

# The Double-Edged Sword of Backward Compatibility: The Adoption of Multi-Generational Platforms in the Presence of Intergenerational Services

**Il-Horn Hann**

Robert H. Smith School of Business  
University of Maryland  
College Park, MD 20742  
ihann@rhsmith.umd.edu

**Byungwan Koh**

Haskayne School of Business  
University of Calgary  
Calgary, AB T2N 1N4  
bkoh@ucalgary.ca

**Marius F. Niculescu**

Scheller College of Business  
Georgia Institute of Technology  
Atlanta, GA 30308  
marius.niculescu@scheller.gatech.edu

Information Systems Research, 2016, Vol 27(1), pp. 112-130

Permalink: <http://dx.doi.org/10.1287/isre.2015.0615>

## Abstract

We investigate the impact of the intergenerational nature of services, via *backward compatibility*, on the adoption of multi-generational platforms. We consider a mobile Internet platform that has evolved over several generations and for which users download complementary services from third party providers. These services are often intergenerational: newer platform generations are backward compatible with respect to services released under earlier generation platforms. In this paper, we propose a model to identify the main drivers of consumers' choice of platform generation, accounting for (i) the migration from older to newer platform generations, (ii) the indirect network effect on platform adoption due to same-generation services, and (iii) the effect on platform adoption due to the consumption of intergenerational services via backward compatibility. Using data on mobile Internet platform adoption and services consumption for the time period of 2001 – 2007 from a major wireless carrier in an Asian country, we estimate the three effects noted above. We show that both the migration from older to newer platform generations and the indirect network effects are significant. The surprising finding is that intergenerational services that connect subsequent generations of platforms essentially engender backward compatibility with two opposing effects. While an intergenerational service may accelerate the migration to the subsequent platform generations, it may also, perhaps unintentionally, provide a fresh lease on life for earlier generation platforms due to the continued use of earlier generation services on newer platform generations.

**Keywords:** Platform economics, multi-generation diffusion, backward compatibility, lease on life, network economics

## 1. Introduction

Many IT platforms are being released in a multi-generational fashion, with the intervals between generation releases dwindling and multiple generations overlapping in the market over certain periods of time. For consumers, the value of a particular platform generation and the decision to adopt it are directly related to the value they can derive from complementary value-adding services (Gawer and Cusumano 2002). A large ecosystem of valuable *compatible* services makes a platform generation more attractive. Moreover, for customers considering an upgrade, the ability to continue to use various legacy services lowers the

switching costs associated with the migration. Hence, with each new platform generation release, it is quite common for platform producers to offer a smoother inter-generational transition for the consumers by implementing *backward compatibility* with respect to existing services. This, in turn, creates additional value for the new generation platform by carrying over the value of earlier generation complementary services to the new generation platform (Gandal et al. 2000, Claussen et al. 2012).<sup>1</sup>

However, with backward compatibility, services become *intergenerational*, allowing for more complex interactions between adopters of different platform generations. Backward compatibility extends the useful life and potential market for older services, which in turn elevates the value of the older generation platforms that were compatible with such services all along. In addition, all other things equal, some users may prefer the older generation platforms in spite of all the new bells and whistles of the newer generations. This is due to the fact that many IT platforms exhibit *no free disposal* (Dewan and Freimer 2003, Chellappa and Shivendu 2010) whereby more is not always better for some of the users – updates in functionality may complicate the interface, require additional resources, and may lead to integration breakdown. The backward compatibility for services, in parallel with price markdowns for older generations, may be enough to expand the market and bring in some of the potential adopters who did not deem any of the platform generations worthwhile in isolation before. Nevertheless, as discussed above, some of these new adopters may not choose the newer generation platform. As such, backward compatibility can also provide a *lease on life* for the older generation platform.

Point in case, let us consider Microsoft Windows operating system. In April 2014, Microsoft ended support for Windows XP, its 12-year-old version of the operating system. Concurrently, Microsoft offered additional monetary incentives for users to upgrade from an XP system (Motti 2014) with a visible effort to direct them towards Windows 8 (with a free update to 8.1), the latest version of the operating system, which had just been released half a year earlier (Newman 2014). However, as of May 2014, many users

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<sup>1</sup> In the handheld video-game industry, it has been argued that new generation consoles (e.g., Game Boy Advance) were adopted faster because of backward compatibility (Claussen et al. 2012). Game Boy Advance was backward compatible with the games that were originally written for the earlier generation console, Game Boy Color.

still held on to Windows XP (25.27% of the market). Among those who decided to go with a newer version (new adopters or upgrading ones), more chose Windows 7, a 4-year-old version of the operating system, instead of Windows 8.1 (Net Applications 2015). In terms of market share, from April to May 2014, Windows 7 gained 0.79% while Windows 8.1 gained only 0.47%.<sup>2</sup> Newer Windows versions exhibit extensive backward compatibility in terms of additional software that can run on top of the operating system. However, new features in Windows 8 “have polarized critics and alienated mouse-and-keyboard users, who feel Microsoft put too much emphasis on touchscreens” (Newman 2014). Due to backward compatibility, use cases and benefits of the two successive generations of Windows (7 and 8.1) overlapped greatly, which led some users to go with the older generation.

In this paper, we explore the adoption of multi-generational IT platforms over time, zooming in on the complex role played by backward compatibility of platforms with respect to services. While the impact of backward compatibility on newer platform adoption has been previously explored (e.g., Clemens and Ohashi 2005), the “shot in the arm” (lease on life) that backward compatibility gives to the older platform has not been analyzed in depth before. This research question is of great managerial interest to platform and services providers alike. Platform providers want to know how backward compatibility impacts the co-diffusion of multiple generations of the platform in the market, which in turn impacts their costs when quality assurance and tech support efforts are spread across many generations (e.g., development and release of security patches). Such insights influence both product design and retirement. On the other hand, backward compatibility influences the size of the installed base for each platform generation, affecting the strategies of services providers. For example, if adoption of a newer platform generation is slow but there is a strong loyal consumer base for the older generations, a service provider may choose to focus its efforts on older platform generations. If the platform provider removes backward compatibility, then the market size may become significantly smaller for a service provider which, in turn, may force it to move further away from platform provider exclusivity and embrace a multi-homing strategy.

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<sup>2</sup> The prices of Windows 7 Professional and Windows 8.1 Full version at Amazon.com in June 2014 were \$119 and \$105.69 respectively.

We frame our study in the context of a mobile Internet platform offered by a major wireless carrier. The wireless carrier, as a platform provider, designs and provides all the platform generations. Handset manufacturers produce devices for each platform generation based on the specifications of the wireless carrier. The supporting services for each platform generation are provided by third-party service providers. A newer-generation platform is backward compatible with the services originally developed for the earlier generations, i.e., services are intergenerational through backward compatibility; hence, a new generation platform user can always consume its own-generation services as well as earlier generation services.

We propose a novel multi-generation adoption model that accounts for the complex tensions induced by backward compatibility on the diffusion process. One major contribution of this work is that we identify and quantify a significant lease on life effect on older platforms as a result of backward compatibility and consumption of intergenerational services on multiple platform generations. Hence, while intergenerational services foster the migration to newer generation platform for some of the user base, we confirm that they can, at the same time, lengthen the lifecycle of the earlier generation platforms. Through our model and results, we thus advance the understanding of multi-generational IT platform adoption.

The rest of the paper is organized as follows. In Section 2, we position our paper in the context of the relevant literature. In Section 3, we discuss the conceptual model and assumptions. We describe the research context and data in Section 4, and empirical specification, methodology, and estimation results in Section 5. In Section 6, we discuss the detailed economic impact of backward compatibility and the managerial implications of the uncovered effects. We include the concluding remarks in Section 7.

## **2. Literature Review**

Our study is related to several research streams. Our model and research question are framed in the context of the diffusion of multiple generations of IT platforms. In addition, we draw inspiration from the literature on planned obsolescence and no free disposal.

The literature on multi-generational diffusion of technological innovation is well established (e.g., Blackman 1974, Norton and Bass 1987, Mahajan and Muller 1996, Islam and Meade 1997, Jun and Park 1999, Kim et al. 2000, Danaher et al. 2001, Chu and Pan 2008, Zhang et al. 2008, Bohlin et al. 2010, Jiang

and Jain 2012). Many of these studies do not explicitly model the indirect network effects induced by complementary services and also do not account for backward compatibility. The models in Gupta et al. (1999), Nair et al. (2004), Li et al. (2006), Dewan et al. (2010), and Niculescu and Whang (2012) include the indirect network effects but do not dive deep into the exploration of interactions between generations.

The aforementioned literature has in most cases treated the adoption of multi-generational products across time as a generation handover - a technological substitution of the earlier generations by the newer ones. Once the new generation product is introduced, the adopters of the earlier generation products gradually migrate to the new generation product over time and eventually the demand for earlier generation products dies out. Backward compatibility, where accounted for, was considered to give an advantage to the newer generation, accelerating the migration process. Clemens and Ohashi (2005) considered backward compatibility in this flavor and their study is the closest to ours among extant research. In that study, the authors incorporate backward compatibility in their model and measure indirect network effects in the video game industry. Nevertheless, there are three major differences between our paper and theirs. First, in their model, backward compatibility affects newer platform generations but it does not affect older generations. Their study focuses on consoles and video games between 1994 and 2002. At that time, in general, games were issued to be played on a single console. So a PS2 user that was playing a game that was originally released for PS1, could not do so in a network with another PS1 user. As such, the fact that more PS2 users could play games compatible with PS1 would not directly increase the value of the PS1 consoles. Thus, Clemens and Ohashi model newer generations of the consoles as competing with the older generations but not enhancing the value of the latter in any way. In contrast, in our model, through mobile data services, mobile platform users can interact with each other across platform generations. For example, platform users communicate to each other using text-based or multimedia-based messaging or can play a network game together. As such, if users of a new platform generation consume services released originally for an older generation, this gives them a way to interact with older platform generation users. Hence, older platform generation users benefit if newer platform generations exhibit backward compatibility with respect to the services. Therefore, we identify two effects of backward compatibility: (i) the (known) forward effects of

backward compatibility and (ii) the (new) backward effect of backward compatibility (the “lease on life”). To the best of our knowledge, our work is the first one to conceptualize the two effects of backward compatibility and to subsequently develop an empirical model that allows us to identify and measure the effect of the intergenerational nature of services (via backward compatibility) on generation handover. Because we account for how backward compatibility (of newer platform generations with respect to services initially released for older generations) impacts both older and newer generation platforms, unlike in Clements and Ohashi (2005), we do not implicitly assume that backward compatibility gives an edge to the newer generations. In our analysis, we let the data tell us the magnitude of each effect.

Second, the model in Clements and Ohashi (2005) does not include direct network effects at platform level. In their paper, the utility from owning a particular console is not modeled to depend on the installed base of that particular console. In contrast, our model accounts for and estimates direct network effects for each mobile platform generation. Mobile platforms exhibit direct network effects as they have inter-user communication capabilities (Niculescu and Whang 2012). Third, Clements and Ohashi use the number of available game titles for each console to measure indirect network effects assuming a consumer values all available game titles equally. In contrast we use the actual consumption data (i.e., traffic volume downloaded by users). We believe that in our context such a measure is more accurate, especially taking into consideration the explosion in available services, apps, and downloadable pieces of content available for mobile platforms. Just as an example, as of June 2014, there were 1.2 million apps available for the iOS platform (Perez 2014). It is clear that in this sea of content and apps, there are many pieces that are substitutes and, moreover, due to obvious resource constraints (such as time, money, attention span, interest, etc.), users discover and tap only a fraction of what is available. As such, we believe that quantifying indirect network effects via traffic volume is more relevant in the mobile Internet context. If some services attract significant traffic, that makes them popular, which attracts potential new customers to the compatible platforms for such services.

