Telecommunications Policy ∎ (∎∎∎∎) ∎∎∎–∎∎∎

Contents lists available at ScienceDirect

Telecommunications Policy

URL: www.elsevier.com/locate/telpol

An empirical analysis of switching cost in the smartphone market in South Korea

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ARTICLE INFO

Keywords:
Switching costs
Smartphone
Telecommunication policy
Bayesian multinomial logit

ABSTRACT

Switching cost is an important factor for policy makers to consider because it sets a higher price for locked-in consumers by making the market less competitive. Though there has been some empirical research analyzing switching costs in the mobile telecommunications market, studies considering the characteristics of smartphones, which have their own operating systems and applications, are still rare. In this study, we conduct a hypothetical conjoint survey to analyze switching cost in the smartphone handset market and derive the cost by using the hierarchical Bayesian multinomial logit model to consider respondents' heterogeneity. Switching costs of handsets and OS are empirically estimated, and the magnitudes depend on the levels of searching cost, learning cost, and uncertainty when purchasing new smartphones.

1. Introduction

As noted in the previous research conducted by Farrell and Klemperer (2007) and Klemperer (1995), switching cost sets a higher price for locked-in consumers by making the market less competitive. The lock-in effect due to switching cost may also restrict consumer's choices, decrease utility, and cause less innovative firm behavior (Cline, 2012).

Switching costs have received much attention both theoretically and empirically because switching costs play an important role in analyzing market competition, firms' price strategies, and consumer welfare. Like other products, a smartphone also has important issues with the relationship between its switching cost and market competitiveness. Frank (2015) argues that consumers' switching costs should be critically considered because they affect market entry barriers or a dominant firm's discriminating behavior. Kenney and Pon (2011) note that several layers can arise due to the lock-in effect from Google with search engines, email, maps, and YouTube; Apple with their App store; Microsoft with MS office; and others. They also note that switching cost would be increased due to subsidies for smartphone devices from telecommunication companies inducing a one- or two-year contract and due to incompatibility between CDMA and GSM technologies.

Cullen and Shcherbakov (2010) and Nakamura (2010) estimated switching costs in mobile in the wireless industry. Nakamura (2010) evaluated lock-in effects of Subscriber Identity Module (SIM) cards in Japan and showed SIM unlock policies reduce consumer switching costs. Cullen and Shcherbakov (2010) concluded that switching costs for changing

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http://dx.doi.org/10.1016/j.telpol.2016.01.004
0308-5961/

Please cite this article as: Park, Y., & Koo, Y. An empirical analysis of switching cost in the smartphone market in South Korea. *Telecommunications Policy* (2016), http://dx.doi.org/10.1016/j.telpol.2016.01.004

mobile service providers ranged from $225.7 to $236.3. They noted that there are additional hassle costs because early termination fees in the U.S. range from $175 to $200. Lee, Kim, Lee, and Park (2006) and Maicas, Polo, and Javier Sese (2009) investigated the effect of mobile number portability on switching costs. The adoption of mobile number portability significantly reduced switching costs in both studies. Although there have been a few studies that empirically analyze switching costs in the mobile telecommunications market, studies considering the characteristics of smartphones are hardly found. Although, up to now, contracts, mileage, and mobile number portability have been considered as major factors in mobile handset change, we should consider additional factors related to smartphone characteristics because market situations have changed. Smartphone users face new switching factors such as operating systems and the applications market.

One of the important characteristics of a smartphone is that it is possible to install various applications on it. However, the applications are not compatible among different operating systems (OS). This means a customer cannot use his/her own purchased applications after switching to a smartphone with a different operation system. In addition, there is a learning cost for using other smartphones. That is, a consumer accustomed to a current smartphone needs time and effort to be familiar with other smartphones with different operation systems or user interfaces.

In this study, we will discuss some implications of making a competitive mobile market, based on the empirical evidence on smartphone switching cost. The rest of this study is structured as follows: Section 2 briefly explores the switching costs of smartphones. Section 3 provides data and an econometric model for measuring switching costs. Estimation results are presented in Section 4 and Section 5 discusses the main findings.

2. Switching costs of a smartphone

Before smartphones emerged, the major players in the mobile market were telecommunication companies, device manufacturers, and mobile content providers. The telecommunication companies took important roles not only by providing mobile service but also by controlling mobile content distribution as gateways. However, as the smartphone came out, mobile content distribution has changed to open markets, such as in online application stores. This has limited the role of telecommunication companies to network service only.

Apple Inc. launched the iPhone and attracted third party content providers to their distribution platform where anyone could buy and sell applications freely. The downloaded applications were easily installed on smartphones and this extended the role of the mobile device from voice message exchange to a number of services. This change made the role of the OS providers, such as Apple or Google, much more important in the mobile market.

The application market, which is typically a two-sided market, shows network externalities. That is, the more customers and providers participate in the application market, the greater the utility given to both sides. In case of the OS, the iOS and Android OS, which are made by Apple and Google, respectively, are multisided markets that connect smartphone device manufacturers, application providers, and users. Hardware manufacturers, such as Samsung, Nokia, and Xiaomi, have tried to develop their own mobile OS because the OS platform has a powerful influence on both supply and demand. Application developers who want to provide their apps to a specific application market should follow the rules made by OS platform providers. The quantity and quality of applications affects consumers who want to use apps through their smartphones. Using these kinds of network effects, OS platform providers take the lead in the mobile ecosystem. The hardware manufacturers' endeavor to provide a heavyweight mobile OS has yet to produce any tangible results.

The switching costs of a mobile phone are economic and psychological costs caused by changing a mobile device or telecommunication service provider. In the case of smartphone change, the switching costs can be due to three reasons: change of telecommunication company, device, and/or OS platform. That is, changing an OS platform should be considered as an additional factor when we estimate the switching cost of smartphones, while device or telecommunication company only are usually considered for conventional mobile phones. If switching cost is high, consumers are likely to adhere to using current services or products. Switching cost hinders competition among service providers or manufacturers, though a number of players exist in the market. For this reason, switching cost is a worthy topic for analysis.

Klemperer (1987) classifies switching costs by transaction costs, learning costs, and artificial costs based on transaction stages. The transaction costs are incurred at the time of transaction, learning costs are incurred with the initial time of use it takes to be familiar with the products, and artificial costs are incurred while using the products due to firm strategies such as saving points or mileage.

Klemperer (1995) subdivides switching costs into six categories in his following study. The transaction costs and learning costs are the same as in previous studies, and the discount coupon is similar to the artificial costs. One of the added factors is incompatibility causing additional costs when purchasing a new product that is not compatible with a previously used product. For example, in the case of a smartphone, power cables, supplementary batteries, and other accessories may not be compatible with a new smartphone. In addition, applications may not be compatible with a new smartphone in general if the OS is different. The other factor is uncertainty indicating additional cost when a consumer is uncertain to the quality of a new product. The last factor is psychological costs such as brand loyalty.

Jones, Mothersbaugh, and Beatty (2002) classify the switching cost by three categories. The first factor is continuity costs, which are divided again by lost performance costs and uncertainty costs. The lost performance costs are benefits lost by changing a service or product and the uncertainty costs are the costs caused by anxiety that a new service or product might have lower quality than a current service or product. The second factor is learning costs, composed of pre-switching search and evaluation costs that are incurred by gathering information and evaluating it, post-switching behavioral and cognitive costs that are incurred when becoming familiar with a new service or product, setup costs that are needed to inform companies about consumer preferences, and sunk costs that have already been invested in a relationship with previous companies.

In this research, referring to the classifications of previous studies, we divide total switching cost into the following five factors. First, searching costs are the costs needed to gather and evaluate information about smartphones introduced in the current market. Second, learning costs are the time and costs required to be familiar with a new smartphone. Third, artificial costs are the penalty for breach of contract and losses of benefit such as rate discounts based on long-term contracts or saved points. In addition, artificial costs include initially installed or freely downloaded applications which may not be available with a new smartphone. Fourth, sunk costs are the costs that have been paid for the smartphone currently in use and its applications and accessories. Lastly, uncertainty costs are the psychological costs from anxiety about the quality of a new service or product.

3. Data and model description

3.1. Data

There are two types of data to analyze switching behavior of smartphones: revealed preference (RP) data composed of market transaction data and stated preference (SP) data from a survey. The RP data represent consumer behaviors more precisely but they have several problems. Aside from the multicollinearity problem, one of the critical problems in analyzing switching behavior is that the RP data only shows transaction behavior. That is, we are not allowed to analyze non-transaction behavior. This makes it difficult to identify factors related to switching behavior. The other problem is that the average number of people changing smartphones is too small to analyze patterns. Since the iPhone was introduced in South Korea in November 2009, our survey shows that the average number of smartphones respondents have used is only 1.8, though the survey was conducted for smartphone users. In other words, most consumers have only used one or two smartphones so far, which is definitely insufficient for analyzing switching behavior.

It seems, therefore, to be more appropriate to use SP data if a survey is conducted properly. We used the choice-based conjoint methodology because it had the advantage of decreasing gaps between survey responses and purchasing behavior by reproducing realistic choice situations.

The survey was conducted for smartphone users between 15 and 59 years old in South Korea. The purpose of this survey was analyzing smartphone users' switching behavior from their current smartphones according to OS platform. However, in South Korea, there is some concern that an insufficient number of iOS users are selected as samples because 90% of

Table 1
Attributes and levels used in the conjoint survey.

Attributes	Levels
Operating system	A-type OS B-type OS C-type OS
Screen size (in.)	3 4 5
Weight (g)	100 150 200
Performance	High Medium Low
Retail price (without subsidy) (KRW)	600,000 900,000 1,200,000

OS provider names are blinded in this paper although we used real name of OS providers in the survey.

smartphone users use Android OS. Therefore, we included 135 iOS users and another 1235 smartphone users regardless of current OS. The socio-demographics and information on current use of smartphone services are described in Appendix A.

3.2. Conjoint survey design

Conjoint analysis assumes it is possible to represent total utility of a service or product as the sum of the part-worth of each attribute composing the service or product. For example, the total utility of a smartphone is sum of its attributes such as performance, weight, size, brand, and OS, and the utility varies according to the level of each attribute. A researcher can estimate the part-worth of each attribute from hypothetical choice situations and also predict choice probability of a specific alternative based on the choice model theory.

Conjoint analysis is widely used to analyze consumer behavior with telecommunication services or devices (Kim, 2005; Koo, 2012; Lee et al., 2006; Nikou, Bouwman, & De Reuver, 2014, 2012). In this research, we consider five factors as smartphone attributes. The first attribute is OS. For example, iOS by Apple and Android by Google are two dominant OS in the smartphone and Tablet PC markets. The applications a consumer can use are dependent on OS and each OS has different application markets which it is not compatible with. In addition, because each OS has its unique characteristics learning costs are required to start using other OS. In addition to iOS and Android OS, Microsoft and Blackberry have their own mobile OS and Tizen, developed by Samsung Electronics, Intel and Firefox Mozilla have also emerged as alternative mobile OS. The second attribute is screen size. The screen size of a smartphone has increased from 3–3.5 in. to 4–6 in. Large screen size increases readability and shows more information simultaneously. At the same time, however, the large screen size decreases portability. Thus, individual preference for screen size can be heterogeneous. The third attribute is weight, which affects portability as well. The fourth attribute is performance in terms of application running speed, which is critical to set up new applications and the latest updated OS. The last, but most important, attribute for purchasing a smartphone is price. All of the attributes and levels used in our survey are shown in Table 1. Note that service providers are not considered in this study because several other studies (Lee and Feick, 2001; Kim, Park, & Jeong, 2004; Lee et al., 2006) have already analyzed the effects of switching costs from telecommunications service providers. Although a change in device is usually a consequence of a change in the service provider, the stated preference, obtained from the conjoint survey, has the advantage of effectively controlling the other conditions we do not intend to analyze, such as service providers, device design, etc.

All possible alternatives from 5 attributes with 3 levels each is 35=243. We chose, however, 18 alternatives using an orthogonal test because selecting the best alternative among 243 alternatives was a heavy burden for a respondent. Three different conjoint cards were grouped as a choice set, noted in Appendices B1 and B2. Half of the respondents faced Appendix B1—type choice sets, and the other half faced Appendix B2—type choice sets. A respondent was supposed to select nothing, and keep his or her current smartphone, if a new alternative was inferior to the current smartphone. The total number of observations of each alternative is also shown in Appendices B1 and B2.

3.3. Hierarchical Bayesian multinomial logit model

The conjoint survey designed in this research makes a respondent choose only one option. Therefore, the estimation method should be different from regression analysis, where the dependent variable is continuous. The methodology generally used for discrete choice is the conditional logit model that is based on the random utility model as in Eq. (1) (McFadden, 1974).

$$\mathbf{U}_{nj} = \mathbf{V}_{nj} + \boldsymbol{\varepsilon}_{nj} = \boldsymbol{\beta}_{nk}\mathbf{x}_{kj} + \boldsymbol{\varepsilon}_{nj} \tag{1}$$

In Eq. (1), $\mathbf{U}_{nj}$ represents a respondent n's utility by obtaining an alternative j. $\mathbf{V}_{nj}$ is a deterministic term which is observed by a researcher whereas $\boldsymbol{\varepsilon}_{nj}$ is a stochastic term representing random effect. The deterministic term is explained by attribute k for each alternative j, $\mathbf{x}_{kj}$ and its coefficient $\boldsymbol{\beta}_{nk}$. If a respondent chooses the alternative j, the alternative j should give a larger utility than any other alternatives. That is, the probability of choosing the alternative j among total number of J alternatives is the same as the probability U_{nj} is larger than U_{nm} for $\forall m \neq j$ as shown in Eq. (2).

$$P_{nj} = \Pr(U_{nj} > U_{nm}, \forall m \neq j) = \Pr(\varepsilon_{nm} - \varepsilon_{nj} < V_{nj} - V_{nm}, \forall m \neq j) \tag{2}$$

The choice probability is dependent on distribution of the stochastic term, which represents differences between the utility felt by a respondent and the utility measured by a researcher. The stochastic term should be included because a researcher cannot derive the true value of utility by observing a respondent's selection behavior due to personal characteristics not captured by the model, misspecifications, or mistakes during the survey, etc. In order to derive closed form solution, if ε is supposed to have Gumbel distribution (type I extreme value) and $\boldsymbol{\beta}_{nk}$ is assumed to be homogeneous across respondents, the choice probability is simply reduced to Eq. (3) (McFadden, 1974).

$$P_{nj} = \frac{\exp(V_{nj})}{\sum_{k=1}^{J} \exp(V_{nk})} \tag{3}$$

Though the multinomial logit model shown in Eq. (3) has advantage in having a closed form, it does not represent heterogeneity of respondents with fixed parameter of β. Additionally, the multinomial logit model has a strong assumption that preference between two alternatives is not changed by some other alternatives' variation, which is called independence of irrelevant alternatives (IIA). One of the methods to incorporate consumer heterogeneity and relax IIA assumption is considering the coefficients β as random parameters. For example, if β follows a normal distribution with a mean of b and variance of W, the choice probability is changed to Eq. (4) where L_{nj} is the same as choice probability in Eq. (3) (Train, 2009). This is called the mixed logit model.

$$P_{nj} = \int L_{nj}(\boldsymbol{\beta}_n)\Phi(\boldsymbol{\beta}_n|\mathbf{b},\mathbf{W})d\boldsymbol{\beta}_n \tag{4}$$

Moreover, the coefficient $\boldsymbol{\beta}_{nk}$ has another hierarchy that is explained by l characteristics of a respondent n, $\mathbf{z}_{ln}$ as Eq. (5). $\boldsymbol{\Gamma}_{kl}$ are coefficients of individual characteristics $\mathbf{z}_{ln}$, which are different across attribute k and covariate l, and $\boldsymbol{\zeta}_{kn}$ is random term following normal distribution. It is difficult to estimate $\boldsymbol{\Gamma}_{kl}$ and $\boldsymbol{\Sigma}_{\beta}$ directly because the likelihood function is too complicated. To overcome the computational shortcomings of conventional estimation methods such as maximum likelihood estimation, we will use the Bayesian estimation approach with the Gibbs sampling method (Koop, Poirier, & Tobias, 2007; Rossi, Allenby, & McCulloch, 2012), which has the advantage of estimating the complex likelihood function with iteration instead of calculating the integration.

$$\boldsymbol{\beta}_{kn} = \boldsymbol{\Gamma}_{kl}\mathbf{z}_{ln} + \boldsymbol{\zeta}_{kn}, \quad \boldsymbol{\zeta}_{kn} \sim N\left(0, \boldsymbol{\Sigma}_{\beta}\right) \tag{5}$$

The model where heterogeneity of respondents is explained by their characteristics and estimated with Bayesian method is called the hierarchical Bayesian multinomial logit model. Finally, we will use this method to estimate the switching cost of smartphone users based on Eq. (6) below.

$$\begin{aligned} U_{nj} = {} & \beta_{n,OS\_A}x_{OS\_A,j} + \beta_{n,OS\_B}x_{OS\_B,j} + \beta_{n,OS\_C}x_{OS\_C,j} + \beta_{n,size}x_{size,j} + \beta_{n,weight}x_{weight,j} \\ & + \beta_{n,perform\_low}x_{perform\_low,j} + \beta_{n,perform\_mid}x_{perform\_mid,j} + \beta_{n,perform\_high}x_{perform\_high,j} \\ & + \beta_{n,price}x_{price,j} + \beta_{n,change\_dev}x_{change\_dev,j} + \beta_{n,non-change\_dev}x_{non-change\_dev,j} \\ & + \beta_{n,change\_OS}x_{change\_OS,j} + \beta_{n,non-change\_OS}x_{non-change\_OS,j} + \varepsilon_{n,j} \end{aligned} \tag{6}$$

The description of each variable is explained in Table 2, and βs are coefficients of corresponded variable. All of the dummy variables are taken as effect coding that makes the sum of all of the levels zero, while the other continuous variables are normalized to mean-centered value.

In addition, to analyze how consumer characteristics and switching costs affect smartphone preference, we set up the covariates corresponding to z_n in Eq. (6) as Eq. (7). The explanation for each covariate is found in Table 3. Factors related to switching behavior are period of possession of a current smartphone, purchased applications or accessories, early adapter tendency, searching cost, learning cost, and uncertainty by changing a device. The switching cost items are determined based on the previous literature described in Chapter 2. The stochastic term ζ_n represents the uncertainty in determining preferences for each attribute that are not explained by covariates, and is assumed to be normal distribution.

$$\begin{aligned} \beta_{kn} = {} & \alpha_{k,0} + \alpha_{k,age}z_{age,n} + \alpha_{k,gender}z_{gender,n} + \alpha_{k,edu}z_{edu,n} + \alpha_{k,time}z_{time,n} \\ & + \alpha_{k,app\_total}z_{app\_total,n} + \alpha_{k,app\_\cos t}z_{app\_\cos t,n} + \alpha_{k,acc\_\cos t}z_{acc\_\cos t,n} + \alpha_{k,early}z_{early,n} \\ & + \alpha_{k,search\_1}z_{search\_1,n} + \alpha_{k,search\_2}z_{search\_2,n} + \alpha_{k,search\_3}z_{search\_3,n} \\ & + \alpha_{k,learn\_1}z_{learn\_1,n} + \alpha_{k,learn\_2}z_{learn\_2,n} + \alpha_{k,uncert\_1}z_{uncert\_1,n} + \alpha_{k,uncert\_2}z_{uncert\_2,n} \\ & + \alpha_{k,uncert\_3}z_{uncert\_3,n} + \alpha_{k,uncert\_4}z_{uncert\_4,n} + \alpha_{k,uncert\_5}z_{uncert\_5,n} \\ & + \alpha_{k,uncert\_6}z_{uncert\_6,n} + \zeta_n \end{aligned} \tag{7}$$

Table 2
Explanation for variables, x_k.

Variables	Explanation
x_{OS_A}	Dummy variables for A-type OS
x_{OS_B}	Dummy variables for B-type OS
x_{OS_C}	Dummy variables for C-type OS
x_{size}	Continues variables for screen size
x_{weight}	Continues variables for weight
x_{price}	Continues variables for price
$x_{perform\_low}$	Dummy variables for low performance (high delay)
$x_{perform\_mid}$	Dummy variables for medium performance (medium delay)
$x_{perform\_high}$	Dummy variables for high performance (low delay)
x_{change_dev}	Dummy variables for device change (if a new alternative is selected, $x_{change\_dev}=1$, otherwise 0)
$x_{non-change\_dev}$	Dummy variables for device change (if a new alternative is selected, $x_{non-change\_dev}=0$, otherwise 1)
x_{change_OS}	Dummy variables for OS change (if a different OS is selected, $x_{change\_OS}=1$, otherwise 0)
$x_{non-change\_OS}$	Dummy variables for OS change (if a different OS is selected, $x_{non-change\_OS}=0$, otherwise 1)

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Table 3
Explanation for covariates, z_n.

Covariates	Explanation
$z_{age,n}$	Age
$z_{gender,n}$	Male = 0, female = 1
$z_{edu,n}$	Education level (years)
$z_{time,n}$	Time since purchase of current using smartphone (months)
$z_{app\_total,n}$	Total number of installed applications
$z_{app\_\cos\ t,n}$	Total amount of payment for applications
$z_{acc\_\cos\ t,n}$	Total amount of payment for smartphone accessories
$z_{early,n}$	Early adopter tendency (5-point Likert scale, early adopter tendency is increased when the level increases)
$z_{search\_1,n}$	Level of difficulty to find information for newly introduced smartphones (5-point Likert scale; difficulty is decreased when the level increases)
$z_{search\_2,n}$	Level of difficulty to compare price of smartphones (5-point Likert scale; difficulty is decreased when the level increases)
$z_{search\_3,n}$	Level of difficulty to compare functions of smartphones (5-point Likert scale; difficulty is decreased when the level increases)
$z_{learn\_1,n}$	Level of difficulty to learn how to use a new smartphone (5-point Likert scale; difficulty is decreased when the level increases)
$z_{learn\_2,n}$	Level of difficulty to learn how to be familiar with the application store (5-point Likert scale; difficulty is decreased when the level increases)
$z_{uncert\_1,n}$	Level of uncertainty from compatibility of smartphone accessories (5-point Likert scale; uncertainty is decreased when the level increases)
$z_{uncert\_2,n}$	Level of uncertainty from compatibility of smartphone applications (5-point Likert scale; uncertainty is decreased when the level increases)
$z_{uncert\_3,n}$	Level of uncertainty from compatibility of currently owned smart devices (5-point Likert scale; uncertainty is decreased when the level increases)
$z_{uncert\_4,n}$	Level of uncertainty from service quality of device after transition (5-point Likert scale; uncertainty is decreased when the level increases)
$z_{uncert\_5,n}$	Level of uncertainty from additional cost after transition (5-point Likert scale; uncertainty is decreased when the level increases)
$z_{uncert\_6,n}$	Level of uncertainty from customer service quality after transition (5-point Likert scale; uncertainty is decreased when the level increases)

Table 4
Estimation results of coefficients.

Attribute			Estimates of mean	Estimates of Variance
OS	A-type OS (β_{OS_A})		0.9990**	1.5966**
	B-type OS (β_{OS_B})		−0.0317	2.1945**
	C-type OS (β_{OS_C})		−0.9673**	–[a]
Screen Size (β_{size})			1.2623**	3.5138**
Weight (β_{weight})			−0.5644**	6.1603**
Performance		High ($\beta_{perform\_high}$)	1.8162**	3.6720**
		Medium ($\beta_{perform\_mid}$)	0.6328**	4.9810**
		Low ($\beta_{perform\_low}$)	−2.4490**	–[a]
Price (β_{price})			−4.5455**	21.4242**
Device Change		Change (β_{change_dev})	1.1205**	5.6777**
		Non-change ($\beta_{non-change\_dev}$)	−1.1205**	–[a]
OS Change		Change (β_{change_OS})	−1.0834**	1.3569**
		Non-change ($\beta_{non-change\_OS}$)	1.0834**	–[a]

** Posterior distribution does not include 0 at the 99% level.
[a] Variance of one of the dummy variables is not estimated due to identification.

4. Empirical results

Table 4 shows the estimated mean and variance of βs, which are assumed to have normal distribution.[2] The concept of significance of each estimated parameter is different from classical estimation methodologies because Bayesian estimation usually determines significant level by whether posterior distribution includes zero or not (Hong, Koo, Jeong, & Lee, 2012; Koo, Kim, Hong, Choi, & Lee, 2012). If posterior distribution of β, which is normal distribution in this study, has a large portion of negative values when mean value is positive, it is not reasonable to regard the mean value as significantly

[2] Note that the variances in Table 1 do not mean standard errors used to test statistical significance in maximum likelihood estimation or least square estimation. The variances indicate level of respondents' heterogeneity for each attribute.

Table 5
Estimation results for α.

	Price	Device change	Device non-change	OS change	OS non-change
Constant	−0.507	−2.794**	2.794**	0.544	−0.544
Age	−0.020	0.014	−0.014	−0.001	0.001
Gender	0.662	0.098	−0.098	−0.381*	0.381*
Education	−0.224*	0.088*	−0.088*	−0.023	0.023
Possession period	−0.050*	0.037**	−0.037**	−0.001	0.001
Number of applications	−0.012*	−0.003	0.003	−0.002	0.002
Application cost	0.028**	−0.001	0.001	−0.009**	0.009**
Accessory cost	0.011**	0.000	0.000	−0.003**	0.003**
Early adopter	1.327**	0.267*	−0.267*	−0.064	0.064
Search cost_1	−0.684*	0.034	−0.034	−0.246	0.246
Search cost_2	−0.551*	0.151	−0.151	0.035	−0.035
Search cost_3	0.559	0.112	−0.112	0.033	−0.033
Learning cost_1	−0.952*	0.167	−0.167	−0.101	0.101
Learning cost_2	0.915*	−0.267	0.267	0.075	−0.075
Uncertainty_1	−0.500*	0.033	−0.033	−0.030	0.030
Uncertainty_2	−1.072**	0.458**	−0.458**	0.045	−0.045
Uncertainty_3	0.376	−0.331*	0.331*	0.014	−0.014
Uncertainty_4	−0.138	0.107	−0.107	0.153*	−0.153*
Uncertainty_5	0.733*	0.027	−0.027	−0.219*	0.219*
Uncertainty_6	0.435	−0.260*	0.260*	0.090	−0.090

* Posterior distribution does not include 0 at the 90% level.
** Posterior distribution does not include 0 at the 99% level.

different from zero. Additionally, vice versa, if posterior distribution has large portion of positive value with negative mean, then it is difficult to insist the negative mean value is significantly different from zero. However, all of the posterior distributions of βs do not include zero at the 99% level. That is, all of the estimated means and variances have statistical meaning here. The sign and magnitude of the estimated mean value represent direction and level of preference, respectively, whereas the magnitude of estimated variance represents the level of consumer heterogeneity.

In the case of OS preference, the A-type OS, which has largest magnitude among three OS coefficients, is most preferred while the C-type is least preferred. Consumer heterogeneity of B-type OS preference is larger than that of A-type OS preference. In line with common sense, the utility increases when screen size and performance increase and weight and price decrease.

The most important attributes in this study are device and OS change variables. As a result, consumers prefer to change their device to new smartphones, but prefer to use the same OS as their previous smartphones. In the case of device change, consumers may prefer to have new smartphones due to obsolescence of current smartphones although the other attribute levels are the same as the current smartphone.

With the estimated mean values, it is possible to infer marginal willingness-to-pay (MWTP) for each attribute level. As shown in Eq. (8), the MWTP for attribute k is measured by ratio of the coefficient of k and coefficient of price (Train, 2009).

$$MWTP_{kn} = -\frac{\partial U/\partial x_k}{\partial U/\partial x_{price}} = -\frac{\beta_{k,n}}{\beta_{price,n}} \tag{8}$$

We calculate total 1370 MWTP for each respondent by using the mean of $\beta_{change\_dev,n}$, $\beta_{change\_OS,n}$, and $\beta_{price,n}$. The median value of WTPs for device change and OS change are 215.5 thousand Korean won (KRW)[3] and −202.7 thousand KRW. The level of switching cost for changing the OS is coincidentally similar to the switching cost for changing mobile service providers, \$225.70–\$236.30, as analyzed by Cullen and Shcherbakov (2010). However, the WTPs can vary across socio-demographic groups and characteristics of consumers.

The estimation results of parameter α for the coefficients of price, device change, and OS change in Eq. (7) are shown in Table 5. If signs of β_k and its corresponding α_{kl} are the same, preference for attribute k will be more sensitive when z_{ln} increases. For example, in the case of device change, if early adopter tendency increases, preference for device change also increases. That is, an early adopter is more likely to change his/her device. In the case of OS change, if the total cost of purchased applications increases, negative preference for OS change increases in absolute value. That is, the more applications a consumer purchases, the more sensitive to OS change he/she will be.

WTPs for device and OS change depending on covariates' variation can be calculated for each respondent based on the estimated β_k and α_{kl}. However, it is reasonable to interpret the effect of covariate variations only if estimates are significant for both price and device or OS change. In the case of device change, the estimates of education level, period of possession of

[3] 1 U.S. dollar was equal to 1071.65 Korean Won on average in 2014.

current smartphone, early adopter tendency, and uncertainty from compatibility for previously purchased applications are significant for both price and device change. Increased MWTPs for each case are 5.6 thousand KRW when education year increases by 1 year, 3.7 thousand KRW when period of possession increases by 1 month, 18.0 thousand KRW when early adopter tendency increases by 1 level, and 40.8 thousand KRW when uncertainty from application compatibility decreases by 1 level.

In the case of OS change, the estimates of application purchasing cost, accessory purchasing cost, and uncertainty from the possibility of additional payment after transition are significant for both price and OS change. Increased MWTPs for each case are 2.2 thousand KRW when total payment for applications increases by 1.0 thousand KRW, 0.9 thousand KRW when total payment for accessories increases by 1.0 thousand KRW, and 58.6 thousand KRW when uncertainty from the possibility of additional payment after transition decreases 1 level.

5. Policy implications and discussion

In this study, we conduct a conjoint survey to analyze switching costs in the smartphone market by using the hierarchical Bayesian multinomial logit model, which considers consumers' heterogeneous preference. The switching costs are categorized into two types: those derived from a device change and those derived from an OS change. We empirically estimate the two types of switching costs, and find that the levels of switching costs depend on the users' characteristics.

In terms of switching costs from smartphone device changes, the results demonstrate that the coefficient for changing smartphones is not negative, but positive, unlike our expectation. This means that consumers prefer to replace, rather than keep, their old smartphones, ceteris paribus. The results are in opposition to those in previous studies (Kim et al., 2004; Lee et al., 2006) that analyze switching costs from changing telecommunications service providers. However, it is not irrational for consumers to prefer a new device because the value of devices deteriorates over time due to obsolescence. Koo (2012) also concludes that consumers benefit from switching their smartphone devices to new ones. The switching cost from device change is dependent on consumers' education level, period of possession of current smartphone, early adopter tendency, and the uncertainty of previously purchased applications' compatibility.

On the other hand, in terms of OS change, switching the mobile OS decreases consumers' utility. Consumers who have experience using a certain mobile OS have a tendency to prefer the same OS when they change smartphones. The switching cost from OS changes increases as application purchasing cost, accessory purchasing cost, and uncertainty from the possibility of additional post-transition payment increase. Moreover, as consumers use various smart devices, including tablet PCs, smart watches, and connected TVs, the OS switching costs will have a more significant effect on the purchase decision for various devices with mobile OS, though we did not analyze this in this study.

We suggest some policy alternatives based on the results. The Korean government has enforced an act of "Improvement for Mobile Device Distribution Structure" in October 2014, to prevent unnecessary subsidy competition. The ultimate purpose of the bill is the maximization of consumer welfare through encouraging competition based on service and service charges instead of subsidy level. According to this policy, telecommunications service providers are not allowed to discriminate against consumers based on subscription types, such as number portability, changing terminals, or new subscribers. This policy could be meaningful for decreasing consumers' searching costs, caused by comparing smartphone prices. However, in this study we cannot find a significant relationship between searching costs and switching costs regarding device change. Thus, it is inconclusive as to whether the policy stimulated competition in the mobile device market. Rather, we believe that by allowing differentiated subsidies, as the OS conditions change, this will be effective. For example, if the maximum level of subsidy is increased when a consumer purchases a smartphone with a different OS, it will lower the barrier for using a different mobile OS.

In addition, as demonstrated by the empirical results, the policies and strategies are considerable for decreasing uncertainty from compatibility, for previously purchased applications, and from the possibility of additional payment after transition. From this perspective, pre-loaded applications, which are not compatible with different OS, could be a factor that increases switching costs. Regulatory agencies have provided guidelines that require a decrease in the number of pre-loaded apps in Korea, but the effects of this policy are limited because the pre-loaded app issue is global, not local. However, though the regulation decreasing pre-loaded applications was not effective, switching costs due to uncertainty will decrease if more information is provided. For example, regulatory agencies or mobile device manufacturers can provide a cross-checking application, verifying whether currently used applications and accessories are compatible with different OS. If an additional cost for changing OS becomes clear, the switching cost will decrease.

In summary, our study has contributed to the field in terms of empirically analyzing smartphone users' average switching costs, for both devices and the OS platform. There are some limitations to this study. First, the results of this study do not reflect actual switching behaviors because survey respondents expressed their intention to switch service providers or smartphones in a hypothetical situation. Second, unlike other countries, more than 90% of smartphone users in South Korea had adopted the Android OS; thus, the switching costs of the OS platform may be underestimated. Despite these caveats, we hope that policymakers who are interested in stimulating competition in the telecommunications market to increase social welfare may gain some insight from this study.

We suggest for further research that the econometric model consider both mobile service and device selection. We focused solely on smartphones; thus, telecommunications services were not taken into account in spite of their importance. The choice model, with both selections, will be more appropriate for analyzing consumers' actual smartphone choice behaviors. The comparisons of switching costs among other countries would also be a compelling research subject. As we noted, the switching costs will differ depending on market environment, government regulations, or consumer characteristics. The information regarding switching costs across countries will be useful for both companies and regulators. Although the study does not consider changes in corporate strategy with consumers' switching costs, a model that reflects company strategies would also be meaningful.

Acknowledgment

The survey conducted in this research was supported by the Korea Information Society Development Institute (KISDI).

Appendix A

See Appendix Table A1.

Table A1
Description of respondents' characteristics.

Total		Number of respondents 1370	Ratio (%) 100.0
Gender	Male	685	50.0
	Female	685	50.0
Age	10–19	146	10.7
	20–29	387	28.2
	30–39	398	29.1
	40–49	309	22.6
	50–59	130	9.5
Mobile Telecom Company	SKT	637	46.5
	KT	496	36.2
	LG UPlus	228	16.6
	MVNO	9	0.7
Device Manufacturer	Samsung Electronics Inc.	703	51.3
	Apple Inc.	260	19.0
	LG Electronics Inc.	222	16.2
	Etc	185	13.5
Education	~middle school	78	5.7
	High school	149	10.9
	Bachelor's degree	1001	73.1
	Master/Ph.D. degree	142	10.4
Average Income of Household (monthly, thousand KRW)	–1,999	161	11.8
	2,000–2,999	204	14.9
	3,000–3,999	270	19.7
	4,000–4,999	236	17.2
	5,000–5,999	205	15.0
	6,000–9,999	235	17.2
	10,000–	59	4.3

Appendix B

See Appendix Tables B1 and B2.

Table B1
Conjoint cards used in the type-A survey.

(SET A-1)	Alternative 1	Alternative 2	Alternative 3	Status Quo
OS	A-type	B-type	C-type	
Screen Size	5-in.	4-in.	4-in.	
Weight	150 g	100 g	150 g	
Performance	Low	Medium	Medium	
Retail Price	900,000 KRW	900,000 KRW	600,000 KRW	
Total number of choices	52	166	37	425
(SET A-2)	Alternative 1	Alternative 2	Alternative 3	Status Quo
OS	A-type	B-type	C-type	
Screen Size	3-in.	3-in.	5-in.	
Weight	100 g	150 g	100 g	
Performance	High	Low	High	
Retail Price	600,000 KRW	600,000 KRW	900,000 KRW	
Total number of choices	152	57	86	385
(SET A-3)	Alternative 1	Alternative 2	Alternative 3	Status Quo
OS	A-type	B-type	C-type	
Screen Size	5-in.	3-in.	3-in.	
Weight	150 g	150 g	200 g	
Performance	Medium	Medium	Medium	
Retail Price	1,200,000 KRW	900,000 KRW	600,000 KRW	
Total number of choices	102	111	31	436
(SET A-4)	Alternative 1	Alternative 2	Alternative 3	Status Quo
OS	A-type	B-type	C-type	
Screen Size	4-in.	4-in.	5-in.	
Weight	200 g	100 g	100 g	
Performance	High	High	Low	
Retail Price	600,000 KRW	1,200,000 KRW	1,200,000 KRW	
Total number of choices	194	127	9	350
(SET A-5)	Alternative 1	Alternative 2	Alternative 3	Status Quo
OS	A-type	B-type	C-type	
Screen Size	5-in.	4-in.	3-in.	
Weight	150 g	100 g	200 g	
Performance	High	Low	Low	
Retail Price	600,000 KRW	600,000 KRW	1,200,000 KRW	
Total number of choices	319	68	1	292
(SET A-6)	Alternative 1	Alternative 2	Alternative 3	Status Quo
OS	A-type	B-type	C-type	
Screen Size	4-in.	5-in.	4-in.	
Weight	200 g	200 g	150 g	
Performance	Low	High	Low	
Retail Price	900,000 KRW	1,200,000 KRW	1,200,000 KRW	
Total number of choices	71	204	1	404

Please cite this article as: Park, Y., & Koo, Y. An empirical analysis of switching cost in the smartphone market in South Korea. *Telecommunications Policy* (2016), http://dx.doi.org/10.1016/j.telpol.2016.01.004

Table B2
Conjoint cards used in the type-B survey.

(SET B-1)	Alternative 1	Alternative 2	Alternative 3	Status Quo
OS	A-type	B-type	C-type	
Screen Size	3-in.	5-in.	3-in.	
Weight	100 g	200 g	200 g	
Performance	Low	Low	High	
Retail Price	900,000 KRW	600,000 KRW	900,000 KRW	
Total number of choices	30	119	73	468
(SET B-2)	**Alternative 1**	**Alternative 2**	**Alternative 3**	**Status Quo**
OS	A-type	B-type	C-type	
Screen Size	4-in.	3-in.	4-in.in.	
Weight	200 g	150 g	150 g	
Performance	High	High	High	
Retail Price	600,000 KRW	1,200,000 KRW	900,000 KRW	
Total number of choices	224	67	41	358
(SET B-3)	**Alternative 1**	**Alternative 2**	**Alternative 3**	**Status Quo**
OS	A-type	B-type	C-type	
Screen Size	3-in.	5-in.	5-in.	
Weight	100 g	200 g	100 g	
Performance	Medium	Medium	Medium	
Retail Price	1,200,000 KRW	900,000 KRW	600,000 KRW	
Total number of choices	25	170	108	387
(SET B-4)	**Alternative 1**	**Alternative 2**	**Alternative 3**	**Status Quo**
OS	A-type	B-type	C-type	
Screen Size	5-in.	4-in.	3-in.	
Weight	150 g	100 g	200 g	
Performance	Low	Medium	Medium	
Retail Price	900,000 KRW	900,000 KRW	600,000 KRW	
Total number of choices	48	174	33	435
(SET B-5)	**Alternative 1**	**Alternative 2**	**Alternative 3**	**Status Quo**
OS	A-type	B-type	C-type	
Screen Size	3-in.	3-in.	5-in.	
Weight	100 g	150 g	100 g	
Performance	High	Low	High	
Retail Price	600,000 KRW	600,000 KRW	900,000 KRW	
Total number of choices	139	69	86	396
(SET B-6)	**Alternative 1**	**Alternative 2**	**Alternative 3**	**Status Quo**
OS	A-type	B-type	C-type	
Screen Size	4-in.	5-in.	4-in.	
Weight	200 g	200 g	150 g	
Performance	Medium	Low	Medium	
Retail Price	1,200,000 KRW	600,000 KRW	600,000 KRW	
Total number of choices	48	92	87	463

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Please cite this article as: Park, Y., & Koo, Y. An empirical analysis of switching cost in the smartphone market in South Korea. *Telecommunications Policy* (2016), http://dx.doi.org/10.1016/j.telpol.2016.01.004