Journal of Contemporary Eastern Asia, Volume 14, No.1: 45-55
http://dx.doi.org/10.17477/jcea.2015.14.1.045

An Empirical Analysis of Smartphone Diffusions in a Global Context[1]

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This paper examines the diffusion of smartphones with a special emphasis on the diffusive interactions between Apple iOS and Google Android in a global context. Since the two mobile platforms were first introduced in the market, the use of smartphones has skyrocketed, suggesting that the dramatic diffusion of smartphones may be explained in part by the growth and competition of these two platforms. To study this, an extended Bass model is applied to a data set of quarterly smartphone sales between 2008 and 2013 for 15 countries. Our findings suggest that the innovation effect was more salient for iOS than for Android in developed countries, whereas the imitation effect was more striking for Android than for iOS in developing countries. Furthermore, our results from the co-diffusion model suggest that the diffusion of Android negatively affected by the diffusion of iOS, but not vice versa.

Keywords: Smartphone, Technology Diffusion, Co-diffusion, Bass model, Network effect

I. INTRODUCTION

It is believed that one of the most widely and most rapidly adopted digital devices is the smartphone (DeGusta 2012). According to Gartner Inc., global smartphone sales reached 32 million units in the first quarter of 2008, and this number increased dramatically by the third quarter of 2013, when it reached 250 million. During the same period, the proportion of smartphones rose from 10.9% to 54.9% in the global mobile handset market, indicating that the core of mobile handset competition had moved from traditional feature phones[3] to smartphones. Simultaneous with this growth, the functions of smartphones have increased from browsing the web, taking pictures, and listening to music to include shopping, making online payments and managing one's personal health.

One additional salient characteristic of the smartphone market is that its competition within the market tends to rely on a mobile operating system (OS), which is complex smartphone

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[1] The author would like to thank Yeawon Yoo, Nancy Downes and seminar participants at the INFORMS Annual Meeting, San Francisco, and Daegu Gyeongbuk International Social Network Conference, Daegu.

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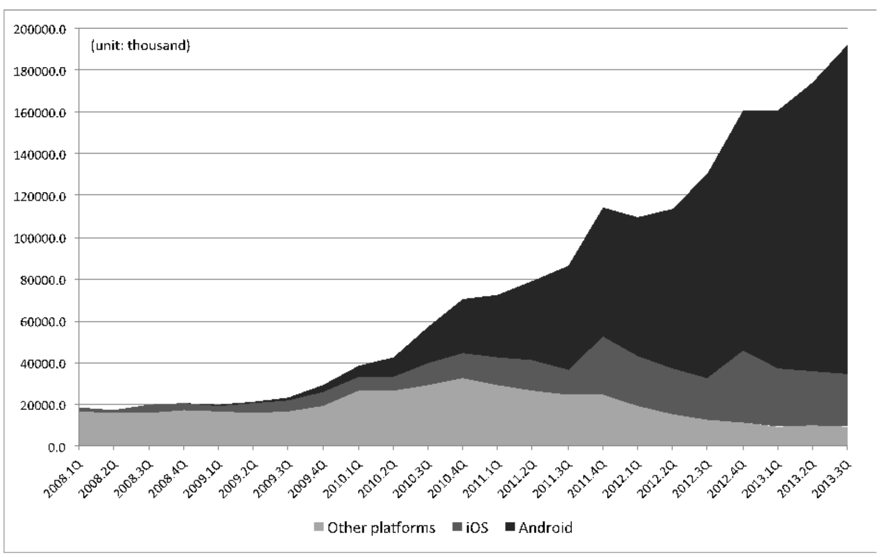
[3] Feature phones can be defined as cellphones containing a fixed set of functions such as voice calling, text messaging, and basic Internet capabilities. These middle- or low-end mobile phones have a limited capability and are not as extensive as smartphones.

system connected to both smartphone devices (hardware) and mobile applications (software). In other words, the adoption of smartphones has led to a new mobile ecosystem by creating a mobile marketplace that can accommodate multiple platforms. The mobile platform determines important characteristics such as performance, user interface, security and add-on applications, which, as a group, affect consumers' preferences.