The multi-generational nature of product innovation is also discussed in the planned obsolescence literature. However, the literature has thought of planned obsolescence in the context of optimal durability

(Bulow 1986), R&D investment (Waldman 1996), and pricing decisions (Lee and Lee 1998) of multi-generational products, rather than in the context of consumer adoption and migration. Furthermore, while several studies look at the role of compatibility in planned obsolescence, most studies do not explicitly model backward compatibility. Exceptions include Waldman (1993) and Choi (1994), who investigate the condition under which the firm makes a subsequent version incompatible (or compatible) and Ellison and Fudenberg (2000), who investigate the firm's incentives to release a backward-compatible newer version. These studies, however, consider backward compatibility (or incompatibility) as a tool for planned obsolescence, i.e., by making a new version backward compatible (or incompatible) the firm gives it an advantage and makes an old version obsolete. In contrast, our main focus is identifying and quantifying the (hitherto undiscovered) lease on life effect of backward compatibility for an old version. Lastly, while many studies see planned obsolescence as a phenomenon that leads to less durability or more frequent updates than is socially optimal, Fishman et al. (1993) and Bharadwaj et al. (2013) highlight the positive outcomes of planned obsolescence (such as technological progresses) but do not explicitly discuss the role of backward compatibility in these positive outcomes.

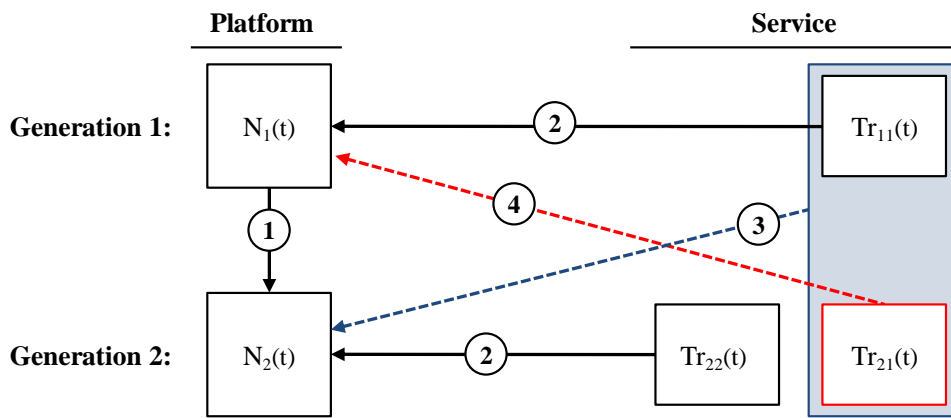
Last but not least, we also draw inspiration from the literature on no free disposal in the context of several IT platforms (Dewan and Freimer 2003, Chellappa and Shivendu 2010, Chellappa and Mehra 2013). In our model, net of any price effects, in the presence of backward compatibility some new adopters may choose the older platform generation.

### **3. The Conceptual Model and Assumptions**

For expositional clarity, we first introduce the model and build the theory using a hypothetical market that has two generations of platforms (platform 1 and 2) and supporting/complementary services released for each of them (generation 1 and 2 services). The parameterization for the full model is discussed in Section 5.1. Platform 2 is an update (a subsequent generation) of platform 1. Platform 2 exhibits backward compatibility in that platform 2 users can consume both generation 1 and 2 services, but platform 1 users can consume only generation 1 services. As an illustration, a newer generation of the iPhone can run all apps and services that older versions could run. However, Apple Pay, a service for iOS introduced shortly

after the release of iPhone 6 and 6 Plus, requires a near-field communication chip to pay for in-store purchases (Apple 2014). This technology is only embedded in the more recent versions of the hardware platform and, hence, Apple Pay cannot be used on older iOS devices to pay for in-store purchases.

Let  $N_i(t)$  be the installed base of platform  $i$  by time  $t$ ,  $Tr_{ij}(t)$  be the cumulative traffic volume (volume of data packets<sup>3</sup>) of generation  $j$  services consumed by platform  $i$  users by time  $t$ , and  $Tr_j(t)$  be the cumulative traffic volume of generation  $j$  services consumed by *all* compatible platforms ( $j$  and newer) by time  $t$ . Figure 1 illustrates the relationship between platforms and services, highlighting four effects:



Note: 1. Migration; 2. Indirect network effect; 3. Forward effect of backward compatibility (FEBC); 4. Backward effect of backward compatibility (BEBC)

**Figure 1.** The relationship between platforms and services – two generations case

- **Effect 1: Migration.** Platform 1 adopters may gradually migrate to platform 2 over time once the latter has been released. As such, at any given time, adopters of platform 2 consist of new (first-time) adopters and those adopters who have migrated from platform 1.
- **Effect 2: Indirect network effect.** A platform becomes more valuable (which is manifested in the form of a positive effect on adoption) when the consumption of its same-generation complementary services (those services compatible exclusively with this and subsequent platforms, but not with older ones) increases.

<sup>3</sup> 1 packet = 512 bytes of data.



- **Effect 3: Forward effect of backward compatibility (FEBC).** Since platform 2 is backward compatible with generation 1 services, the value of platform 2 is also associated with the value of generation 1 services, which in turn is related to their consumption (whether it originated on platforms 1 or 2). We call this effect of consumption of generation 1 services on the value of platform 2 the *forward effect of backward compatibility*.
- **Effect 4: Backward effect of backward compatibility (BEBC).** As more platform 2 users consume generation 1 services through backward compatibility, platform 1 gets additional value in the following ways. First, generation 1 services do not get discontinued due to the continued demand, which allows platform 1 users to continue to derive value from these earlier services. Second, through continued generation 1 services (i.e., intergenerational services), platform 1 users can interact with platform 2 users, which pushes the obsolescence of platform 1 further in the future. As such, through backward compatibility, platform 1 gets a backward-compatibility-induced *lease on life* which we call the *backward effect of backward compatibility*.

Consistent with the relationship illustrated in Figure 1,  $N_1(t)$  and  $N_2(t)$  can be written as:

$$N_1(t) = \widehat{N}_1(t) - Mig_1(t) + Lol_1(t), \quad (1)$$

$$N_2(t) = \widehat{N}_2(t) + Mig_1(t), \quad (2)$$

where  $\widehat{N}_i(t)$  is the estimated cumulative number of adopters of platform  $i$  generation by time  $t$  due to market expansion induced by the introduction of this platform generation, in the absence of newer platform generations,  $Mig_1(t)$  is the cumulative number of platform 1 adopters who have migrated to platform 2 by time  $t$  net of traffic externalities, and  $Lol_1(t)$  is the cumulative *lease on life* for platform 1 by time  $t$  (measured as the cumulative number of *additional* adopters of platform 1 due to platform 2 adopters' consumption of generation 1 services and to the price difference between platforms).

The (single-generation) diffusion literature introduced several functional forms for  $\widehat{N}_i(t)$  for various contexts (Mahajan and Muller 1979, Mahajan et al. 1990, Meade and Islam 2006). Most of those functional forms share the same underlying structure for a diffusion process. They assume that there is a

maximum number of potential adopters (i.e., the market potential) and that the adoption penetration rate (derived from a hazard rate function) follows a probability distribution curve (e.g., modified exponential, logistic, or Gompertz). Following the same underlying diffusion structure, we define  $\hat{N}_i(t)$  as:

$$\hat{N}_i(t) = m_i F_i(t), \quad (3)$$

where  $m_i$  is the maximum *increase* in the number of adopters for platform  $i$  (i.e., the increase in the market potential due to the introduction of platform  $i$ ), and  $F_i(t)$  is the cumulative *diffusion rate* of platform  $i$  by time  $t$ . Building on the generalized Bass model (GBM) introduced in Bass et al. (1994), we parameterize  $F_i(t)$  as:

$$F_i(t) = \mathbf{1}_{t \geq \tau_i} \cdot \frac{1 - e^{-\left[ (z_i + q_i) \left( (t - \tau_i) + \beta_i \log[1 + Tr_{ii}(t) - Tr_{ii}(t-1)] + \gamma_i \log \left[ 1 + \sum_{k < i} [Tr_k(t) - Tr_k(t-1)] \right] \right) \right]}}{1 + \frac{q_i}{z_i} e^{-\left[ (z_i + q_i) \left( (t - \tau_i) + \beta_i \log[1 + Tr_{ii}(t) - Tr_{ii}(t-1)] + \gamma_i \log \left[ 1 + \sum_{k < i} [Tr_k(t) - Tr_k(t-1)] \right] \right) \right]}}, \quad (4)$$

where  $\tau_i$  is the *time* at which platform  $i$  was introduced in the market (generation  $i$  services were introduced at or after  $\tau_i$ ) and  $\mathbf{1}_{t \geq \tau_i}$  is the indicator function that equals 1 if  $t \geq \tau_i$  and 0 otherwise. The derivation of the expression for the cumulative diffusion rate  $F_i(t)$  is included in Appendix A. Consistent with the diffusion literature (Bass et al. 1994), we name  $z_i$  the coefficient of innovation and  $q_i$  the coefficient of imitation (often referred to as the measure for the *direct network effect*). As discussed in Appendix A, based on equation (A.3),  $\beta_i$  measures the impact of the percent change in platform  $i$  users' consumption of generation  $i$  services on the diffusion rate of platform  $i$  - the *indirect network effect*. Similarly,  $\gamma_i$  measures the impact of the percent change in consumption of the older generation services ( $k < i$ ) on the diffusion rate of the new generation platform (platform  $i$ ), i.e. the magnitude of the *FEBC*.

The multi-generation diffusion literature (Blackman 1974, Norton and Bass 1987, Mahajan and Muller 1996, Jun and Park 1999, Kim et al. 2000, Chu and Pan 2008; Jiang and Jain 2012) extends (single-generation) diffusion models by adding parameters to capture user migration to subsequent generations (similar to  $Mig_1(t)$  in equations (1) and (2)). These models generally assume that (i) adopters migrate from

earlier to new generations, but not vice-versa, and (ii) the install base for an earlier generation continues to shrink once it starts decreasing. Consistent with these assumptions, we define  $Mig_1(t)$  as:

$$Mig_1(t) = m_1 F_1(t) F_2(t). \quad (5)$$

The migration from platform 1 to 2 manifests in a stronger way when the installed base for platform 2 increases (i.e., the attractiveness of platform 2 is proportional to the existing installed base) and the number of platform 1 adopters becomes zero when platform 2 is saturated (i.e.,  $F_2(t) = 1$ ).

Lastly, we model the *lease on life* for platform 1 (denoted  $Lol_1(t)$ ) as follows:

$$Lol_1(t) = \mathbf{1}_{t \geq \tau_2} \cdot \left[ \alpha_1 Tr_{21}(t) + \zeta_1 e^{-\eta(t-\tau_2)} \sum_{s=\tau_2}^t \Delta P_1(s) \right], \quad (6)$$

where  $\Delta P_1(t) = p_2(t) - p_1(t)$  and  $p_i(t)$  is the average of real prices of platform  $i$  handsets. We measure the lease on life for platform 1 as its *additional* installed base due to (i) platform 2 adopters' consumption of generation 1 services (*backward-compatibility-induced lease on life*) and (ii) the price difference between handsets supporting two successive generations of platforms (*price-induced lease on life*).

Platform 2 users' consumption of generation 1 services (made possible by backward compatibility) increases the value of platform 1 by extending the lifespan of generation 1 services and by allowing platform 1 users to interact with platform 2 users. For instance, Microsoft Office 2007 introduced the new .docx format. Yet, Office 2007 was backward compatible with the old .doc format, i.e., it could read and edit .doc files, which gave one less reason for users to choose it over an earlier Office version (an older standard continued to be supported which made it less urgent to migrate to the new one). Furthermore, as more Office 2007 users wrote their documents in .doc format, an earlier Office version would have been even more attractive to some users since they could collaborate with Office 2007 users without many constraints. In general, users who were not considering the earlier platform in the absence of backward compatibility or price advantage may now consider this older platform even as a newer generation is released in the market – these adopters are the ones accounted under the lease on life effect. Correspondingly, we call  $\alpha_i$  the coefficient of the backward-compatibility-induced lease on life for platform  $i$  (measuring *BEBC*).

The lease on life for platform 1 can also be influenced by price. In markets for multi-generation products, it is quite common for an earlier generation platform to be marked down after a new generation platform is released and some adopters choose the earlier generation platform because of this discounted price (Zhang et al. 2008). In order to make sure that what we identify as the backward-compatibility-induced lease on life is identified separately from the price-induced lease on life, we control for the price effect by including the price difference  $\Delta P_1(t)$  between handsets supporting the two successive platform generations in equation (6). It has been discussed that the effects of marketing activities (e.g., price promotion) dissipate over time (Hanssens et al. 2001). Other studies (e.g, Niculescu et al. 2012), indicated that later adoption might be the result of valuation learning rather than price. Hence, we assume that the price-induced lease on life effect diminishes over time at the rate of  $\eta$ . In period  $t$ , as long as the consumption of generation 1 services by platform 2 owners continues at a strong pace (i.e.,  $Tr_{21}(t) - Tr_{21}(t - 1)$  is large enough) that overcomes the decay in the strength of the price effect, then the aggregate number of additional consumers of platform 1 increases. Otherwise it decreases. As platforms 1 and 2 age more, then backward compatibility induced traffic effect ends up dominating the price effect in the lease on life. We call  $\zeta_i$  the coefficient of the price-induced lease on life for platform  $i$ .

Our model allows for the backward-compatibility lease on life for platform 1 to exist even in the absence of any price difference between platform generations. In general, newer platforms contain all features and capabilities of older platforms and then some more. Nevertheless, for some economic goods (IT platforms included) and some consumer segments, it may be the case that less is better (beyond a certain point the consumer utility may decrease in the number of features or quantity of a given good) – a property commonly known in economics literature as “*no free disposal*” (e.g., Dewan and Freimer 2003, Chellappa and Shivendu 2010, Chellappa and Mehra 2013). Newer features may lead to design changes and increased complexity in the user interface. As discussed in the Introduction, new features added in Windows 8 (and subsequent 8.1 release) supporting touch screen devices have been a source of vast consumer complaints, leading to Windows 7 market share increasing more than that for 8 and 8.1 versions together in the period June 2014-June 2015 (Net Applications 2015). In addition, newer platforms may require additional

resources, which may congest or render completely obsolete the supporting technology. For example, in the case of iOS mobile operating system, versions 6.0 and beyond cannot be installed on the first generation of iPad hardware. Thus, for a user to adopt the newer generation of iOS, she would have to spend additional funds on supporting hardware as well. Last but not least, platform design updates may break down integration with other complementary products. For example, when Apple redesigned the connectivity for iPod, iPhone, and iPad to move away from 30-pin format to Lightning 8-pin format for the adaptors/connectors, this in turn made connectivity to older docking devices harder (consumers would have to buy adaptors to continue to use those complementary devices with the new Apple products).

As illustrated in equations (4) and (6), the number of adopters of a platform is influenced by the consumption of its compatible services (whether they were released for this current platform or older platforms). At the same time, consumption of a certain generation of services could be influenced by the number of platform users whose platforms are compatible with these services. Hence,  $Tr_{ii}(t)$ ,  $Tr_{ki}(t)$  with  $k > i$ , and  $Tr_i(t)$  could be endogenous to the model. To control for this potential endogeneity, along with the rest of the model, we jointly estimate the following two equations parameterizing traffic:

$$Tr_{ii}(t) = \mathbf{1}_{t \geq \tau_i} \cdot \frac{a_i \sum_{s=\tau_i}^t N_i(s)}{1 + e^{-(t-\tau_i)}}, \quad (7)$$

$$Tr_i(t) - Tr_{ii}(t) = \sum_{l>i} Tr_{li}(t) = \mathbf{1}_{t \geq \tau_i} \cdot \frac{b_i \sum_{s=\tau_i}^t \sum_{l>i} N_l(s)}{1 + e^{-(t-\tau_i)}}. \quad (8)$$

Following the diffusion literature (Griliches 1957), we assume that the cumulative consumption of services ( $Tr_{ii}(t)$  and  $\sum_{l>i} Tr_{li}(t)$ ) grows following a logistic diffusion process while the susceptible consumption levels ( $a_i \sum_{s=\tau_i}^t N_i(s)$  and  $b_i \sum_{s=\tau_i}^t \sum_{l>i} N_l(s)$ ) are proportional to the installed base.

## 4. Mobile Internet Market and Data

### 4.1. Description of the Mobile Internet Platform

We obtained monthly data on mobile Internet platform adoption and services consumption between May 2000 and Dec. 2007 from a major wireless carrier in an Asian country with a highly developed mobile

telecommunication infrastructure. During this time period, the wireless carrier sequentially introduced four generations of the mobile Internet platform with backward compatibility.<sup>4</sup> Here backward compatibility is unidimensional, covering only the platform side, i.e., the newer generation platforms were backward compatible with earlier generation services but newer generation services were not backward compatible with earlier generation platforms. Services supporting each platform were introduced by third-party providers via the wireless carrier’s distribution channels. Table 1 summarizes these platforms and services.

**Table 1.** Summary of each platform and service

Platform Generation	Release date	Novel Characteristics	Complementary Services/Apps
1 <sup>st</sup>	May 2000	<b>Content based:</b> The platform supports mobile web browsing and content downloading.	Ringtones, wallpapers, and short-text-based instant messengers
2 <sup>nd</sup>	Dec. 2001	<b>Application based:</b> The platform supports more sophisticated application-based services through the application embedded or installed on the platform.	Mobile (network) games, mobile banking, and mobile stock trading
3 <sup>rd</sup>	Apr. 2002	<b>Enhanced communication:</b> The platform provides enhanced mobile communication tools that enable users to send and receive long-text messages and attach images and/or video files on it.	Multimedia Messaging Service (MMS)
4 <sup>th</sup>	Feb. 2003	<b>Streaming video:</b> The platform supports mobile video streaming and uploading services.	Live TV, Video on demand (VOD), and User generated video (UGV)

#### 4.2. Data Description

In our dataset, we have monthly data for the time period 2001 – 2007 for (i) the installed base of platform  $i$  by time  $t$  (denoted  $N_i(t)$ ), (ii) the cumulative traffic volume of service  $j$  by time  $t$  (denoted  $Tr_j(t)$ ), and (iii) the number of platform  $i$  users who consume service  $j$  in time period  $t$  (denoted  $S_{ij}(t)$ ). Figure 1 gives an overview of our data. Panel (a) describes the installed base for each platform. It shows some commonly observed features of multi-generational diffusion models such as the sequence of the rise and decline of the

<sup>4</sup> After the 4th generation platform was introduced in February 2003, no new platform generation was introduced until 2008 when the smartphone platform was released (beyond the time window for this study).

installed base with the introduction of subsequent generations. On the other hand, it also shows some unusual characteristics that are not common in multi-generational models. For example, platform 1 actually never dies out and even experiences a revival at the end of the product cycle. In addition, platform 2 has markedly fewer adopters than all other platforms. Panel (b) depicts the cumulative traffic for each service generation. Not surprisingly, generation 4 services traffic (video streaming) rises quickly and faster than all other service generations. Panels (c) – (f) describe the cumulative number of users of each service generation for each platform. These panels reveal that backward compatibility was utilized – new generation platform users consumed older generation services.

For these data, some of the early time period points were missing. There are a few alternative ways to estimate the model when there is missing data (Grover and Vriens 2006). Following a regression substitution (imputation) approach, we first interpolate the missing data using available data via polynomial trend approximation methods and then estimate the model.<sup>5</sup> Details about the imputation of the missing data are included in Appendix B.1.

There are a few other categories of data that we have in our set which we do not use for the estimation of the main model but we use in the revenue sensitivity analysis in Section 6.5. To avoid any distraction in the flow of the presentation, we discuss these data in that section.

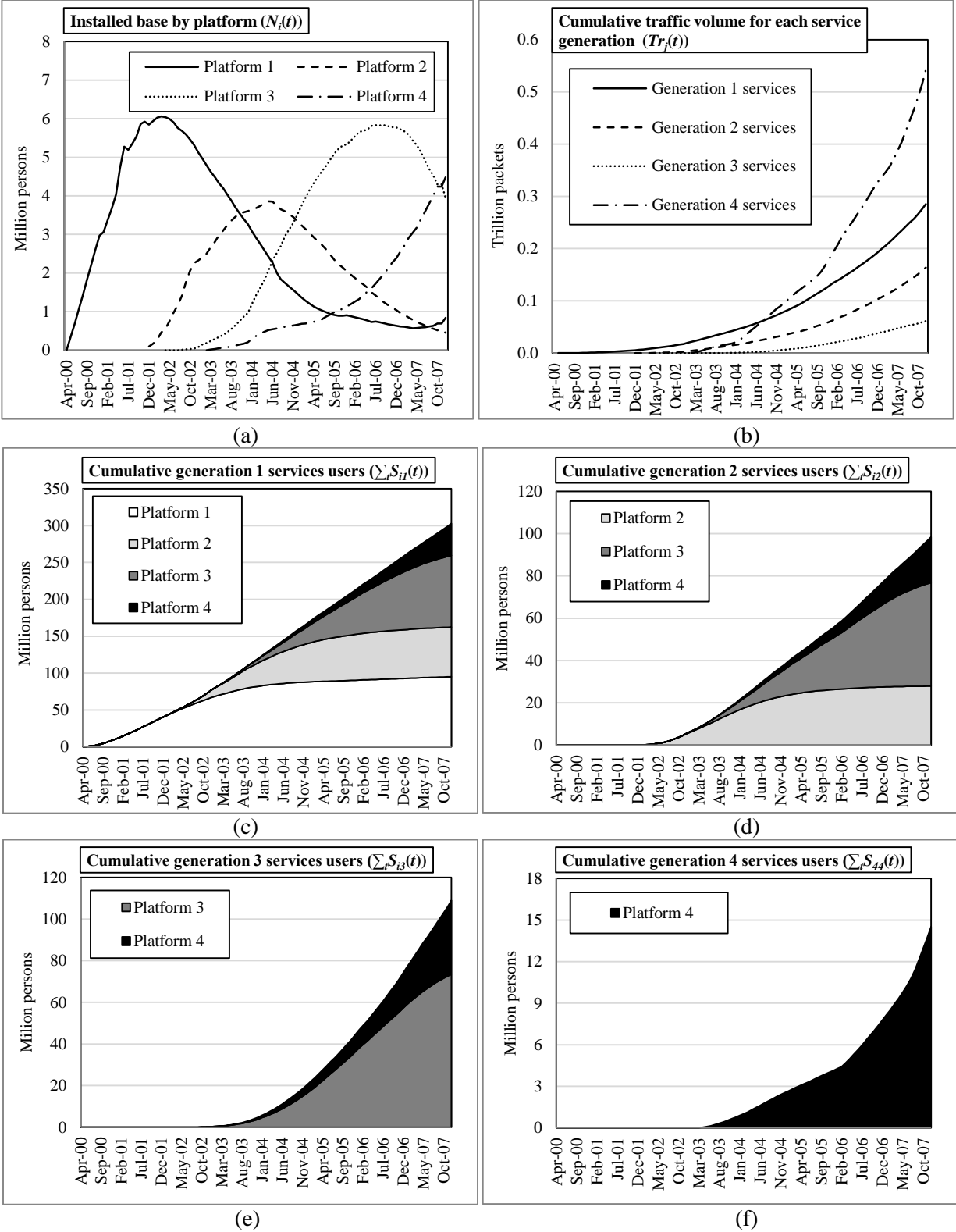
#### **4.3. Estimation of the Consumption of Each Service by Corresponding Platform Generation**

Using the cumulative traffic volume of service  $j$  by time  $t$  ( $Tr_j(t)$ ) and the number of platform  $i$  users who consume service  $j$  in time period  $t$  ( $S_{ij}(t)$ ), we estimate the cumulative traffic volume of service  $j$  consumed by platform  $i$  users by time  $t$  ( $Tr_{ij}(t)$ ). We assume the following relationship between  $Tr_{ij}(t)$  and  $S_{ij}(t)$ :

$$Tr_{ij}(t) - Tr_{ij}(t-1) = \begin{cases} \phi_j S_{ij}(t) & \text{if } i = j, \\ \phi_j \phi_i S_{ij}(t) & \text{if } i > j, \end{cases} \quad (9)$$

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<sup>5</sup> An alternative approach would have been listwise deletion (i.e., ignore the observations with missing data and estimate the model with what remains). However, this approach is recommended only when the missing data is completely random. Furthermore, it has been discussed that the diffusion model parameters estimates can be biased (left-hand truncation bias) if early adoption data points are not available (Jiang et al. 2006).

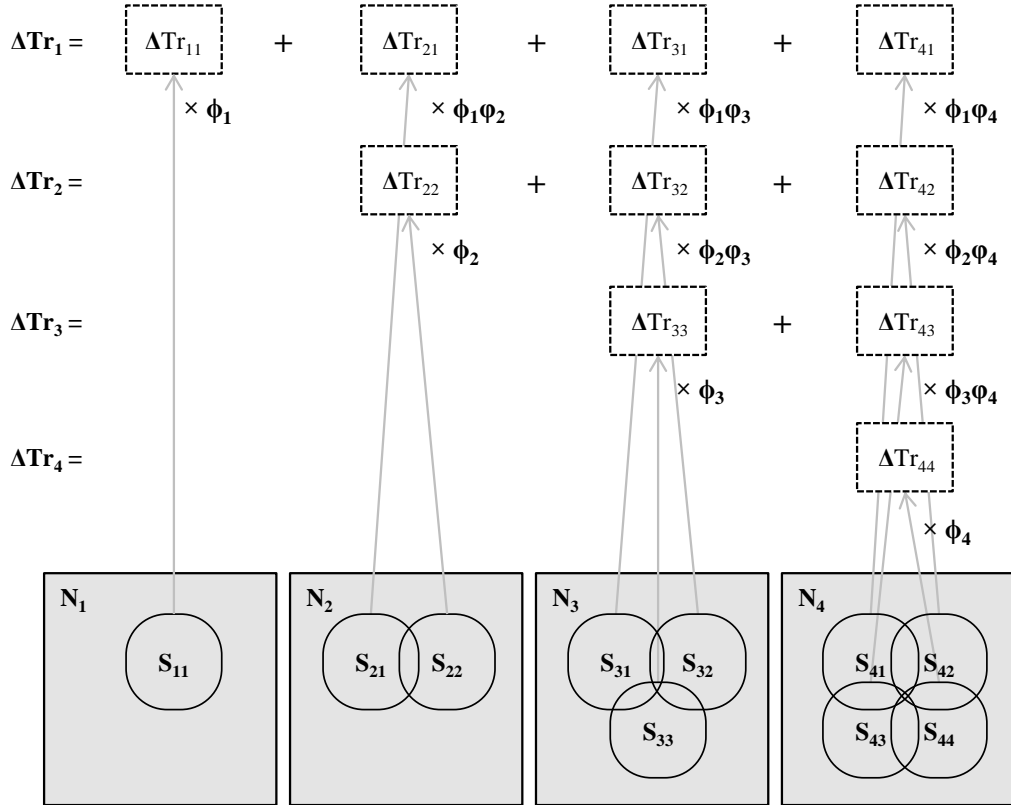


**Figure 1.** (a) Installed base by platform ( $N_i(t)$ ). (b) Cumulative traffic volume for each service generation ( $Tr_j(t)$ ). (c) – (f) Cumulative users of each service generation by platform ( $\sum_t S_{ij}(t)$ ).



where  $\phi_j$  is the service multiplier (i.e., marginal same-generation service consumption) and  $\varphi_i$  is the platform (or backward compatibility) multiplier (i.e.,  $\phi_j\varphi_i$  represents the marginal consumption of generation  $j$  services by platform  $i$  users). We account for the fact that users might consume intergenerational services (via backward compatibility) and same-generation services at different rates. The intuition behind equation (9) is that the traffic volume of generation  $j$  services consumed by platform  $i$  users in period  $t$  is a function of the number of users on that platform who consume this service generation in this time period. Given that we know for each period of time exactly how many users of a specific platform use services of a given generation allows us to estimate the corresponding traffic volume. Using (9), from  $Tr_j(t) - Tr_j(t-1) = \sum_i [Tr_{ij}(t) - Tr_{ij}(t-1)]$ , we have:

$$Tr_j(t) - Tr_j(t-1) = \phi_j \left[ S_{jj}(t) + \sum_{i>j} \varphi_i S_{ij}(t) \right] \quad (10)$$



**Note:**  $\Delta Tr_j(t) = Tr_j(t) - Tr_j(t-1)$ ; We omitted  $(t)$  for brevity.

**Figure 2.** The relationship between  $Tr_j(t)$  and  $S_{ij}(t)$ .

**Table 2.** Traffic fee rates

Service/Application type	Rate (Unit: local currency per packet; per message for Multimedia message)	
	Before Feb. 2007	After Feb. 2007
Text	6.5	4.55
Application	2.5	1.75
Multimedia Message	0 – 100 packets: 200 101 – 300 packets: 500	
Multimedia	1.3	0.91

Figure 2 illustrates the relationship between  $Tr_j(t)$  and  $S_{ij}(t)$  as defined in equation (10). We estimate the parameters  $\phi_j$  and  $\varphi_i$  – using simultaneous nonlinear regression (SNLR). Note that since there are four generations, we have a system of four equations, each corresponding to equation (10) for a different service generation. In general, estimates can be biased if there are price effects. However, in the particular case of the platform and services in our study, there was little change in per-packet traffic fees over the time window of our study. In addition, for the same service the same fee was charged to all users regardless of their platforms. All packet transactions that were sent and received by each user were charged by four different rates as described in Table 2. The rates for text, application, and multimedia packets were reduced by 30 percent in February 2007.

For robustness, we also considered a more complex parameterization of the model including learning effects in equation (10) but those turned out not significant. Therefore, we dropped those parameters. Table 3 shows the parameter estimates and model fit. All parameters are significant and adjusted R-square values are considerably high.

**Table 3.** Parameter estimates and model fits for the service and platform multipliers

		Estimates	Std. Err.	Significance
<b>Service multiplier</b>	$\phi_1$	0.2618	0.0248	***
	$\phi_2$	0.3416	0.0317	***
	$\phi_3$	0.1067	0.0096	***
	$\phi_4$	37.2788	1.0269	***

<b>Platform multiplier</b>	$\varphi_2$	1.6049	0.2674	***
	$\varphi_3$	3.5549	0.3691	***
	$\varphi_4$	12.7139	1.1863	***
<b>Adj. R-Square</b>	$Tr_1(t) - Tr_1(t - 1)$		0.9776	
	$Tr_2(t) - Tr_2(t - 1)$		0.9869	
	$Tr_3(t) - Tr_3(t - 1)$		0.8556	
	$Tr_4(t) - Tr_4(t - 1)$		0.8863	
<b>Number of observations</b>			93	

Note: \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.1$ .

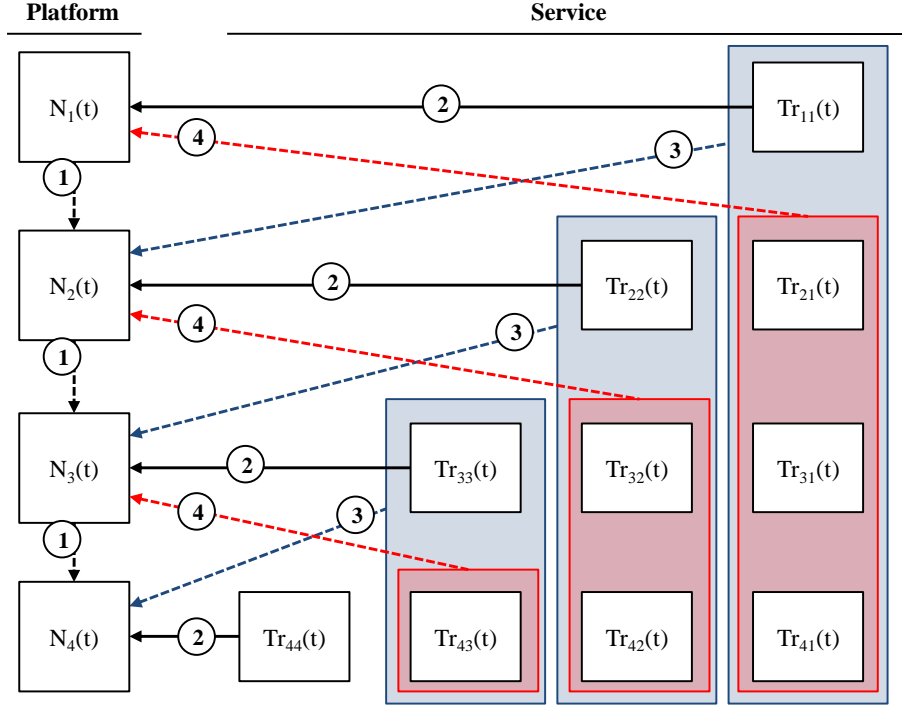
#### 4.4. Price of Handsets

We collected monthly handset store prices from online blogs and forums. For the earlier part of the time window of our study, prices are not publicly available and had to be imputed (details are included in Appendix B.2). Next, we derive the real average prices of platform  $i$  handsets -  $p_i(t)$  - by adjusting the observed and estimated average handset prices using the consumer price index using April 2000 as base. All of these handsets were locked on the network of the wireless carrier that we study. In the Asian country that we study marketing promotions were regulated by the government and fixed-term contracts were restrictively allowed. Therefore, the store price fairly represents what each consumer paid.

### 5. The Impact of Backward Compatibility on Platform Adoption Decisions

#### 5.1. Empirical Specification

In this section, extending the model in Section 3 to a four-generation model, we investigate the impact of backward compatibility on platform adoption decisions. Our model and analysis can be easily extended to an  $n$ -generation model. We illustrate in Figure 3 the relationship between platforms and services when there are four generations of each. As before, we are conceptualizing four effects: (1) the migration effect, (2) the indirect network effect, (3) the forward effect of backward compatibility, and (4) the backward effect of backward compatibility.



**Figure 3.** The relationship between platforms and services – four generations case

Adjusting equations (3), (5), and (6) for 4 generations, the adoption model is captured by the following system of equations:

$$N_1(t) = m_1 F_1(t) [1 - F_2(t)] + 1_{t \geq \tau_2} \left[ \alpha_1 \sum_{l>1} Tr_{l1}(t) + \zeta_1 e^{-\eta(t-\tau_2)} \sum_{s=\tau_2}^t \Delta P_1(s) \right], \quad (11)$$

$$N_2(t) = [m_2 + m_1 F_1(t)] F_2(t) [1 - F_3(t)] + 1_{t \geq \tau_3} \left[ \alpha_2 \sum_{l>2} Tr_{l2}(t) + \zeta_2 e^{-\eta(t-\tau_3)} \sum_{s=\tau_3}^t \Delta P_2(s) \right], \quad (12)$$

$$N_3(t) = [m_3 + [m_2 + m_1 F_1(t)] F_2(t)] F_3(t) [1 - F_4(t)] + 1_{t \geq \tau_4} \left[ \alpha_3 \sum_{l>3} Tr_{l3}(t) + \zeta_3 e^{-\eta(t-\tau_4)} \sum_{s=\tau_4}^t \Delta P_3(s) \right], \quad (13)$$

$$N_4(t) = [m_4 + [m_3 + [m_2 + m_1 F_1(t)] F_2(t)] F_3(t)] F_4(t), \quad (14)$$

where  $F_i(t)$  was given in (4). Further, equations (7) and (8) are included in the model in order to control for potential endogeneity as it is discussed in the context of the simplified illustrative model. Please note that equations (7) and (8) can be applied to a general model without an adjustment.

While it is beyond the purpose of this paper, we also point out that our model allows us to distinguish between platform *switching* (from  $i$  to  $i + 1$ ) and platform *leapfrogging* (adopters who would have got platform  $i$  in the absence of any newer generation but who, when facing multiple available options that co-exist in the market, choose a platform  $k > i$ ). Jiang and Jain (2012) explain how to differentiate between switching and leapfrogging by using multipliers<sup>6</sup>, while keeping intact the underlying structure of the Generalized Norton Bass model with respect to the adoption of each generation. Similar to their approach, in our model, the new adoption and migration terms (combined as first term in equations 11-14) are not lagged in terms of time, which allows leapfrogging to be accounted for. Among people who are considering adopting platform  $i$  at time instant  $t$ , some of them will be *instantaneously* drawn to newer platforms (if they exist in the market) based on how popular the latter are by that moment. We explain in detail in Appendix C how this can be conceptualized but omit this discussion here for brevity.

## 5.2. Model Estimation

We estimate a system of 11 simultaneous equations (equations (11) – (14) along with correspondents for (7) and (8) in the context of 4 generations) using non-linear system Generalized Method of Moments (GMM). We chose this method because it allows us to control for serial correlation in the error terms and heteroscedasticity of unknown forms.<sup>7</sup>

The GMM estimation requires instruments. We implemented our estimation using SAS 9.3. By default, in SAS, a constant term is added as instrument. In addition, we include the lags of the platform age for each generation platform. Arguably, the release of a new platform depends a lot on the ability of handset manufacturers to produce devices that support the new technology at reasonable prices, R&D efforts, the available infrastructure (towers), etc. As such, we believe that while the release of a new platform (and its age over time) influences platform adoption, this is not the case in the reverse direction. We use the lags of the platform age parameters as instruments for the platform ages.

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<sup>6</sup> Danaher et al. (2001) also use multipliers to account for leapfrogging in multi-generational diffusion.

<sup>7</sup> The heteroscedasticity and autocorrelation consistent (HAC) covariance matrix and corresponding parameter estimates and standard errors are computed using the approach proposed by Newey and West (1987) using the Parzen density kernel. Comprehensive explorations of GMM methods can be found in Hall (2005) and Wooldridge (2010).

We also include two instruments representing the one-period lags of cumulative service (e.g., app) sales (monetary value) over all platforms of the other two competing wireless carriers in the market as instruments.<sup>8</sup> We adjust sales to real values (at April 2000 base) using the consumer price index. In general, wireless carriers in this market charge service fees (for the sale of the service) and traffic fees per use of the service separately. A consumer who purchases (downloads) a service (accessible usually via an app) pays the price for the service first, and, based on packets she uses to download the service to her handset, she pays traffic fees. In addition, she may pay for traffic associated with using the service. Some services are sold for free and a heavier-traffic service is not necessarily more expensive. As such, for a given carrier, service sales are likely associated with the number of adopters of these carriers but not traffic pattern. We assume that the overall demand for services may be correlated between carriers and may be driven by consumer tastes and trends. Thus, the demand for paid services (proxied by sales) at the competitors' end may be correlated with the demand for paid services at the firm that is the subject of our study, which, in turn, may be correlated with the overall installed base at the latter firm (across all platforms) but not necessarily with traffic volume (for the above mentioned reasons). To further ensure that traffic volume does not affect service sales, we take the lag of service sales as an instrument.

In addition, we include the lags of the three sums of average price differences for handsets over time ( $1_{t \geq \tau_{i+1}} \cdot \sum_{s=\tau_{i+1}}^{t-1} \Delta P_i(s)$  with  $i \geq 1$ ) as instruments for the sums of price differences in equation (6). The market for handset manufacturers is highly competitive and there are many devices compatible with each carrier platform. As such, the price of a handset device is not necessarily related to the performance of that device in the market. Moreover, we consider the average price of handsets rather than any particular handset price. Thus, we assume that these sums of price differences are to some degree exogenous to the model. Nevertheless, to further control for endogeneity, we use the lags of these variables as instruments.

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<sup>8</sup> During the period of this study, in the respective Asian country that we considered, precisely three wireless carriers (including the one that we study) provide mobile Internet services. We collected the monthly revenue from mobile Internet services for the two competing carriers from their websites.

Last, we consider five more instruments: broadband Internet penetration, consumer expenditure on the telecom sector, the number of employees in the information and communication technology (ICT) industry, ICT production, and the total eCommerce transactions. These instruments are exogenous to the model. Broadband Internet penetration makes people more open to services and information being delivered over the Internet influencing the adoption of mobile Internet platforms but not impacting directly the traffic volume. The demand for the mobile Internet platforms is also impacted by ICT industry growth, captured by ICT production as well as R&D and service level (no. employees in the ICT industry). On the other hand, consumer expenditure on the telecom sector and total eCommerce transactions capture overall consumption patterns and, as such, may be correlated with the traffic.

Table 4 shows the parameter estimates, model fit, and Hansen’s J Statistic.<sup>9</sup> The adjusted R-squares are noticeably high and the insignificant Hansen’s J statistic suggests that the instruments are valid. In the following sections, we discuss the estimation results regarding the diffusion parameters (market potential, innovation and imitation effects), indirect network effects, forward effects of backward compatibility, and backward effects of backward compatibility.

**Table 4.** Parameter estimates and model fit

		<b>Estimates</b>	<b>Std. Err.</b>	<b>Significance</b>
<b>Market potential</b>	$m_1$	7.3527	0.2651	***
	$m_2$	1.7125	0.2747	***
	$m_3$	0.0025	0.1682	
	$m_4$	0.5779	0.1151	***
<b>Innovation effect</b>	$z_1$	0.0061	0.0008	***
	$z_2$	0.0047	0.0005	***
	$z_3$	0.0051	0.0004	***
	$z_4$	0.0003	0.0001	***
<b>Imitation effect (Direct network effect)</b>	$q_1$	0.1040	0.0069	***
	$q_2$	0.0947	0.0014	***
	$q_3$	0.0676	0.0013	***
	$q_4$	0.0362	0.0040	***

<sup>9</sup> For the estimation we used normalized values of  $N_i$ ,  $Tr_j$ ,  $Tr_{ij}$ , and  $p_i$ . We divided  $N_i$  and  $S_{ij}$  by  $10^6$ ,  $Tr_j$  by  $10^9$ , and  $p_i$  by 100.  $Tr_{ij}$  is estimated using normalized  $Tr_j$  and  $S_{ij}$  as it is discussed in Section 4.3.

<b>Indirect network effect</b>	$\beta_1$	37.1988	2.4667	***
	$\beta_2$	9.2535	1.6733	***
	$\beta_3$	42.9961	4.5564	***
	$\beta_4$	17.5798	2.6221	***
<b>FEBC</b>	$\gamma_2$	4.9752	0.6132	***
	$\gamma_3$	0.2839	1.0512	
	$\gamma_4$	4.4954	5.0604	
<b>BEBC</b> (Backward-compatibility-induced lease on life)	$\alpha_1$	0.0029	1.9E-05	***
	$\alpha_2$	1.7E-5	0.0002	
	$\alpha_3$	0.0023	0.0013	*
<b>Price-difference-induced lease on life</b>	$\zeta_1$	0.0247	0.0094	**
	$\zeta_2$	0.6623	0.0622	***
	$\zeta_3$	0.0030	0.0109	
<b>Time control on price effect</b>	$\eta$	0.1881	0.0156	***
<b>Other parameters</b>	$a_1$	0.1079	1.7E-05	***
	$a_2$	0.0706	1.4E-05	***
	$a_3$	0.0383	8.0E-06	***
	$a_4$	8.2471	0.0063	***
	$b_2$	0.5070	0.0002	***
	$b_3$	0.4845	0.0001	***
	$b_4$	0.5978	0.0001	***
<b>Adj. R-Square</b>	$N_1$		0.9960	
	$N_2$		0.9974	
	$N_3$		0.9980	
	$N_4$		0.9762	
	$Tr_{11}$		0.9568	
	$Tr_{22}$		0.9423	
	$Tr_{33}$		0.9918	
	$Tr_{44}$		0.9620	
	$\Sigma Tr_{i1}$		0.9363	
	$\Sigma Tr_{i2}$		0.9848	
	$\Sigma Tr_{i3}$		0.9984	
<b>Number of observations</b>			92	
<b>Number of instruments</b>			15	
<b>Hansen's J statistic</b>			52.61	
<b>Degree of freedom</b>			132	
<b>P-value</b>			1.0000	

Note: \*\*\* p<0.01; \*\* p<0.05; \* p<0.1.



### **5.3. Diffusion Parameters and Indirect Network Effects**

The market potential of platform 1 ( $m_1$ ) is 7.35 million and it is increased by 1.71 million for platform 2 ( $m_2$ ) and by 0.58 million for platform 4 ( $m_4$ ).  $m_3$  is relatively small and not significant, which suggests that there is no significant increase in the market potential for platform 3. This is consistent with the observed action of the wireless carrier. Platform 3 was launched only four months after platform 2 and the difference between platforms 2 and 3 in terms of functionality and features was marginal (see Table 1).

All the estimates for the coefficients of innovation ( $z_i$ ) and imitation ( $q_i$ ) are positive and significant, as expected. Similarly, all the estimates for the indirect network effect coefficients ( $\beta_i$ ) are also positive and significant, confirming that the value of a platform, and thereby, the number of adopters of a platform increase as the percent change in traffic volume of its supporting services increases. While the indirect network effect is relatively strong for generation 1 ( $\beta_1= 37.1988$ ) and generation 3 services ( $\beta_3= 42.9961$ ), it is relatively weak for generation 2 ( $\beta_2= 9.2535$ ) and generation 4 services ( $\beta_4= 17.5798$ ). This result is consistent with the service offerings introduced for each platform. While generation 3 services (e.g., multimedia messaging service) and some portion of generation 1 services (e.g., short-text-based instant messengers) require extensive communication between users, a big portion of generation 2 services (e.g., single-player mobile games, banking, and stock trading) and generation 4 services (e.g., live TV and video on demand) require relatively little communication between users. This suggests that the services that require more communication between users induce stronger indirect network effects on the diffusion rate of a platform compared to other services that require less communication between users.

### **5.4. FEBC**

While  $\gamma_2 (= 4.9752)$  is significant,  $\gamma_3$  and  $\gamma_4$  are not. That is, via backward compatibility, generation 1 services add significant value to platform 2 yet consumption of earlier generation services on platforms 3 and 4 does not impact their adoption in a significant way. Given that the indirect network effect of generation 2 services ( $\beta_2$ ) is relatively weaker than that of other service generations, this result suggests that backward compatibility carries over the value of the earlier generation services (intergenerational

services) to the new generation platform if the indirect network effect of same-generation services is not sufficiently strong. If the indirect network effect of same-generation services is sufficiently strong then the additional value that the intergenerational services provide to a new generation platform is likely to be marginal and not significant.

### **5.5. *BEBC***

As discussed in Section 3, there are two components of lease on life: backward-compatibility-induced and price-induced. Controlling for the impact of the price difference between two successive generations of handsets (which is statistically significant for between platforms 1 and 2) allows us to isolate the backward-compatibility-induced lease on life, which is the *BEBC*. The major finding of this study is the confirmation that *BEBC* is significant for platform 1 ( $\alpha_1 = 0.0029$ ) and platform 3 ( $\alpha_3 = 0.0023$ ). For platform 2, the effect is not significant. Paired with the relatively weaker indirect network effect for generation 2 services ( $\beta_2$ ), this indicates that generation 2 services (whether consumed on platform 2 or newer platforms) may be inducing to a lower degree inter-user communication compared to other service generations and, as such, may provide a smaller-magnitude added incentive for users to join platform 2.

The lack of significance of the price-induced lease on life between platforms 3 and 4 indicates that the price difference alone is not enough to dissuade users from platform 4. The substantial upgrades (e.g., catering to faster data transfer technologies, better screen resolution, and more mainstream integration of cameras with video capabilities in the handsets) that platform 4 provides along with backward compatibility in fact separate the market. While some users find it worth to pay a premium for these upgrades, some other users do not. Backward compatibility (i.e., the platform 4 users' consumption of generation 3 services) induces this latter user group to choose platform 3.

## **6. The Economic Effects of Backward Compatibility and Managerial Insights**

In this section, we focus on the economic impact of backward compatibility (i.e., intergenerational nature of services) in the platform market. In particular, in Sections 6.2 and 6.3, we perform a sensitivity analysis of both *BEBC* and *FEBC* by simulating adoption scenarios when  $\alpha_1$  or  $\gamma_2$  change, while keeping all other

parameters as derived in Table 4 (with the statistically insignificant terms normalized to 0). In order to better highlight the impact of backward compatibility on adoption, we focus on platform 1. In Sections 6.4 and 6.5, we extend this analysis, considering the overall impact of backward compatibility (both *BEBC* and *FEBC*) on adoption and revenue.

### 6.1. Description of the Adoption Simulation

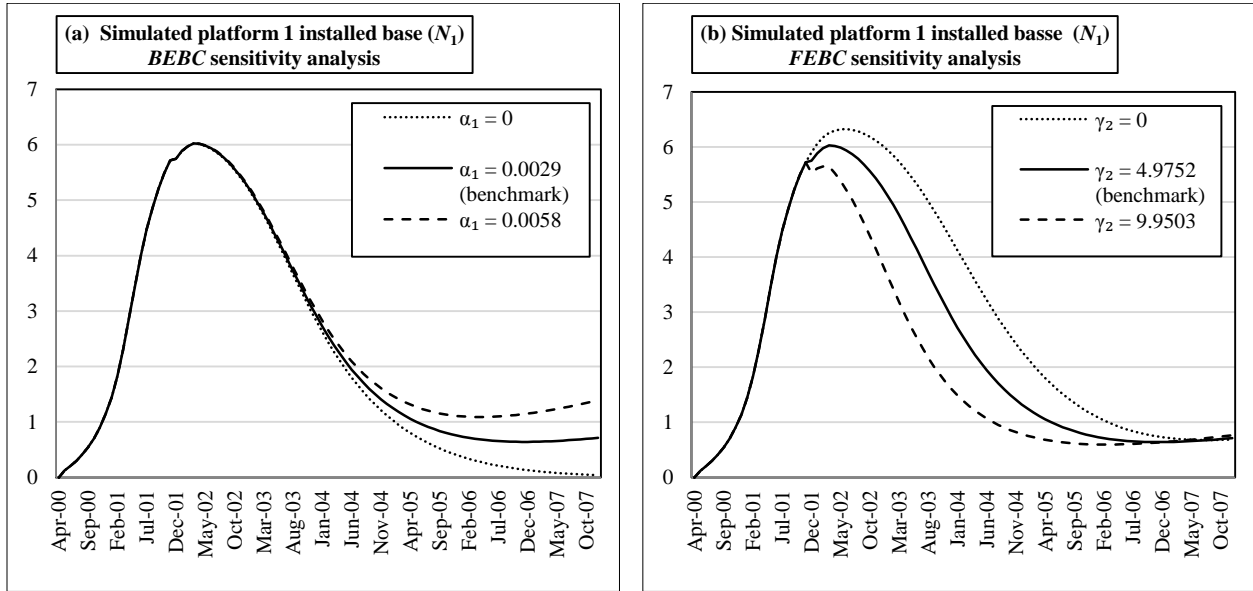
Because we are dealing with a system of simultaneous nonlinear equations for traffic and adoption, teasing out the overall magnitude of the effects of backward compatibility (*BEBC* and *FEBC*) on adoption is a very involved process. Adoption depends on traffic, traffic in turn depends on adoption, and platform generations are inter-related via the consumption of services due to backward compatibility. As such, a change in one parameter has a very complex ripple effect on how platform adoption and service consumption would unfold in the future for each generation.

To get a measure of these effects, we did the following. First, we simulated the benchmark adoption trajectories using exactly the parameter estimates in Table 4. Then we simulated what happens if we change  $\alpha_1$  (or  $\gamma_2$ ) by making them either 0 or double the value in Table 4. The impact of the changes on the adoption of platform 1 is illustrated in Figure 4. We estimated adoption and traffic progressively, one period at a time as illustrated below:

- At time  $t = 1$ , we only have platform 1 and generation 1 services. As such, the only unknown values to simulate are  $N_1(1)$  and  $Tr_{11}(1)$ . There are no lease on life, *FEBC*, or migration. We substitute equation (7) into the reduced form equation (11), basically substituting traffic into  $F_1(1)$  in equation (4). Then equation (11) becomes a reduced-form non-linear equation in  $N_1(1)$  which we solve. Then, we construct  $Tr_{11}(1)$  from equation (7).
- At every time period  $t \geq 2$ , we take the simulated traffic and adoption from all past periods. Subsequently, we fit them into equations (8) and (9) for all platform generations. We then obtain a set of equations where traffic at time  $t$  depends on past simulated numerical values of platform adoption and traffic (for periods 1, 2, ...,  $t - 1$ ) as well as the yet-unknown install

base values  $N_1(t)-N_4(t)$ . We substitute these traffic parameterizations into equations (11-14). We end up with a system of 4 non-linear equations with 4 unknowns ( $N_1(t)-N_4(t)$ ). We finally solve this system and compute simulated installed base values for each platform at time  $t$ . From there, using equations (7) and (8), we construct simulated traffic for each service at time  $t$ . Then we move to the next time period, all the way until we reach the end of the time window of our simulation.

In order to isolate the impact of backward compatibility from other random or unobserved shocks in consumer behavior, we measure effects with respect to the simulated benchmark curve instead of real adoption (solid line in Figure 4). This simulated adoption for platform 1 is very similar to the real one (see Figure 1.a). Note that in Figure 4 we only report simulated  $N_1$  in order to keep the figure simple – we point out that these simulated curves for  $N_1$  were derived together with the simulated curves for  $N_2-N_4$  (which are just omitted).



**Figure 4.** (a) *BEBC* sensitivity analysis. All parameter values except  $\alpha_1$  are as in Table 4. All simulated curves are derived as described in Section 6.1. (b) *FEBC* sensitivity analysis. All parameter values except  $\gamma_2$  are as in Table 4. In both panels, the benchmark curve is simulated using all values (including  $\alpha_1$  and  $\gamma_2$ ) from Table 4.

## **6.2. Market Impact of Forward Effect of Backward Compatibility (*FEBC*)**

Intergenerational services (via backward compatibility) motivate (i) more potential new (first-time) adopters to choose a newer generation platform earlier and (ii) more existing and potential adopters of an earlier generation platform to migrate to the new generation platform faster. A higher  $\gamma_2$  translates into a faster adoption of platform 2 (as can be seen from Appendix A), which, in turn, accelerates the migration away from platform 1. Compared to the benchmark scenario, if there was no *FEBC* ( $\gamma_2 = 0$ ), within one year after platform 2 was launched (by the end of December 2002), an additional 0.91 million consumers would have chosen to adopt or continue to use platform 1 (a 17.86% increase). On the other hand, if the *FEBC* was twice as strong ( $\gamma_2$  twice the benchmark value), then the installed base for platform 1 would have decreased by 1.21 million customers, who would have migrated to future generations (a 52.3% decrease).

We point out that *FEBC* is stronger early on after the introduction of a subsequent platform, because at that stage there is a considerably-sized pool of potential migrators (from earlier generations) or new adopters. Thus, accelerating adoption of newer generations has a strong impact on the older generation. As time passes, this pool decreases in size and the impact of *FEBC* diminishes. As can be seen from panel (b) of Figure 4, eventually (6 years after the release of platform 2), the impact of *FEBC* on platform 1 adoption is negligible as its installed base would have reached that point pretty much with or without it. Many users would have migrated gradually based on the attractiveness of newer platforms alone (following the pattern in the original Norton and Bass model). Nevertheless, faster migration to future generations will alter the pattern of services consumption, significantly affecting the net present value of the revenue stream.

## **6.3. Market Impact of Backward Effect of Backward Compatibility (*BEBC*)**

The consumption of intergenerational services on newer platforms via backward compatibility prolongs the lifespan of earlier generation platforms (platforms 1 and 3). On average, per time period, every 1 million packets of generation 1 services consumed on platforms 2, 3, or 4, attracted 2.9 additional adopters to

platform 1. Similarly, per time period, every 1 million packets of generation 3 services consumed on platform 4 attracted 2.3 additional adopters to platform 3.<sup>10</sup>

By December 2007, via *BEBC*, intergenerational services had allowed platform 1 to gain 0.67 million additional adopters. Compared to when the platform reached its peak installed base, this represents 11% recovery of the consumer base. Stronger *BEBC* leads to even higher adoption of platform 1 as can be seen from Figure 4 (a). This illustrates the impact of the *BEBC* on enhancing the value and extending the useful life of an older generation platform.

#### **6.4. The Combined Impact of Backward Compatibility**

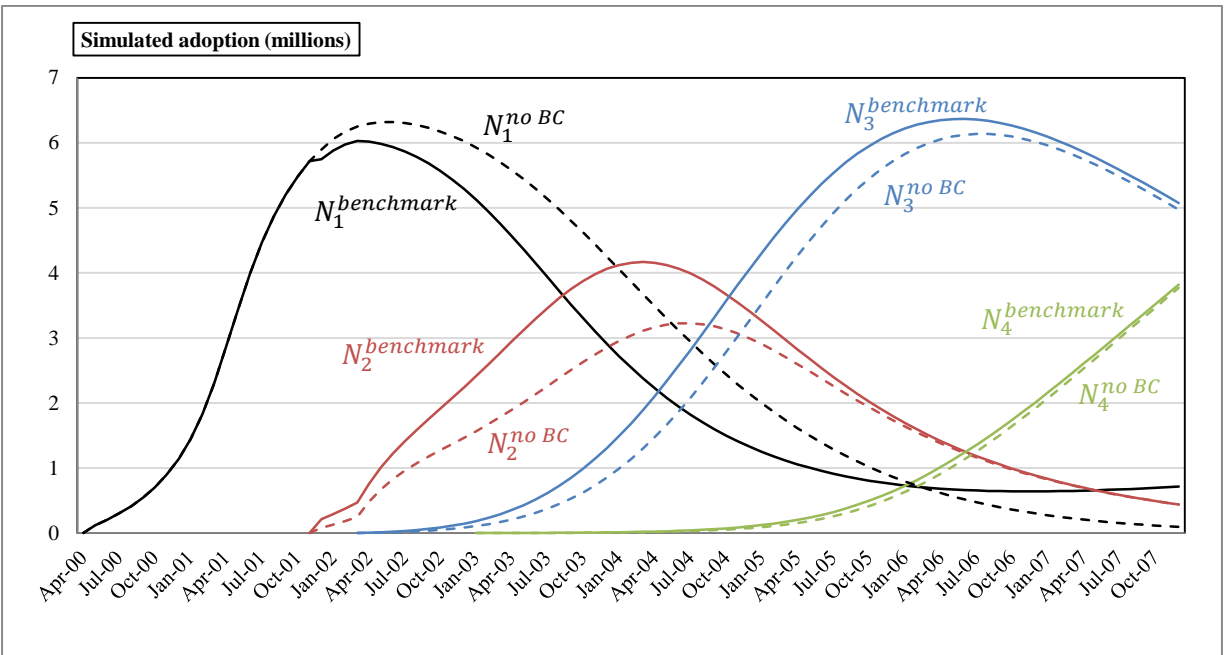
For illustration purposes, we consider in more depth the impact of the *FEBC* and *BEBC* on the lifespan and overall adoption of various platforms. Note that the impact of *FEBC* and *BEBC* cannot be easily compared in the benchmark case when both effects are significant (in the case of platform 1). Once one effect is removed, the adoption unfolds in a different way which affects the magnitude of the other effect as well. In Figure 4, we quantified one effect at a time, simulating again all adoption paths over time when one parameter was changed. This allowed us to see what would be different if one of the effects were not present. As we saw in Figure 4, *FEBC* is strong earlier in the adoption, while *BEBC* tends to be strong later in the adoption of the product. *FEBC* represents accelerated adoption and migration and its overall impact is significant if there are many potential customers that can still migrate and many new customers that did not adopt yet. *BEBC* on the other hand gets stronger when there is a lot of consumption of services of a particular generation on newer platforms, which happens once there number of adopters of newer platforms grows significantly.

The above discussion suggests that *FEBC* will dominate *BEBC* for platform 1 in the beginning (shortly after the release of platform 2) but the trend might reverse later on. To actually see the net effect

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<sup>10</sup> An average Apps/contents size of a generation 1 service 1 is 100 – 150 packets, and hence, 1 million packets of service 1 consumption is equivalent to 6,500 – 10,000 Apps/contents downloaded. The traffic of generation 3 services consists mainly of multimedia messages (MMS) sent and received. Our data shows that the average size of one MMS message during the time that we study was 61 packets; hence, 1 million packets of generation 3 services consumption is equivalent to about 16,000 MMS messages sent or received.

of backward compatibility and get a better sense of how both effects simultaneously impact adoption, we compare the benchmark simulated case with a simulated scenario without any backward compatibility effects (no *BEBC* or *FEBC* – all  $\alpha_i$  and  $\gamma_j$  equal to 0). The simulated adoption paths are included in Figure 5. We look in particular at the adoption of platform 1, where both effects were significant. Indeed, compared to the benchmark case, as mentioned before, in the absence of any backward compatibility effects, the adoption of platform 1 is stronger immediately following the release of platform 2, suggesting that in the beginning *FEBC* is the dominant of the two effects. However, with time, the migration induced by *FEBC* dwindles as there are fewer remaining consumers of platform 1. At the same time we see more adoption of platforms 3 and 4. Consumers with newer handset platforms consumer on average more of generation 1 services and, with time, the overall consumption of generation 1 services increases, as can be seen from Figure 1(b). This helps *BEBC* become stronger over time, and we see that this effect dominates during 2006-2007, with the benchmark simulated curve riding above the simulated curve without backward compatibility.



**Figure 5.** Adoption curves  $N_i^{benchmark}$  with  $i \in \{1,2,3,4\}$  are simulated using parameter values as in Table 4. Adoption curves  $N_i^{no BC}$  with  $i \in \{1,2,3,4\}$  are simulated in the absence of any backward compatibility effects (no *BEBC* and no *FEBC*, i.e.,  $\alpha_1 = \alpha_3 = \gamma_2 = 0$ ).

We also note that the other adoption curves shift. Note that the impact of removing  $\alpha_3$  is less visible (*BEBC* on platform 3 adoption). That is due to the fact that the consumption of generation 3 services on newer platforms (platform 4) did not yet have a chance to get very strong by the end of 2007. Given that only  $\gamma_2$  was significant before, we see adoption curves for platforms 3 and 4 shifting slightly in response to how platforms 1 and 2 were affected. Basically, in the absence of backward compatibility, there will be less migration out of platform 1, which in turn results in fewer adopters for platforms 3 and 4 too (as these platforms would also benefit from migration out of older platforms). This rippling effect is almost entirely due to *FEBC* (the fact that *BEBC* induces additional consumers to adopt platform 1, which in turn affects the consumption of generation 1 services, does not have a direct impact on platforms 3 and 4 since  $\gamma_3$  and  $\gamma_4$  were not significant).

By the end of December 2007, we can see that in the absence of backward compatibility (more precisely, in the absence of *BEBC*), platform 1 would lose almost all of its installed base. So while in the short run backward compatibility accelerates migration, in the long run it does extend the life of older platform generations.

### **6.5. The Impact of Backward Compatibility on Revenue**

In this section, we analyze the impact of backward compatibility on the revenue from the consumption of services (excluding any revenue from the sales of handsets, accessories, and SMS).<sup>11</sup> We picked the window between the release of platform 2 (Dec. 2001) and the last period of our sample (Dec. 2007) because this analysis is relevant when there are at least two platform generations in the market. We considered the following two scenarios:

- Scenario A – corresponding to the benchmark case in the paper where both *BEBC* and *FEBC* exist.
- Scenario B – in this case there is no backward compatibility ( $\alpha_1 = \alpha_3 = \gamma_2 = 0$ , and all other values as in Table 4 in the paper). We assume that the average percentage of platform 2 users who

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<sup>11</sup> We do not observe the purchase of handsets (customers can replace handsets frequently but may not change platform). Thus, we cannot directly compute the revenue from handsets.



consumer generation 1 services and generation 2 services (there can be overlap between these) stays consistent with the benchmark case.

Using our dataset, for any given period  $t$  we can compute the fraction of platform  $i$  adopters that consume generation  $j$  services as  $\sigma_{ij}(t) = \frac{S_{ij}(t)}{N_i(t)}$ .

During the window of our extensive study (2000-2007), service revenue came from traffic fees (upload and download) as well as fees for particular services. For example, customers paid for an app and then paid an additional amount for the data traffic to download the app. To be able to estimate the revenue, we came up with a rough estimate for the average revenue per packet due to traffic and the average revenue due to the purchase of services. For simplicity, we assume that the average per-packet fee for traffic associated with the consumption of generation 1 services is, on average, similar to that for generation 2 services (there are many types of traffic, including text-related, app-related, etc.). We lack the data to create more precise estimates that are generation specific. We compute the per-packet fee estimate during period  $t$  as  $p_{packet}(t) = \frac{rtr(t)}{tr_1(t)+tr_2(t)+tr_3(t)+tr_4(t)}$ , where  $rtr(t)$  is the revenue from all traffic (on all platforms) during period  $t$ , and  $tr_j(t) = Tr_j(t) - Tr_j(t - 1)$  is the traffic associated with the consumption of generation  $j$  services on any platform during period  $t$ . These data ( $rtr(t)$  and  $tr_j(t)$ ) are available in our dataset.

Last, we compute  $SARPU_{ij}(t)$ , the average revenue during period  $t$  per adopter of platform  $i$  from the purchase of generation  $j$  services (aside from any traffic fees). To do so, we make an additional assumption that the percentage of the revenue from the purchase of generation  $j$  services that originates from platform  $i$  users is the same as the percentage of traffic associated with consumption of generation  $j$  services that originates from platform  $i$  users ( $tr_{ij}(t)/tr_j(t)$ ). Then  $SARPU_{ij}(t) = \frac{tr_{ij}(t)}{tr_j(t)} \cdot \frac{rs_j(t)}{S_{ij}(t)}$ , where  $rs_j(t)$  is the overall revenue from the purchase of generation  $j$  services (aside from any traffic fees) during period  $t$ . All the data points necessary for this computation are in our dataset as well.

One last simplifying assumption for this exercise is to consider  $\sigma_{ij}(t)$ ,  $p_{packet}(t)$ , and  $SARPU_{ij}(t)$  exogenous to the adoption process (and we utilize them also for Scenario B). All these quantities are estimated using the benchmark case in the paper and the available dataset. Under each scenario  $Z \in \{A, B\}$ , the service revenue between Dec. 2001 (after the introduction of platform 2) and Dec. 2007 is computed according to the following formula:

$$R^Z = \sum_{t=Dec,2001}^{Dec,2007} \left[ p_{packet}(t) \sum_{j=1}^4 tr_j^Z(t) + \sum_{i=1}^4 N_i^Z(t) \left( \sum_{k=1}^i \sigma_{ik}(t) SARPU_{ik}(t) \right) \right], \quad \forall Z \in \{A, B\}.$$

To compute the revenue under Scenario A, we use the simulated benchmark adoption. For Scenario B, we simulate  $N_i^B(t)$  and  $tr_j^B(t)$  as discussed in Section 6.4 in the paper.

After performing all simulations and computations, in adjusted units, we obtain  $R^A = 1259$  and  $R^B = 1123$ . By introducing backward compatibility, the provider is able to obtain an overall increase of 12% in revenues from the consumption of services during the explored period. While this simple exercise does not take into account the difference in costs incurred by the provider under the two scenarios, the increase in revenues alone is quite significant warranting the need for close consideration of a backward compatibility strategy.

## 6.6. Additional Managerial Insights

While backward compatibility positively impacts service revenues, its backward effect (*BEBC*) does extend the life of older platforms and the need to maintain their obsolete infrastructure (e.g., the mobile networks) and the distribution channels for the supporting services. Moreover, older generation handsets and accessories generate less profit for the firm compared to newer ones. In addition, the service revenue per user is usually lower for older generation platforms. A provider might find it more profitable to speed up the obsolescence of an old platform by discontinuing it or by removing backward compatibility once enough migration occurred. Perhaps in order to escape from the negative consequence of *BEBC*, IT platform providers often take drastic measures in the later phase of lifecycle, discontinuing legacy products and services. In January 2008, the wireless carrier that we study merged the distribution channels for generation

1 and 4 services into one and in early 2012 it terminated the 2G mobile network that supported the earlier generation platforms and services. Several other industry examples mirror this approach. Microsoft also recently shut down the support for probably the most popular operating system of all times, Windows XP, due to the continuous demand. Similarly, Sony designed PlayStation 3 (PS3), the video game console released in 2006, such that only the first models are 100% backward compatible with the game titles for its previous version console, PlayStation 2 (Reeves 2014). Subsequently, after benefitting from *FEBC*, the backward compatibility was reduced and eventually removed, which not only limited *BEBC*, but also reduced production cost.<sup>12</sup> If backward compatibility is not strategically planned considering both forward and backward effects, by catering extensively to the needs of users of older technology the firm may divert vital resources and attention away from platform R&D and infrastructure improvement, failing to sustain the pace of innovation and technological disruption needed to retain competitive advantage in the market (Christensen 2013). Several studies in the planned obsolescence literature highlight that planned obsolescence is a necessary condition for the technological progress (Fishman et al. 1993) and fundamental to a firm's competitive success and survival under digital business conditions (Bharadwaj et al. 2013).

The unintended or unplanned *BEBC* can also cause significant tension within the ecosystem of a platform provider. One example in the mobile Internet domain that can illustrate such consequences of an unintended *BEBC* can be seen in the fragmentation of the Android platform. While Android is commonly thought of being 'owned' by Google, the Android platform is actually sponsored by the Open Handset Alliance (OHA), which includes all the main wireless providers as well as handset manufacturers. Due to this shared control, Android as a platform has experienced a high level of fragmentation. New generation handsets and high-end handsets are equipped with the latest version of Android, while older generations and low-end handsets are equipped with earlier versions of Android that offer fewer functionalities.<sup>13</sup> Since

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<sup>12</sup> See <http://www.sempertthree.com/backwards-compatibility.html>

<sup>13</sup> Google, who competes against Apple's iOS ecosystem, has a vital interest in having as many handsets as possible updated to the latest generation of Android. This makes the platform more secure and perhaps more importantly, it reduces the effort of App developers to manage different platforms. However, handset producers and wireless service providers do not share that interest at the same level since an update of Android is associated with many testing procedures, an increase in customer service demands and very little, if any, additional revenue.

the vast majority of apps work on many different generations of Android, handset producers often do not adopt the newest version of Android and consumers often opt for handsets with earlier versions of Android. They do so, knowing well that they will still be able to interact, communicate, and share content with users that own newer generations of Android. In other words, they exploit the *BEBC*. As a consequence, more than 75 % of Android devices do not use the latest version.<sup>14</sup>

Apple's iOS platform can serve as a point in contrast. Since Apple is the sole provider of the platform, it is not burdened by considerations of other handset makers (there are none) or wireless service providers. Consequently, Apple has experienced problems with fragmentation to a much lesser degree. About two weeks into the release of iOS 8, nearly half of all devices were running the newest version of the operating system (Whittaler 2014). Apple clearly considers low fragmentation as an advantage; this makes the iOS platform more attractive to developers. Perhaps not surprisingly, Apple has been known to actively nudge consumers to the newest iOS platform to minimize the *BEBC* for earlier versions through automatic downloads and by blocking the ability to revert to an older version of iOS, once a newer version has been installed.<sup>15</sup>

## **7. Concluding Remarks**

Nowadays, we are becoming more and more accustomed to seeing products and platforms diffusing in the market in a multi-generational pattern with simultaneous versions co-existing alongside each other. This pattern is even more visible in the context of IT platforms that are regularly enhanced to harness the extraordinary pace of IT innovation in the industry. We propose a novel model for the adoption dynamics of multi-generation IT platforms over time that allows us to investigate in previously-unexplored depth the impact of the intergenerational nature of complementary services (via backward compatibility) on the platform diffusion process. On the modeling side, we contribute to two streams of literature. On one hand, we complement the diffusion literature by incorporating both the indirect network effects of complementary

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<sup>14</sup> <https://developer.android.com/about/dashboards/index.html>.

<sup>15</sup> <http://appadvice.com/appnn/2013/09/apple-is-automatically-pushing-out-ios-7-to-holdout-devices>.

services and the migration in one model. Most prior literature focuses on either of those but not both. On the other hand, we also complement the subset of the diffusion literature that accounts for backward compatibility by investigating both forward and backward effects of backward compatibility. In contrast, many of the earlier models include only the forward effects of backward compatibility. Our model goes hand in hand with our theoretical contribution as we propose a theory on how backward compatibility, while affecting the speed of migration to newer generation platforms (by carrying over the value of earlier generation services), can also have a possibly unintended consequence by extending the life of an older generation platform. Our main finding in this study is the empirical confirmation, in the context of a multi-generational mobile Internet platform, of the existence of this two-sided impact of backward compatibility (with respect to services) on platform adoption. As discussed in the Introduction and Section 6, this insight has rich managerial implications.

Our framework and analysis can be applied beyond mobile Internet platforms to any multi-generational platform with complementary value-adding services where backward compatibility can be implemented. In this manuscript we did allude to a few other examples (operating systems, productivity software, video-game consoles, etc.). In all these cases, once a new platform generation was introduced, there was, to some degree, continued demand for the older platform when backward compatibility and supporting services were present. Many of these platforms may exhibit both *BEBC* and *FEBC*.

While this analysis does not include the effect of competition (due to lack of some of the necessary data), we strongly believe that the competition would not change our results significantly since the mobile Internet platform market in the Asian country during the time period that we study was relatively stable in market share. There were three platform providers and the average market share of the one that we study during the time period 2001 – 2007 was 32.3 percent with a standard deviation of only 0.67 percent over the entire period. Also, note that our diffusion model as depicted in detail in equation (4) and Appendix A does not incorporate marketing mix variables. If marketing mix variables change at a relatively constant

rate over time, the GBM model works well without specifying them (Bass et al. 1994).<sup>16</sup> As shown in Section 4.4 and Appendix B.2, the prices of handsets were decaying at a relatively constant rate over time. Moreover, while the wireless carrier does not report the marketing expenses for each platform generation, it does report overall marketing expenses. Our data confirmed that the rate of change of wireless carrier's overall marketing expenses over time had been approximately constant.<sup>17</sup> Thus, we believe that incorporating marketing mix variables directly in the GBM formula, while potentially slightly shifting some of the parameter values, would not have changed the nature of our results.

Our study presents several research directions in which it can be extended. With a richer dataset, the impact of the complementary services on adoption could be explored in more depth, controlling for the service variety growth over time for all platforms and service intensities of usage (number of Apps used on average by a user of a specific platform). One could also classify digital services by content and purpose and measure the lease on life effect for each class. It would be very interesting to see if lease on life is affected more by utilitarian consumption (e.g. mobile banking, messaging, weather reports, news) vs. more hedonic consumption (ringtones, online music, etc.). With individual-level adoption and consumption data one could potentially measure also by how much the time gap between hardware purchases (platform upgrades) is increased for different demographic groups in response to backward compatibility.

## Acknowledgements

The authors thank the senior editor, associate editor, and the two anonymous reviewers for their constructive feedback on the manuscript. The authors also extend their gratitude to the participants at the 2012 Workshop on Information Systems and Economics (WISE), 2013 INFORMS Conference on Information Systems and Technology (CIST), 2014 Platform Strategy Research Symposium, as well as the research seminars participants at the University of Calgary and the University of British Columbia for their insightful comments. The authors acknowledge the financial support from the NET Institute (<http://www.NETinst.org>) [Summer Research Grant #12-17].

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<sup>16</sup> Incorporating in equation (A.3) in Appendix A a constant percent change rate of price or advertising would lead to a similar fit, because the effect would be absorbed in the other constants of the model (as can be seen given the formulation of equation (A.1)).

<sup>17</sup> Using the wireless carrier's overall marketing expenses for the time period 2001 – 2007, we estimated the following:  $AD(t) = \psi \cdot AD(t - 1)$ , and obtained an estimate for  $\psi$  of 1.19. The p-value of the estimate was 2.72E-05 and R-square was 0.9559. The estimation results suggest that the percentage change of the overall marketing expenses over time were approximately constant (about 20 percent increase every year).

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## Online Supplement for ISR Manuscript:

### The Double-Edged Sword of Backward Compatibility: The Adoption of Multi-Generational Platforms in the Presence of Intergenerational Services

**Il-Horn Hann**

Robert H. Smith School of Business  
University of Maryland  
College Park, MD 20742  
ihann@rhsmith.umd.edu

**Byungwan Koh**

Haskayne School of Business  
University of Calgary  
Calgary, AB T2N 1N4  
bkoh@ucalgary.ca

**Marius F. Niculescu**

Scheller College of Business  
Georgia Institute of Technology  
Atlanta, GA 30308  
marius.niculescu@scheller.gatech.edu

Information Systems Research, 2016, Vol 27(1), pp. 112-130

Permalink: <http://dx.doi.org/10.1287/isre.2015.0615>

#### A. Derivation of Equation (4) Based on the Generalized Bass Model

The Generalized Bass Model (GBM) introduced in Bass et al. (1994) is specified as  $N(t) = mF(t)$  with

$$f(t) = \frac{\partial F(t)}{\partial t} = [1 - F(t)] \cdot [z + qF(t)] \cdot x(t), \quad (\text{A.1})$$

with  $F(0) = 0$ . Through  $x(t)$ , one can account for various additional effects on the adoption rate

(including the effects of marketing mix variables such as price and advertising). Let  $X(t) = \int_0^t x(s) ds$ .

Then, Bass et al. (1994) show that

$$F(t) = \frac{1 - e^{-(z+q) \cdot [X(t) - X(0)]}}{1 + \frac{q}{z} e^{-(z+q) \cdot [X(t) - X(0)]}}. \quad (\text{A.2})$$

Define  $tr_{ii}(t) = \frac{\partial tr_{ii}(t)}{\partial t}$  and  $tr_i(t) = \frac{\partial tr_k(t)}{\partial t}$  as consumption rates of services. Then, following the steps

of the derivation on page 207 in Bass et al. (1994), if we consider

$$x_i(t) = 1 + \beta_i \frac{\partial tr_{ii}(t)/\partial t}{1 + tr_{ii}(t)} + \gamma_i \frac{\partial \sum_{k < i} tr_k(t)/\partial t}{1 + \sum_{k < i} tr_k(t)}, \quad (\text{A.3})$$

then we obtain

$$X_i(t) = t + \beta_i \log[1 + tr_{ii}(t)] + \gamma_i \log \left[ 1 + \sum_{k < i} tr_k(t) \right]. \quad (\text{A.4})$$

Considering the discrete-time approximations  $tr_{ii}(t) \approx Tr_{ii}(t) - Tr_{ii}(t - 1)$  and  $tr_k(t) \approx Tr_k(t) - Tr_k(t - 1)$ , we obtain equation (4). Coefficients  $\beta_i$  and  $\gamma_i$  represent the impact of the *percent change in traffic* (of generation  $i$  services on platform  $i$  devices vs. generation  $k$  services altogether), where traffic is adjusted by adding one packet to ensure that the object of the log function is always greater or equal to 1.

## B. Interpolation of Missing Data

### B.1. The early time period data for $N_i(t)$ , $Tr_j(t)$ , and $S_{ij}(t)$

The following table summarizes the available data and interpolated time period for each variable.

**Table B.1.** Available data and interpolated time period for each variable

Variable	Available data	Interpolated time period
$N_1(t)$	Jan. 2001 - Dec. 2007	May 2000 - Dec. 2000
$N_2(t)$	Dec. 2001 - Dec. 2007	None
$N_3(t)$	Apr. 2002 - Dec. 2007	None
$N_4(t)$	Feb. 2003 - Dec. 2007	None
$Tr_1(t)$	Jan. 2003 - