manufacturer can successfully launch their own operating systems and stop using Android. We simulate OS and brand market shares when Samsung develops its own OS. The market share of this new OS and hence Samsung depends on its value to consumers and the magnitude of switching costs. We find that if the value of new OS were equal to Android, the vast majority of consumers would continue using Samsung with new OS rather than switch to other brands on Android. We conclude that for such value of new OS, switching costs from Android will not prevent consumers from adopting the new OS.

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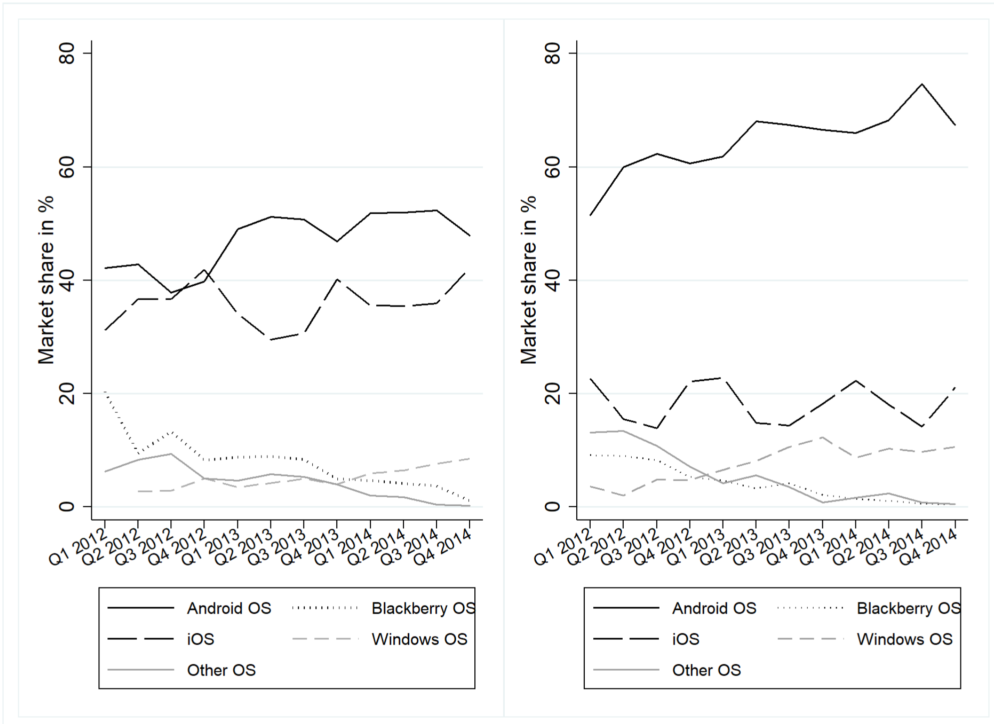
Appendix A

Table A.1: Average prices for handsets and market shares for smartphones and iPhones

	Total			**Sample**		
Quarter	Price (€)	Smartphone (%)	iPhone (%)	Price (€)	Smartphone (%)	iPhone (%)
Q3 2011	272.5	39%	9%	305.78	58%	8%
Q4 2011	299.8	49%	15%	333.33	48%	17%
Q1 2012	296.8	52%	14%	298.99	47%	15%
Q2 2012	287.1	52%	12%	307.95	51%	19%
Q3 2012	294.1	57%	14%	340.56	61%	23%
Q4 2012	328.8	67%	20%	381.87	71%	30%
Q1 2013	302.6	65%	15%	334.31	66%	23%
Q2 2013	301.6	64%	15%	325.29	67%	20%
Q3 2013	300.1	66%	15%	296.27	68%	21%
Q4 2013	333.5	75%	22%	329.03	76%	31%
Q1 2014	313.1	73%	17%	301.79	75%	27%
Q2 2014	313.5	74%	18%	291.06	76%	27%
Q3 2014	321.8	77%	21%	292.51	79%	29%
Q4 2014	362.5	83%	27%	330.82	88%	37%
Total	310.8	63.0%	17.0%	318.61	74%	28%

Total: 84,843 individuals; Sample: 9,799 individuals. Only switching consumers are considered.

Figure A.1: Smartphone OS market share in the sample and for the whole population



Left: sample of 9,799 individuals; Right: Population data based on Kantar Worldwide Panel

Table A.2: Consumer demographics and phone usage in the sample

	Total				Sample			
	Female (%)	Age	Data use	Minutes used	Female (%)	Age	Data use	Minutes used
2011	53	47.8	0.09	172	51	46.3	0.09	160
2012	52	47.3	0.16	171	44	44.7	0.28	227
2013	51	49.4	0.22	163	50	47.3	0.35	233
2014	51	50.9	0.34	170	51	48.7	0.55	208
Total	52	48.3	0.17	170	49	47.3	0.42	220

Total: 84,843 individuals; Sample: 9,799 individuals. Only switching consumers are considered.

Table A.3: Characteristics of available handsets

Variable	Mean	Std. Dev.	Min.	Max.
Handset price (in €)	239.6	172.9	13.6	769.9
Height (mm)	118.7	16.5	67	179
Width (mm)	60.4	9.5	26	92
Thickness (mm)	11.9	3.2	6.2	40
Screen size (inches)	3.5	1.2	1	10.1
Battery life: talk time (hours)	9.3	4.9	2.8	33
Camera	0.9	0.3	0	1
Speed of CPU in Ghz	0.4	0.6	0	2.7
Number of CPU cores	0.7	1.2	0	8

Unweighted average for a sample of 444 unique handsets

Table A.4: Characteristics of available handsets by year

	2011	2012	2013	2014
Handset price (in €)	282.3	259.5	249.5	213.3
Height (mm)	107.3	110.5	114.5	123.5
Width (mm)	54.7	56.2	58.2	62.9
Thickness (mm)	13.2	12.9	12.3	11.1
Screen size (inches)	2.7	3.0	3.2	3.8
Battery life: talk time (hours)	6.6	7.1	8.1	10.6
Camera	0.90	0.90	0.91	0.95
Speed of CPU (GHz)	0.26	0.37	0.42	0.52
Number of CPU cores	0.4	0.5	0.6	0.9

Weighted average across models available each year - 796 observations, 444 unique handsets

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

		OS after switching						
		Android	BlackBerry	Windows	iOS	Other OS	Feature phone	Total
OS before switching	Android	56.5	2.8	5.1	20.8	1.2	13.8	100
	BlackBerry	29.9	14.4	4.7	32.2	2.4	16.4	100
	Windows	40.4	2.9	17.8	26.6	2.6	9.7	100
	iOS	21.0	2.8	2.2	66.1	0.9	7.0	100
	Other OS	40.4	3.6	6.9	22.2	3.8	23.1	100
	Feature phone	33.9	4.1	4.0	11.3	3.2	43.6	100
	Total	36.2	4.1	4.4	27.5	2.2	25.6	100

14,268 observations of switching

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

		Brand after switching									
		Apple	BBerry	HTC	LG	Nokia	Samsung	Sony	Sony-Er	Others	Total
Brand before switching	Apple	66.1	2.8	1.3	1.8	3.6	17.3	2.1	0.7	4.4	100
	BlackBerry	32.2	14.4	1.3	3.7	8.3	26.8	3.4	1.4	8.5	100
	HTC	18.9	2.6	11.0	4.7	8.9	35.6	4.5	1.1	12.8	100
	LG	15.3	3.3	2.4	5.5	12.6	38.6	3.8	1.7	16.9	100
	Nokia	14.6	3.6	1.9	3.7	22.3	35.0	3.2	1.2	14.5	100
	Samsung	12.8	4.4	1.2	5.2	12.8	33.8	4.1	0.9	24.9	100
	Sony	16.5	3.5	1.3	4.3	10.7	44.5	4.5	1.1	13.7	100
	Sony-Ericsson	18.3	1.1	2.1	3.7	8.4	27.8	24.1	0.5	14.1	100
	Other brands	14.1	4.5	2.1	4.2	10.0	34.2	10.0	6.4	14.6	100
	Total	27.5	4.1	1.7	3.8	11.0	33.8	4.2	1.4	12.7	100

14,268 observations of switching

Table A.7: Switching per individual

	Freq.	Percent
1	7,106	72.52
2	1,723	17.58
3	586	5.98
4	212	2.16
5	83	0.85
6	39	0.4
7	19	0.19
8	12	0.12
> 8	19	0.18
Total	9,799	100

9,799 individuals

Table A.8: First stage handset price regression

Handset characteristics		
Apple	266.75***	(6.03)
BlackBerry	136.96***	(4.21)
HTC	57.98***	(3.81)
LG	16.49***	(3.21)
Nokia	19.23***	(2.76)
Samsung	35.73***	(2.51)
Sony	13.89**	(4.50)
Sony Ericsson	46.58***	(3.92)
Other brands	0.00	(.)
Age of handset	-0.68	(0.44)
LTE	29.61***	(3.81)
Screen size	-4.02	(2.62)
Speed of CPU in Ghz	42.41***	(3.36)
Number of CPU cores	17.18***	(1.93)
Height	0.67***	(0.10)
Width	0.77***	(0.20)
Weight	0.51***	(0.04)
Thickness	-2.67***	(0.73)
Battery life: Talk time	5.58***	(0.38)
Camera quality=0	0.00	(.)
Camera quality=3	8.03*	(3.19)
Camera quality=5	76.45***	(3.97)
Camera quality=8	146.82***	(4.70)
Camera quality=10	218.66***	(6.15)
Camera quality=15	264.09***	(9.50)
Camera quality=41	415.34***	(19.65)
Screen size × Age of handset	1.94***	(0.08)
Thickness × Age of handset	0.15***	(0.02)
Battery life: Talk time × Age of handset	-0.35***	(0.02)
Month dummies		
Jul 2011	0.00	(.)
Aug 2011	-3.82	(7.25)
Sep 2011	-8.79	(7.25)
Oct 2011	-13.22	(7.10)
Nov 2011	-18.85**	(7.07)
Dec 2011	-21.84**	(7.00)
Jan 2012	-25.11***	(6.99)
Feb 2012	-30.31***	(6.99)
Mar 2012	-35.05***	(6.98)
Apr 2012	-41.12***	(7.06)
May 2012	-45.01***	(7.06)
Jun 2012	-49.06***	(7.02)
Jul 2012	-50.51***	(7.03)
Aug 2012	-54.62***	(7.03)
Sep 2012	-59.13***	(7.01)
Oct 2012	-60.03***	(6.94)
Nov 2012	-64.26***	(6.97)

Dec 2012	-71.30***	(6.95)
Jan 2013	-72.32***	(6.98)
Feb 2013	-79.75***	(7.03)
Mar 2013	-80.31***	(6.96)
Apr 2013	-88.34***	(7.02)
May 2013	-93.58***	(7.02)
Jun 2013	-116.66***	(7.51)
Jul 2013	-121.67***	(7.42)
Aug 2013	-124.37***	(7.37)
Sep 2013	-128.79***	(7.41)
Oct 2013	-131.53***	(7.56)
Nov 2013	-137.20***	(7.53)
Dec 2013	-142.58***	(7.53)
Jan 2014	-149.67***	(7.52)
Feb 2014	-157.89***	(7.71)
Mar 2014	-167.42***	(7.79)
Apr 2014	-176.59***	(7.80)
May 2014	-180.96***	(7.84)
Jun 2014	-187.54***	(7.87)
Jul 2014	-197.69***	(7.97)
Aug 2014	-203.87***	(7.95)
Sep 2014	-205.38***	(8.04)
Oct 2014	-207.80***	(7.87)
Nov 2014	-225.52***	(8.07)
Dec 2014	-230.30***	(8.08)
Constant	-50.25*	(20.06)
Observations	8,382	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.9: Main estimation results

	Model I		Model II		Model III		Model IV	
Main								
Handset characteristics								
Handset price	-0.001***	(0.00)	-0.002***	(0.00)	-0.002***	(0.00)	-0.002***	(0.00)
Apple	1.72***	(0.18)	1.72***	(0.18)	1.35***	(0.19)	1.27***	(0.19)
BlackBerry	-0.11	(0.11)	-0.00	(0.11)	-0.08	(0.12)	-0.55**	(0.17)
HTC	-0.54***	(0.08)	-0.41***	(0.08)	-0.42***	(0.08)	-1.28***	(0.24)
LG	-0.44***	(0.07)	-0.36***	(0.07)	-0.36***	(0.07)	-0.81***	(0.14)
Nokia	0.09	(0.06)	0.13*	(0.06)	0.12*	(0.06)	-0.20*	(0.08)
Samsung	0.00	(0.05)	0.06	(0.05)	0.04	(0.05)	0.03	(0.05)
Sony	0.04	(0.06)	0.10	(0.06)	0.10	(0.06)	-0.75***	(0.18)
Sony Ericsson	-0.19*	(0.09)	-0.02	(0.09)	-0.03	(0.09)	-0.49*	(0.23)
Battery life: Talk time	0.01**	(0.00)	0.01*	(0.00)	0.01*	(0.00)	0.01*	(0.00)
Screen size	0.20***	(0.04)	0.27***	(0.05)	0.27***	(0.05)	0.27***	(0.05)
Height	-0.00	(0.00)	0.00	(0.00)	0.00	(0.00)	0.00	(0.00)
Weight	-0.00***	(0.00)	-0.00***	(0.00)	-0.00***	(0.00)	-0.00***	(0.00)
Thickness	0.00	(0.01)	0.00	(0.01)	0.00	(0.01)	0.01	(0.01)
Camera	0.20**	(0.07)	0.19**	(0.07)	0.19**	(0.07)	0.19*	(0.08)
Number of CPU cores	0.21***	(0.02)	0.21***	(0.02)	0.21***	(0.02)	0.21***	(0.02)
Speed of CPU in Ghz	0.12*	(0.05)	0.23***	(0.05)	0.23***	(0.05)	0.21***	(0.05)
Android Os	-0.03	(0.07)	-0.16*	(0.08)	-0.20*	(0.09)	-0.27**	(0.09)
Windows Os	0.01	(0.09)	-0.11	(0.09)	-0.26*	(0.10)	-0.62***	(0.16)
Model FE (50 most popular)	Yes		Yes		Yes		Yes	
Switching costs								
feature phone to smartphone (γ_1)	-0.61***	(0.07)	-0.56***	(0.07)	-0.44***	(0.08)	-0.41***	(0.09)
smartphone to feature phone (γ_2)	-1.34***	(0.08)	-1.38***	(0.08)	-1.48***	(0.09)	-1.48***	(0.09)
changing brand (γ_3)	-0.55***	(0.02)	-0.55***	(0.02)	-0.59***	(0.03)	-0.51***	(0.03)
changing OS (γ_4)	-1.40***	(0.03)	-1.40***	(0.03)	-1.08***	(0.09)	-1.04***	(0.10)
changing OS*switched before	1.22***	(0.07)	1.22***	(0.07)	1.18***	(0.07)	1.56***	(0.08)
from Android to iOS					0.12	(0.11)	0.11	(0.12)
from Android to BlackBerry					-0.38*	(0.15)	-0.35*	(0.17)
from Android to Windows					0.54***	(0.13)	0.51***	(0.15)
from Android to other OS					-0.16	(0.21)	-0.23	(0.22)
from iOs to Android					-0.86***	(0.10)	-0.95***	(0.11)
from iOs to BlackBerry					-0.65***	(0.15)	-0.67***	(0.16)
from iOs to Windows					-1.16***	(0.16)	-1.20***	(0.17)
from iOs to other OS					-1.18***	(0.23)	-1.22***	(0.23)
from BlackBerry to Android					-0.56***	(0.13)	-0.41**	(0.15)
from BlackBerry to iOs					0.24	(0.13)	0.32*	(0.14)
from BlackBerry to Windows					-0.41*	(0.20)	-0.23	(0.22)
from BlackBerry to other OS					-0.51	(0.27)	-0.38	(0.27)
from Windows to Android					0.19	(0.16)	0.35	(0.20)
from Windows to iOs					-0.04	(0.18)	0.10	(0.20)
from Windows to BlackBerry					-0.73*	(0.35)	-0.48	(0.37)
from Windows to other OS					0.17	(0.37)	0.17	(0.38)
1st stage residual			0.002***	(0.00)	0.002***	(0.00)	0.002***	(0.00)

Standard Deviation					
Handset price				0.00***	(0.00)
Apple				-0.08	(0.11)
BlackBerry				0.99***	(0.14)
HTC				1.35***	(0.20)
LG				1.00***	(0.14)
Nokia				0.99***	(0.09)
Samsung				0.59***	(0.08)
Sony				1.49***	(0.17)
Sony Ericsson				0.99***	(0.24)
Android Os				0.88***	(0.07)
Windows Os				-0.95***	(0.17)
Observations	2,494,185	2,494,185	2,494,185	2,494,185	
Log Likelihood	-61,543.14	-61,512.76	-61,360.73	-61,121.70	

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

Model IV is fitted using 200 Halton draws

Figure A.2: Estimated switching costs between operating systems (in terms of WTP)

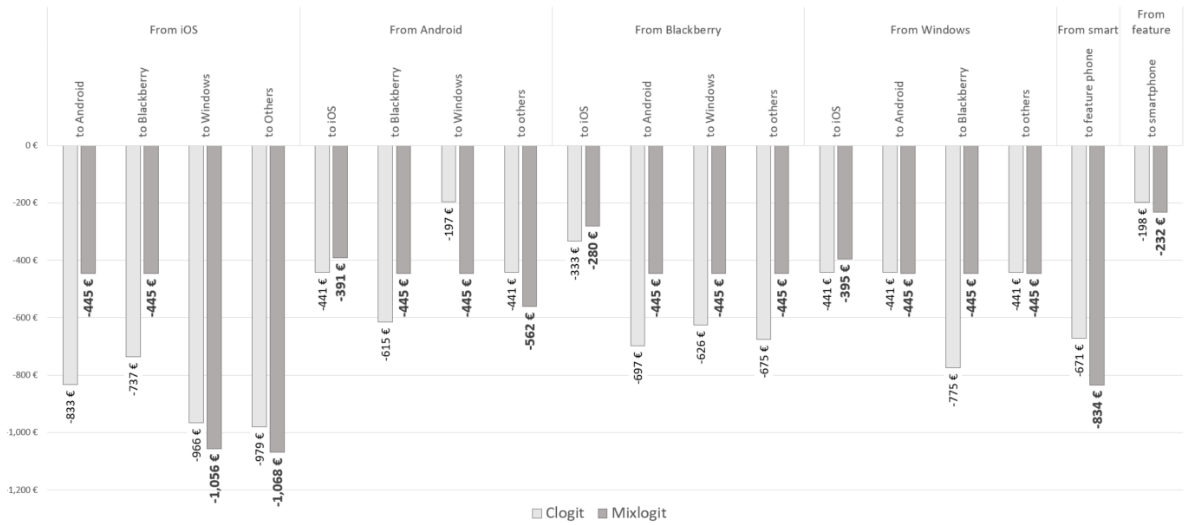
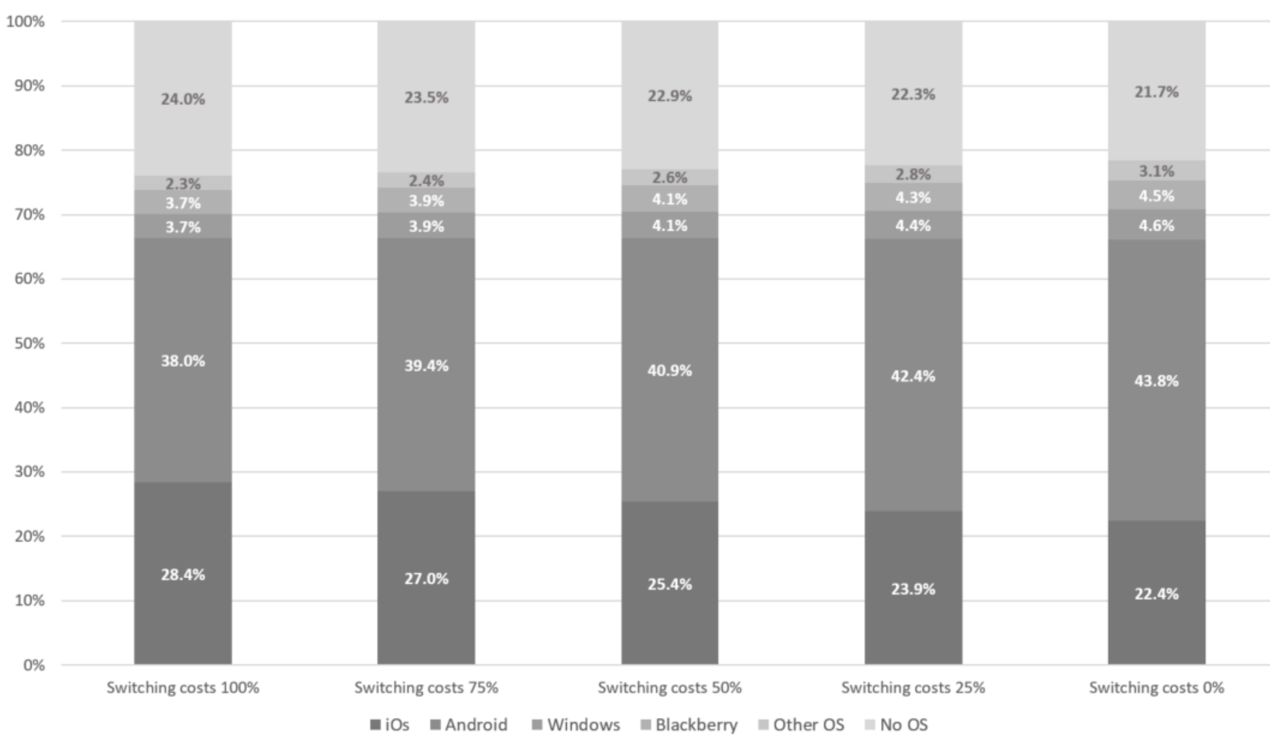
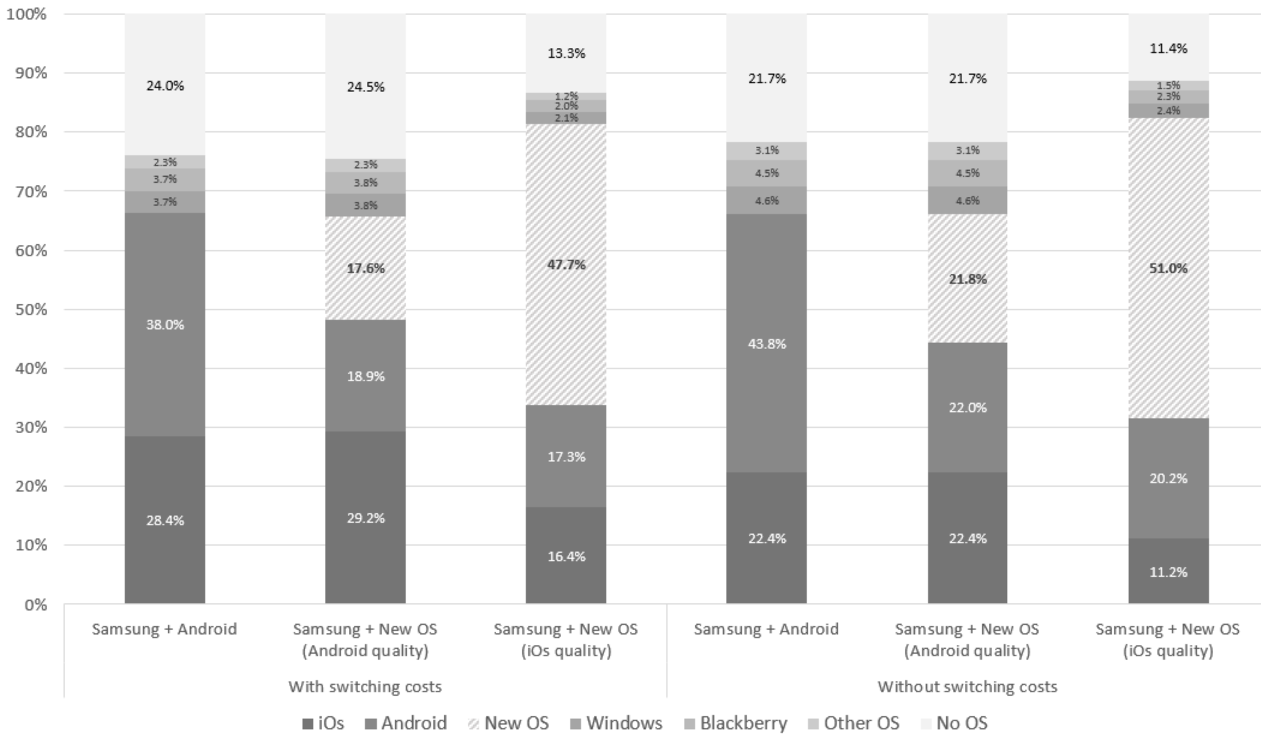


Figure A.3: Reduction in switching costs



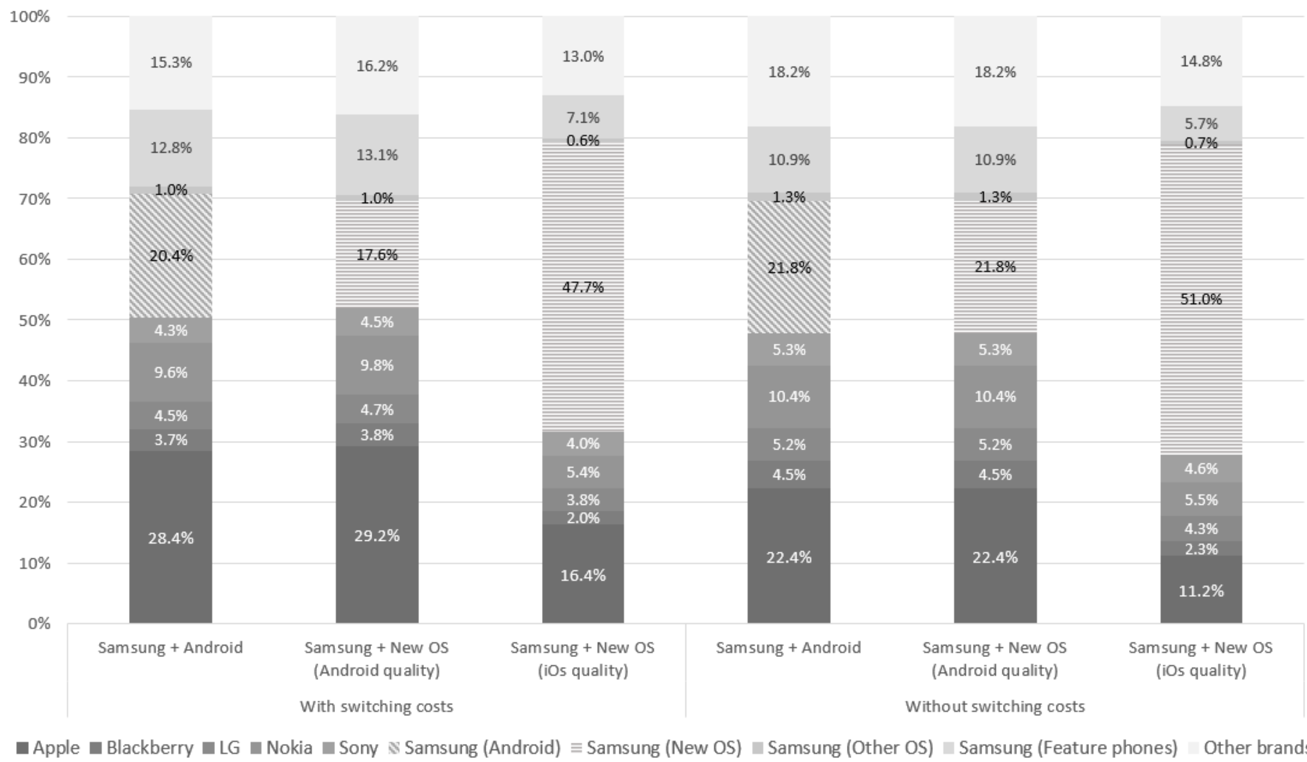
Based on handset choices of 504 consumers in January 2014.

Figure A.4: Samsung leaving Android (OS market shares)



All Samsung smartphones running on Android switch to the new operating system in January 2014. Based on handset choices of 504 consumers in January 2014.

Figure A.5: Samsung leaving Android (brand market shares)



All Samsung smartphones running on Android switch to the new operating system in January 2014. Based on handset choices of 504 consumers in January 2014.

Appendix B: Robustness Checks

Table B.1: Estimation results for modified IC

	Model III		Model IIIb		Model IIIc	
Handset characteristics						
Handset price	-0.002***	(0.00)	-0.003***	(0.00)	-0.004***	(0.00)
Apple	1.35***	(0.19)	1.52***	(0.25)	1.07	(0.73)
BlackBerry	-0.08	(0.12)	0.11	(0.16)	-0.37*	(0.19)
HTC	-0.42***	(0.08)	-0.59***	(0.09)	-0.28*	(0.13)
LG	-0.36***	(0.07)	-0.13	(0.08)	-0.27*	(0.11)
Nokia	0.12*	(0.06)	0.05	(0.06)	0.13	(0.10)
Samsung	0.04	(0.05)	0.12*	(0.05)	0.32***	(0.08)
Sony	0.10	(0.06)	0.07	(0.07)	0.27**	(0.09)
Sony Ericsson	-0.03	(0.09)	0.07	(0.11)	0.06	(0.14)
Battery life: Talk time	0.01*	(0.00)	0.01	(0.00)	-0.01	(0.01)
Screen size	0.27***	(0.05)	0.29***	(0.05)	0.30***	(0.08)
Height	0.00	(0.00)	0.00	(0.00)	-0.01***	(0.00)
Weight	-0.00***	(0.00)	-0.00***	(0.00)	-0.00***	(0.00)
Thickness	0.00	(0.01)	0.00	(0.01)	-0.03	(0.02)
Camera	0.19**	(0.07)	0.20*	(0.08)	0.20	(0.15)
Number of CPU cores	0.21***	(0.02)	0.23***	(0.03)	0.24***	(0.04)
Speed of CPU in Ghz	0.23***	(0.05)	0.05	(0.06)	0.17*	(0.08)
Android Os	-0.20*	(0.09)	0.05	(0.11)	-0.37***	(0.11)
Windows Os	-0.26*	(0.10)	-0.01	(0.13)	-0.38**	(0.14)
Models FE (50 most popular)	Yes		Yes		Yes	
Switching costs						
feature phone to smartphone	-0.44***	(0.08)	-0.52***	(0.10)	1.41***	(0.11)
smartphone to feature phone	-1.48***	(0.09)	-1.28***	(0.12)	-0.48***	(0.14)
changing brand	-0.59***	(0.03)	-0.53***	(0.03)	-0.42***	(0.04)
changing OS	-1.08***	(0.09)	-1.02***	(0.12)	-0.39	(0.20)
changing OS*switched before	1.18***	(0.07)	1.35***	(0.11)	1.46***	(0.21)
from Android to iOS	0.12	(0.11)	-0.02	(0.14)	-0.08	(0.24)
from Android to BlackBerry	-0.38*	(0.15)	-0.58**	(0.23)	-1.15**	(0.40)
from Android to Windows	0.54***	(0.13)	0.44*	(0.18)	0.02	(0.30)
from Android to other OS	-0.16	(0.21)	-0.35	(0.31)	-1.30*	(0.62)
from iOs to Android	-0.86***	(0.10)	-0.87***	(0.13)	-1.50***	(0.27)
from iOs to BlackBerry	-0.65***	(0.15)	-0.90***	(0.22)	-1.22**	(0.47)
from iOs to Windows	-1.16***	(0.16)	-1.25***	(0.21)	-1.37**	(0.44)
from iOs to other OS	-1.18***	(0.23)	-1.05***	(0.31)	-2.30*	(1.03)
from BlackBerry to Android	-0.56***	(0.13)	-0.34*	(0.17)	-0.64*	(0.31)
from BlackBerry to iOs	0.24	(0.13)	0.34*	(0.17)	0.12	(0.33)
from BlackBerry to Windows	-0.41*	(0.20)	-0.16	(0.25)	-0.51	(0.52)
from BlackBerry to other OS	-0.51	(0.27)	-0.12	(0.34)	-0.41	(0.64)
from Windows to Android	0.19	(0.16)	-0.06	(0.23)	-0.50	(0.39)
from Windows to iOs	-0.04	(0.18)	-0.34	(0.26)	0.06	(0.41)
from Windows to BlackBerry	-0.73*	(0.35)	-1.08	(0.61)	-1.40	(1.05)
from Windows to other OS	0.17	(0.37)	0.79	(0.46)	1.24*	(0.55)
1st stage residual	0.002***	(0.00)	0.002***	(0.00)	0.002***	(0.00)
Observations	2,494,185		1,617,418		804,028	

Log Likelihood	-61,360.73	-45,414.53	-20,130.05

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

Model III is our base logit model. Model IIIb includes observations on generated switching from feature phone to smartphone. Model IIIb is estimated on a sample of consumers for whom we observe switching from a feature phone to a smartphone.

Table B.2: Alternative approach à la Goolsbee and Petrin (2004)

	Model III		Model IIId		3SLS	
Handset characteristics						
Handset price	-0.002***	(0.00)			-0.002**	(0.00)
Apple	1.35***	(0.19)			3.05***	(0.49)
BlackBerry	-0.08	(0.12)			0.30	(0.34)
HTC	-0.42***	(0.08)			-0.51	(0.27)
LG	-0.36***	(0.07)			-0.20	(0.24)
Nokia	0.12*	(0.06)			0.30	(0.20)
Samsung	0.04	(0.05)			0.58**	(0.18)
Sony	0.10	(0.06)			-0.04	(0.26)
Sony Ericsson	-0.03	(0.09)			0.06	(0.30)
Battery life: Talk time	0.01*	(0.00)			0.01	(0.01)
Screen size	0.27***	(0.05)			0.13	(0.15)
Height	0.00	(0.00)			0.01	(0.01)
Weight	-0.00***	(0.00)			-0.01*	(0.00)
Thickness	0.00	(0.01)			0.01	(0.03)
Camera	0.19**	(0.07)			0.05	(0.24)
Number of CPU cores	0.21***	(0.02)			0.24*	(0.10)
Speed of CPU in Ghz	0.23***	(0.05)			0.29	(0.21)
Android Os	-0.20*	(0.09)			0.10	(0.22)
Windows Os	-0.26*	(0.10)			-0.12	(0.30)
Models FE (50 most popular)	Yes		Yes			
350 additional Models FE			Yes			
Switching costs						
feature phone to smartphone	-0.44***	(0.08)	-0.51	(0.32)		
smartphone to feature phone	-1.48***	(0.09)	-1.40***	(0.33)		
changing brand	-0.59***	(0.03)	-0.59***	(0.03)		
changing OS	-1.08***	(0.09)	-1.07***	(0.09)		
changing OS*switched before	1.18***	(0.07)	1.18***	(0.07)		
from Android to iOS	0.12	(0.11)	0.14	(0.11)		
from Android to BlackBerry	-0.38*	(0.15)	-0.35*	(0.15)		
from Android to Windows	0.54***	(0.13)	0.51***	(0.13)		
from Android to other OS	-0.16	(0.21)	-0.19	(0.21)		
from iOs to Android	-0.86***	(0.10)	-0.88***	(0.10)		
from iOs to BlackBerry	-0.65***	(0.15)	-0.63***	(0.15)		
from iOs to Windows	-1.16***	(0.16)	-1.21***	(0.16)		
from iOs to other OS	-1.18***	(0.23)	-1.15***	(0.23)		
from BlackBerry to Android	-0.56***	(0.13)	-0.56***	(0.13)		
from BlackBerry to iOs	0.24	(0.13)	0.24	(0.13)		
from BlackBerry to Windows	-0.41*	(0.20)	-0.40*	(0.20)		
from BlackBerry to other OS	-0.51	(0.27)	-0.50	(0.27)		
from Windows to Android	0.19	(0.16)	0.20	(0.17)		
from Windows to iOs	-0.04	(0.18)	-0.01	(0.18)		
from Windows to BlackBerry	-0.73*	(0.35)	-0.69*	(0.35)		
from Windows to other OS	0.17	(0.37)	0.24	(0.38)		
1st stage residual	0.002***	(0.00)				
Constant					0.59	(0.91)
Observations	2,494,185		2,498,401		400	
Log Likelihood	-61,360.73		-59,935.06		-2,804.35	

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

In the 3SLS estimation the price is instrumented with brands, age of handset, LTE, screen size, speed of CPU, number of CPU cores, height, width, weight, thickness, battery life, camera quality, screen size*age, thickness*age, battery life*age, months.

Table B.3: Estimation results with fixed effects and interactions with time

	Model III		Model IIIe	
Handset characteristics				
Handset price	-0.002***	(0.00)		
Apple	1.35***	(0.19)		
BlackBerry	-0.08	(0.12)		
HTC	-0.42***	(0.08)		
LG	-0.36***	(0.07)		
Nokia	0.12*	(0.06)		
Samsung	0.04	(0.05)		
Sony	0.10	(0.06)		
Sony Ericsson	-0.03	(0.09)		
Battery life: Talk time	0.01*	(0.00)		
Screen size	0.27***	(0.05)		
Height	0.00	(0.00)		
Weight	-0.00***	(0.00)		
Thickness	0.00	(0.01)		
Camera	0.19**	(0.07)		
Number of CPU cores	0.21***	(0.02)		
Speed of CPU in Ghz	0.23***	(0.05)		
Android Os	-0.20*	(0.09)		
Windows Os	-0.26*	(0.10)		
Models FE (50 most pop.)	Yes		Yes	
350 additional Models FE			Yes	
Brands*Month dummies			Yes	
OS*Month dummies			Yes	
Switching costs				
feature phone to smartphone	-0.44***	(0.08)	-0.28	(0.76)
smartphone to feature phone	-1.48***	(0.09)	-1.63*	(0.76)
changing brand	-0.59***	(0.03)	-0.59***	(0.03)
changing OS	-1.08***	(0.09)	-1.09***	(0.09)
changing OS*switched before	1.18***	(0.07)	1.17***	(0.07)
from Android to iOS	0.12	(0.11)	0.15	(0.11)
Android to BlackBerry	-0.38*	(0.15)	-0.32*	(0.16)
Android to Windows	0.54***	(0.13)	0.50***	(0.14)
Android to other OS	-0.16	(0.21)	-0.20	(0.21)
iOs to Android	-0.86***	(0.10)	-0.86***	(0.10)
iOs to BlackBerry	-0.65***	(0.15)	-0.60***	(0.15)
iOs to Windows	-1.16***	(0.16)	-1.20***	(0.16)
iOs to other OS	-1.18***	(0.23)	-1.14***	(0.23)
from BlackBerry to Android	-0.56***	(0.13)	-0.56***	(0.13)
from BlackBerry to iOs	0.24	(0.13)	0.25	(0.13)
from BlackBerry to Windows	-0.41*	(0.20)	-0.39	(0.20)
from BlackBerry to other OS	-0.51	(0.27)	-0.50	(0.27)
from Windows to Android	0.19	(0.16)	0.22	(0.17)
from Windows to iOs	-0.04	(0.18)	0.01	(0.18)
from Windows to BlackBerry	-0.73*	(0.35)	-0.66	(0.35)
from Windows to other OS	0.17	(0.37)	0.26	(0.38)

1st stage residual	0.002^{***}	(0.00)	
Observations	2,494,185		2,498,401
Log Likelihood	-61,360.73		-59,603.99

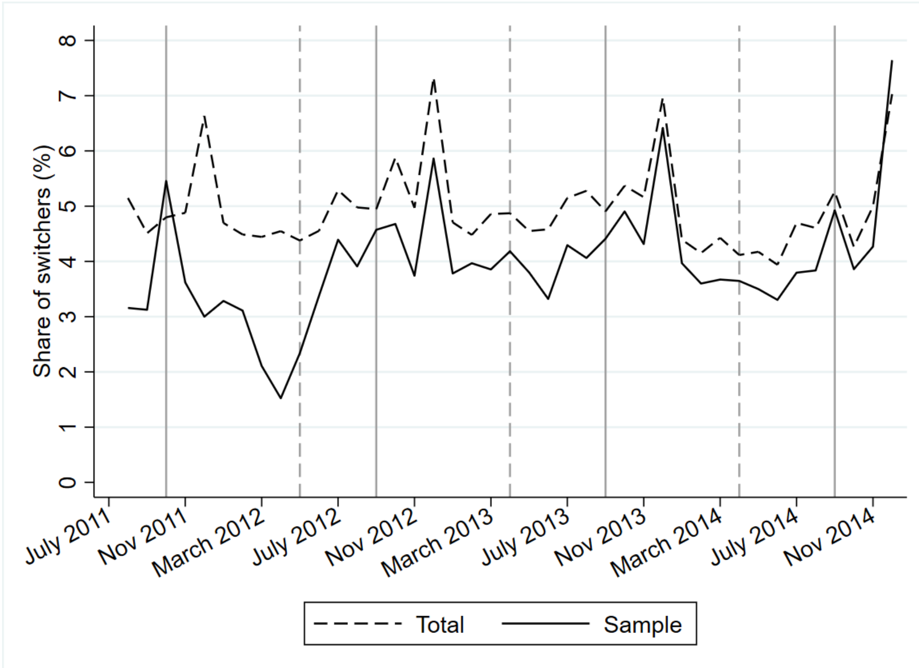
Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Model III is our base logit model. Model IIIe includes 400 product fixed effects and monthly dummy variables interacted with brands and operating systems.

Appendix C: Switching Regression

As shown in Figure B.6, in the time period of our study, releases of new iPhones took place in September of each year, with the exception of 2011, when they were released in October 2011. On the other hand, the releases of Samsung's flagship phones took place between April and May. This figure also shows that there are seasonal increases in switching in December each year, which must be due to the Christmas effect, while there is less switching in summer months. Thus, it does not appear that consumers in our data wait for the release of flagship phones to switch handsets. We also verify this by estimating logit models for the decision to switch handsets. We use observations on 23,663 individuals who had a contract without commitment in the period between July 2011 and December 2014. The estimation includes a set of monthly dummies and selected consumer characteristics including age, gender and a dummy variable for having a smartphone as the previous handset. The estimation results are shown in Table B.1 in the Appendix. Figure B.7 in the Appendix shows the coefficients of the monthly dummy variables, which correspond to the probability and share of consumers switching in each month. There is more switching when new iPhones are released and in December. However, the estimates do not indicate that there is less switching in the months before the release of flagship models.

Figure B.6: Share of subscribers who switch handsets (%)



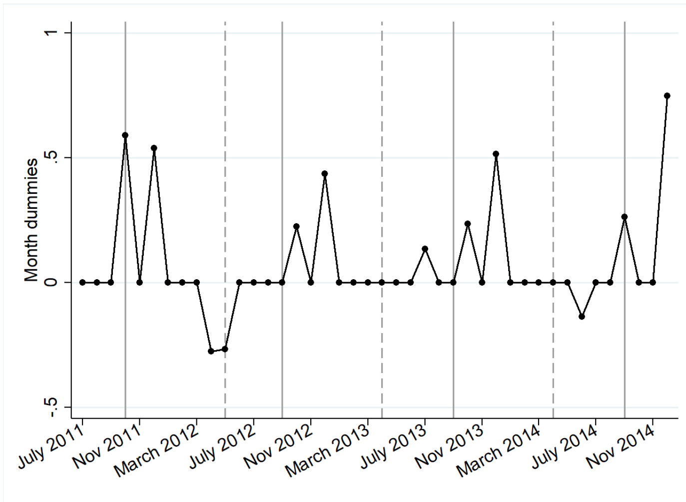
Total: 113,448 individuals; Sample: 23,663 individuals using SIM-only tariffs. Dashed lines correspond to the release of a new Galaxy S by Samsung. Solid lines correspond to the release of a new iPhone by Apple.

Table B.1: Logit model for the decision to switch

	Model (1)		Model (2)	
July 2011	-0.57	(0.72)	-0.57	(0.72)
Aug 2011	-0.28	(0.59)	-0.28	(0.59)
Sep 2011	0.44	(0.37)	0.44	(0.37)
Oct 2011	0.60	(0.31)	0.59	(0.31)
Nov 2011	-0.01	(0.35)	-0.02	(0.35)
Dec 2011	0.56*	(0.23)	0.54*	(0.24)
Jan 2012	0.22	(0.20)	0.19	(0.20)
Feb 2012	-0.10	(0.22)	-0.13	(0.22)
March 2012	-0.07	(0.17)	-0.08	(0.17)
Apr 2012	-0.25*	(0.13)	-0.28*	(0.13)
May 2012	-0.24*	(0.12)	-0.27*	(0.12)
June 2012	-0.11	(0.11)	-0.13	(0.11)
July 2012	0.12	(0.10)	0.10	(0.10)
Aug 2012	-0.02	(0.10)	-0.04	(0.10)
Sep 2012	0.10	(0.10)	0.09	(0.10)
Oct 2012	0.24**	(0.09)	0.22*	(0.09)
Nov 2012	-0.04	(0.09)	-0.05	(0.09)
Dec 2012	0.44***	(0.08)	0.44***	(0.08)
Jan 2013	0.00	(.)	0.00	(.)
Feb 2013	0.04	(0.09)	0.05	(0.09)
March 2013	0.04	(0.08)	0.05	(0.08)
Apr 2013	0.11	(0.08)	0.13	(0.08)
May 2013	0.01	(0.08)	0.03	(0.08)
June 2013	-0.16	(0.08)	-0.13	(0.08)
July 2013	0.10	(0.08)	0.13	(0.08)
Aug 2013	0.06	(0.08)	0.09	(0.08)
Sep 2013	0.08	(0.08)	0.12	(0.08)
Oct 2013	0.20**	(0.08)	0.24**	(0.08)
Nov 2013	0.06	(0.08)	0.10	(0.08)
Dec 2013	0.47***	(0.07)	0.51***	(0.07)
Jan 2014	-0.05	(0.08)	0.00	(0.08)
Feb 2014	-0.13	(0.08)	-0.08	(0.08)
March 2014	-0.07	(0.08)	-0.02	(0.08)
Apr 2014	-0.09	(0.08)	-0.04	(0.08)
May 2014	-0.16*	(0.08)	-0.11	(0.08)
June 2014	-0.20**	(0.08)	-0.14	(0.08)
July 2014	-0.09	(0.08)	-0.02	(0.08)
Aug 2014	-0.07	(0.07)	0.00	(0.08)
Sep 2014	0.19**	(0.07)	0.26***	(0.07)
Oct 2014	-0.10	(0.07)	-0.03	(0.08)
Nov 2014	0.04	(0.07)	0.12	(0.07)
Dec 2014	0.67***	(0.07)	0.75***	(0.07)
Consumer age			-0.01***	(0.00)
Female			-0.07***	(0.02)
Last handset was a smartphone			-0.25***	(0.02)
Constant	-3.15***	(0.06)	-2.29***	(0.07)
Observations	348,677		348,677	
Log Likelihood	-62,583.74		-62,263.69	

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Computed for a sample of 23,663 individuals.

Figure B.7: Logit model for the decision to switch: the coefficients of the monthly dummy variables



Solid lines correspond to the release of a new iPhone by Apple. Dashed lines correspond to the release of a new Galaxy S by Samsung.

Appendix D: 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 in 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 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:

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

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:

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

Table B.1: Most popular products cross and own elasticities

	iPh 5S	iPh 4S	iPh 4	iPh 3GS	iPh 5	E1190	Lumia 520	Galaxy Trend	Galaxy Y	Galaxy S3	Av. price
iPhone 5S	**-1.23**	0.07	0.09	0.08	0.09	0.00	0.02	0.02	0.05	0.01	660
iPhone 4S	0.09	**-0.92**	0.08	0.08	0.08	0.00	0.02	0.02	0.04	0.01	490
iPhone 4	0.11	0.08	**-1.13**	0.09	0.09	0.00	0.02	0.02	0.05	0.01	610
iPhone 3GS	0.06	0.04	0.05	**-1.08**	0.05	0.00	0.01	0.01	0.03	0.01	559
iPhone 5	0.07	0.05	0.06	0.06	**-1.09**	0.00	0.01	0.01	0.03	0.01	570
E1190	0.02	0.01	0.02	0.02	0.02	**-0.07**	0.01	0.01	0.02	0.00	35
Lumia 520	0.03	0.02	0.02	0.02	0.02	0.00	**-0.37**	0.01	0.02	0.00	180
Galaxy Trend	0.02	0.02	0.02	0.02	0.02	0.00	0.01	**-0.37**	0.02	0.01	180
Galaxy Y	0.03	0.02	0.02	0.02	0.02	0.00	0.01	0.01	**-0.95**	0.01	460
Galaxy S3	0.02	0.02	0.02	0.02	0.02	0.00	0.01	0.01	0.02	**-0.23**	110

Computed for January 2014

Table B.2: Brand cross and own elasticities

	Apple	BlackBerry	HTC	LG	Nokia	Samsung	Sony	Sony-Ericsson	Other	Average price
Apple	**-1.09**	0.23	0.30	0.30	0.36	1.02	0.40	0.16	0.48	584
BlackBerry	0.03	**-0.46**	0.03	0.03	0.04	0.12	0.04	0.02	0.05	261
HTC	0.01	0.01	**-0.83**	0.01	0.02	0.04	0.02	0.01	0.02	388
LG	0.02	0.02	0.02	**-0.53**	0.03	0.09	0.03	0.01	0.04	299
Nokia	0.02	0.02	0.03	0.03	**-0.32**	0.11	0.04	0.02	0.05	140
Samsung	0.04	0.03	0.05	0.05	0.06	**-0.50**	0.07	0.03	0.09	234
Sony	0.02	0.02	0.02	0.02	0.03	0.08	**-0.71**	0.01	0.04	355
Sony-Ericsson	0.01	0.01	0.01	0.01	0.02	0.05	0.02	**-0.64**	0.02	331
Other	0.02	0.01	0.02	0.02	0.03	0.08	0.03	0.01	**-0.24**	108

Computed for January 2014