While the smartphone market has constantly been evolving over the last few years, the market leaders in terms of the mobile platform have changed dramatically. Microsoft's Windows Mobile, Nokia's Symbian OS, and Research In Motion's Blackberry OS used to dominate the market, which accounted for the majority of the market in the first quarter of 2008. However, according to Gartner, by the third quarter of 2013, Google's Android OS and Apple's iOS accounted for 94.4% of the global smartphone market. In other words, by introducing their new mobile platforms – iOS in 2007 and Android in 2008, respectively – Apple and Google, the two newcomers to the smartphone market, were primarily responsible for the striking growth in smartphone sales shown in Figure 1, below.

Figure 1: Quarterly Sales of iOS and Android in the 15 Countries (2008.1Q-2013.3Q)



Note: 15 countries include Brazil, Canada, China, France, Germany, India, Italy, Japan, Mexico, Russia, South Africa, South Korea, Spain, United Kingdom and United States.

Several earlier studies have investigated the diffusion of smartphones (e.g., Park and Ueda 2011, Lee and Lee 2014), and this research has identified several driving forces behind the adoption of smartphones. In contrast to these prior studies, we focus on the diffusive interactions of mobile platforms in the process of adopting smartphones. This study examines how the two major mobile platforms evolved in a global context. Specifically, were Android and iOS diffused together? Alternatively, did the two OSs have a relationship of substitutability? While a large body of literature documents the diffusion of innovative information technologies, we are not aware of research that has specifically investigated the cross-country diffusion of mobile platforms using a framework based on diffusion theory (Bass 1969). These important but underexplored issues may be associated with competitive interactions to create a technology standard by utilizing network effects (Farrell and Saloner 1986). Using the diffusion theory framework developed, we empirically examine the diffusion of iOS and Android in the global context. As emphasized in Roger (2003) and Dewan, Ganley and Kraemer (2010), it is important to take into account the interaction of related technology innovations since their diffusions are likely to be mutually dependent. From the perspective of technology diffusions, there are competing arguments about whether competition for establishing standards positively affected the adoption of technology (Bohlin, Gruber and Koutroumpis 2010, Gruber and Verboven 2001). In sum, a careful empirical examination is necessary in order to accurately represent the diffusion of new technology.

To investigate our research questions, we analyzed data from 15 countries for the period between 2008 and 2013. Our data set – which included smartphone sales by mobile platform for each quarter – was applied to the widely used Bass model with appropriate extensions, which allowed us to examine the innovation, imitation and co-diffusion effects in the cross-country diffusion of iOS and Android. Our findings suggest that *innovation* effects were more salient for iOS than for Android in developed countries, whereas *imitation* effects were stronger for Android in most countries. Our further findings suggest that while the diffusion of Android had a negative impact on the diffusion of iOS, Android's diffusion may have benefited from the diffusion of iOS. This co-diffusive effect is stronger in developing countries as compared to developed countries. The results of this study may shed light on how the two competing mobile platforms have evolved differently across countries and provide useful managerial implications for industry practitioners.

II. CONCEPTUAL OVERVIEW

2.1 Literature Review

We begin with an overview of the well-established but still growing body of literature on how technological innovations become diffuse. The innovation diffusion of highly technical products such as smartphones can be mathematically modeled under different assumptions, which may be summarized by showing an S-shaped curve, which reflects the cumulative number of adopters. Such curves illustrate a relatively low adoption rate at the introduction stage of a product, followed by a higher adoption rate when the product takes off, the peak of the adoption rate, and finally the tailing off of the rate of adoption.

With regard to the various mathematical models used to measure the diffusion process, the logistic model, researchers have frequently used the Gompertz model, the ARMA (Autoregressive-moving-average) model and the Bass model (see Meade and Islam (2006) for a comprehensive review of this literature). Among these models, the seminal Bass model captures more intuitive aspects of the diffusion process than other models by distinguishing the effects of innovation (inherent tendency) and imitation (social contagion) (Bass 1969). That is, when the linear function suggested by the Bass model is used, a group of potential adopters of an innovation is seen as being influenced by an external source such as broadcast media, whereas the other group of adopters of an imitation is considered to be influenced by different communication channels such as an interpersonal channel and/or by social contagion. According to the assumption underlying the model, the former is independent of the installed user base of the technology, but the latter correlates linearly with the installed base effect (Takada and Jain 1991).

While there is a rich body of diffusion studies that have used this approach (see Chandrasekaran and Tellis (2006) for an overview of this research), most of these studies tended to investigate the diffusion of a sole technology. By contrast, this paper accounts for the *simultaneous diffusions of two interdependent technologies,* i.e., Apple iOS and Google Android in the growth of the smartphone market. As explained in Dewan et al. (2010), previous work on multi-innovation interrelationships can be divided into two groups: 1) a strand of studies on substitutable relationships, such as the studies by Danaher, Hardie and Putsis (2001) and Mahajan and Muller (1996), which looked at the phenomenon of replacing an old technology with a new technology; and 2) a series of studies on the complementary relationships of related technologies, such as the studies by Bucklin and Sengupta (1993) and Dewan et al. (2010), who examined the co-diffusion effects between scanners and the universal product code (UPC) and between PCs and the Internet, respectively.

At first glance, it appears that two competing mobile platforms (iOS and Android) often have a substitutable relationship, possibly because consumers tend to choose a smartphone compatible with one of the platforms. However, considering the fact that there would be a huge number of potential customers, fierce competition between iOS and Android may have stimulated quicker adoption of the smartphone, which may have resulted in co-diffusion of the competing platforms. Our paper focuses on this aspect, which has been little explored previously.

The topic of this paper is also related to earlier studies on network effects and standard competition (e.g., Shapiro and Varian 1998). One notable group of theoretical studies addressed the fact that a firm may earn higher profits by competing with appropriate competitors than by monopolizing a market (Katz and Shapiro 1985, Xie and Sirbu 1995, Sun, Xie and Cao 2004). This is because encouraging new entrants into the market tends to increase the market size by attracting a greater number of consumers. In addition to this aspect of competition, platform-based businesses generally produce network effects, indicating that, as was noted earlier, a consumer's willingness to buy is likely to increase with the network size of the compatible technology standard (Farrell and Saloner 1986). Many empirical studies have supported positive network externalities by using data from various industries such as the software, VCR, video games and/or PDA industries (Brynjolfsson and Kemerer 1996; Ohashi 2003; Nair, Chintagunta and Dubé 2004).

2.2 Conceptual Framework

According to Rochet and Tirole (2003), there are two types of network effects, same-side and cross-side, which explain how the installed base of a same and other technology in one period can affect the adoption of a particular technology in a subsequent period. This framework can be applied to our study. On the one hand, while the same-side network effect can be regarded as an imitation effect when considered within the framework of diffusion theory, the cross-side network effect may be characterized as resulting from a co-diffusion or substitution effect (Dewan et al. 2010). If the adoption of one platform increases (or decreases) the adoption of another platform, the interactive diffusive process is complementary (or substitutable). On the other hand, as seen in this study, customers who have already either used a feature phone or not used a cell phone at all may consider buying either an iPhone or any of the Android phones. If such purchases are initiated by a tendency inherent to external influence or advertising effect, this process can accurately be described as an innovation effect within the framework of diffusion theory.

III. EMPIRICAL MODEL AND DATA

In this section, we first describe a diffusion model for smartphones, accounting for the interactive aspect of the two mobile platforms. We then present our data.

3.1. Model

Following notations suggested by Dewan et al. (2010), two overlapping platforms are denoted by $i, j \in \{iOS, Android\}$ at time t. Let $F_i(t)$ denote the cumulative fraction of adopters of platform i out of the total potential market size at time t and $f_i(t)$ denote the instantaneous fraction of adopters at time t. Then, the diffusion equation can be formally written as:

$$\frac{f_i(t)}{1-F_i(t)} = a_i + b_i F_i(t) + c_i^j F_j(t). \qquad (1)$$

In Equation (1), a_i and b_i are the innovation parameter and the imitation parameter, respectively, as in a typical Bass model. c_i^j is the influence parameter from overlapping platform j to platform i. If c_i^j turns out to be positive, both platforms can be said to be positively co-diffused (or complementarily co-diffused), but if c_i^j is negative, both platforms would be said to have a substitutive relationship.

While the Equation (1) was specified in continuous time, it can be translated into a discrete time specification by introducing additional notations. That is, $f_i(t)$, the fraction of adopters, can be presented as $s_{ik}(t)/[N_{ik} - S_{ik}(t)]$, where $s_{ik}(t)$ denotes the number of adopters of platform i at time t in country k, N_{ik} denotes the maximum number of potential adopters of platform i in country k, and $S_{ik}(t)$ denotes the installed base of platform i at time t in country k. Accordingly, $F_i(t)$ can be presented as $s_{ik}(t)/N_{ik}$, which indicates the fraction of the cumulative adopters of platform i at time t in country k out of the maximum number of adopters of the platform i in country k. Note that we assume that N_{ik} (or N_{jk}) has a fixed value according to the maximum number of mobile telephony subscribers. In sum, the extended Bass model accounting for the co-diffusion effect is characterized by the following pair of equations where $i, j \in \{iOS, Android\}$:

$$S_{ik}(t) = \left[a_i + b_i \frac{S_{ik}(t)}{N_{ik}} + c_i^j \frac{S_{jk}(t)}{N_{jk}}\right][N_{ik} - S_{ik}(t)], \qquad (2)$$

$$S_{jk}(t) = \left[a_j + b_j \frac{S_{jk}(t)}{N_{jk}} + c_j^i \frac{S_{ik}(t)}{N_{ik}}\right][N_{jk} - S_{jk}(t)]. \qquad (3)$$

3.2. Data

The smartphone sales data was collected by a leading market research firm in the industry. It contains a panel data set for quarterly smartphone sales in15 countries over 23 consecutive quarters, from the first quarter of 2008 to the third quarter of 2013. The 15 countries were then divided into two groups: the countries that the World Bank describes as high-income were labeled as "developed countries" and the countries that it describes as middle- and low-income were labeled as "developing countries," similar to the classification by Dewan et al. (2010).
This classification resulted in nine developed countries (Canada, France, Germany, Italy, Japan, South Korea, Spain, United Kingdom and United States) and six developing countries (Brazil, China, India, Mexico, Russia and South Africa). Some important statistics on the two groups of countries are included in Table 1. There were two reasons for dividing the sample countries into two groups: first, purchasing a smartphone may correlate closely to an individual's income level because the average selling price of a smartphone is higher than that of a phone with traditional features. As can be seen in Table 1, the average GDP per capita of the nine developed countries during our study period was \$36,167 while that of the six developing countries was \$7,099. We believe that this difference in income level may lead to a greater/lesser likelihood of purchasing smartphones, which may lead to different diffusion processes. Second, the characteristics of individual mobile telecommunications markets are substantially different. In particular, consumers usually need to pay more when using smartphones – something indicated by higher average revenue per user and the higher proportion of data revenue– in the group of developed countries than in the group of developing countries.

Table 1. Countries in Data Set and Characteristics of Countries

Group	**Developed Countries**		**Developing Countries**	
Countries	Canada, France, Germany, Italy, Japan, South Korea, Spain, United Kingdom, United States (9)		Brazil, China, India, Mexico, Russia, South Africa (6)	
Country Characteristic	Mean	Std. Dev.	Mean	Std. Dev.
GDP per capita (US\$)	36167.30	10059.45	7099.29	3621.33
Mobile penetration rate	1.11	0.24	0.94	0.35
Average Revenue per User (ARPU) (US\$)	37.97	13.67	11.68	4.83
Proportion of Data Revenue	0.32	0.11	0.21	0.07

(Source: Merrill Lynch (2013))

One may still wonder how the sales of smartphones relate to the suggested country-specific characteristics. Table 2 shows the correlation between smartphone sales per capita and the country-level attributes. As can be seen in the first column of Table 2, smartphone sales per capita are indeed positively and significantly associated with the suggested country factors, indicating the need to take these different market characteristics into account.

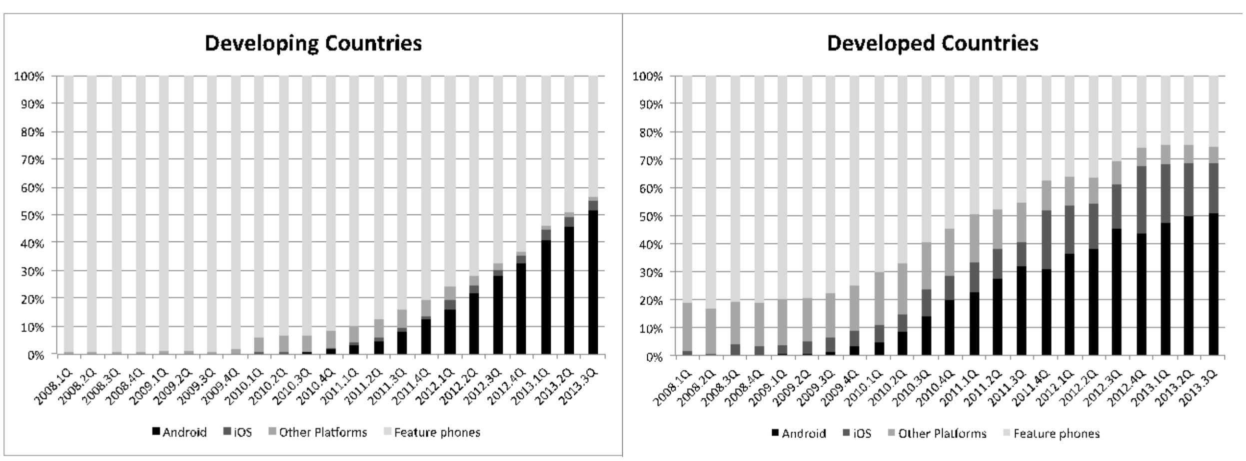
Our primary data source provided smartphone sales data disaggregated for mobile OS (iOS or Android). As noted above and illustrated in Figure 2, iOS and Android, became dominant platforms in the smartphone market during the period of this study, accounting for the majority of total smartphone sales over the this time. It is worth emphasizing that while Apple iOS is a proprietary and closed platform, Android is a free and open source-based platform, meaning that any device vendor can use the OS. As shown in the figure, the rate of adoption of smartphones is faster in developed countries than in developing countries, and the sales growth rate of Android is faster than that of iOS in the period studied. This may be due to the fact that an increasing number of manufacturers produce Android smartphones, whereas the iPhone alone accounts for the market share of iOS. At the end of the period studied (the third quarter of 2013), iOS and Android accounted for almost 70% of smartphone sales in developed countries and over 50% of smartphone sales in developing countries.

Table 2. Correlation Matrix

Variable	Smartphone per capita	GDP per capita	Mobile Penetration Rate	ARPU	Proportion of Data Revenue
Smartphone per capita	1.00				
GDP per capita	0.51***	1.00			
Mobile Penetration Rate	0.23***	0.21***	1.00		
ARPU	0.39***	0.86***	-0.06	1.00	
Proportion of Data Revenue	0.66***	0.59***	0.17***	0.47***	1.0000

Note: Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Figure 2. Shares of iOS and Android in the Mobile Phone Market by Group



IV. EMPIRICAL RESULTS

Estimation results using specifications (2) and (3) are reported. Note that to account for correlation in unobserved factors (error terms in specifications (2) and (3)) for iOS and Android, seemingly unrelated regression (SUR) specifications are estimated for measuring diffusion and co-diffusion parameters (Zellner 1962). Due to the nature of the dependent variables, the errors in both specifications might be correlated, and more efficient estimates may be yielded using this approach.

First, Table 3 shows only diffusion parameters, a and b, without the co-diffusion parameter, c, in specifications (2) and (3). The values of *R*-squared are fairly large, and all of the parameters estimated are statistically significant at the 1% level. By interpreting parameters, it can easily be seen that the innovation effect in developed countries is significantly greater than that in the developing countries for both iOS and Android. The estimated innovation effect for iOS in developed countries is the highest, indicating that consumers in these countries seemed to voluntarily purchase the iPhone.

Table 3. Results: Estimated Diffusion Parameters by Country Group

	iOS		Android	
Group	(1) Developed	(2) Developing	(3) Developed	(4) Developing
a (innovation)	0.0034***	0.0005***	0.0061***	0.0014***
	(0.0007)	(0.0001)	(0.0009)	(0.0003)
b (imitation)	0.1471***	0.1623***	0.2251***	0.3781***
	(0.0056)	(0.0080)	(0.0058)	(0.0045)
R-squared	0.897	0.855	0.934	0.986
N (obs.)	198	132	198	132

Note: Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Regarding the imitation effect, the estimated parameters for Android in Columns (3) and (4) are greater than the matching parameters for iOS in Columns (1) and (2). This finding indicates that the volume of the user base with installed Android OS is more likely to affect other consumers' purchase in previous periods for both developed and developing countries. As mentioned previously, multiple manufacturers have produced a variety of Android phones, so the stronger imitation effect may be related to this salient attribute. For instance, while the iPhone mainly targets high-end customers who can afford its high price, Android phones are accessible to a wider range of potential users, including both low-end and high-end customers.

Regarding estimates of both diffusion and co-diffusion parameters, including the last term in specifications (2) and (3), Table 4 shows that the values of R-squared are sufficiently large, and all estimated parameters are statistically significant at the 1% or 5% level. While the innovation and the imitation parameters show patterns similar to those in Table 1, our main interest is to examine co-diffusion parameters and their magnitude. The most interesting observation based on our findings is that the values for co-diffusion parameters in Columns (1) and (2) are negative but those in Columns (3) and (4) are positive.

Table 4. Results: Estimated Diffusion and Co-diffusion Parameters by Country Group

	iOS		Android	
Group	(1) Developed	(2) Developing	(3) Developed	(4) Developing
a (innovation)	0.0027***	0.0004***	0.0043***	0.0007***
	(0.0007)	(0.0001)	(0.0012)	(0.0002)
b (imitation)	0.1897***	0.4064***	0.1762***	0.1830***
	(0.0146)	(0.0398)	(0.0202)	(0.0138)
c (co-diffusion)	-0.0276**	-0.0349***	0.0790**	1.3513***
	(0.0088)	(0.0058)	(0.0313)	(0.0922)
R-squared	0.899	0.886	0.936	0.994
N (obs.)	198	132	198	132

Note: Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

These contradictory values indicate that while the diffusion of the Android OS negatively affected that of iOS, the diffusion of iOS positively affected that of the Android OS in both developed and developing countries. Comparing magnitudes, the impact of the competing platform (Android OS) seems to be stronger in developing countries than in developed countries. These findings would imply that the Android OS's entry into a market might decrease iPhone sales in most countries, but vendors selling Android OS-based smartphones might benefit from the existence of well-established smartphone markets created by the success of the iPhone.

V. DISCUSSION AND CONCLUSIONS

This study quantitatively analyzed the diffusion and co-diffusion effects of competing smartphone operating systems for fifteen countries. We emphasized that the imitation effect within the diffusion theory framework can be regarded as a same-side network effect, and the co-diffusion effect can be regarded as a cross-side network effect in the corresponding economic theory.

By using extended Bass model specifications, our findings first showed that the innovation effect was stronger for the iOS, which is in line with findings in previous studies. That is to say, our cross-country analysis demonstrates the differential effects of innovation and imitation, and that Apple products are more likely to attract potential consumers due to established market presence. Our finding further showed that the diffusion of Android benefitted from the competing platform (i.e., iOS)'s diffusion, but not vice versa. This differential observation corresponds to previous findings in the literature (Lee and Lee 2014).

These findings may prove useful to practitioners such as device manufacturers. For instance, Android handset manufacturers may benefit from employing differential country-level marketing strategies corresponding to the different characteristics of the diffusion process. Also, to increase their sales, Apple may benefit from establishing new product strategies to compete with a growing number of Android smartphones, particularly in developing countries. Furthermore, Apple initially entered the smartphone market in most countries after signing exclusivity contracts with selected wireless carriers. This strategy was found to potentially restrict the market for the iPhone, and Apple changed their exclusivity strategy when competitive Android phones, e.g., Samsung Galaxy S-series, started to become popular. This changed strategy corresponds with the findings of this study regarding the slow diffusion process of the iPhone in markets with competition against Android phones.

This study is not without limitations, and these limitations may suggest avenues for future research. First, the study did not account for some salient characteristics of the mobile handset market – e.g., compatibility with mobile applications marketplaces such as the Apple AppStore and Google Play, and the replacement cycle and generation substitution effect. Further consideration of these attributes may yield more precise data on diffusion effects. Second, the adoption of smartphones may be closely related to price. Analysis of detailed price information across time and country is available would allow study of how varying prices affect diffusion. Finally, the Android OS is used in a very wide variety of handset models produced by many different manufacturers, whereas iOS is used in only a few iPhone models in a given period. Comparing a few popular Android models (e.g., Samsung Galaxy S-series and Galaxy Note-series) with competing iPhone models may provide more specific results that would allow better understanding of the diffusion process of smartphones and smartphone operating systems.

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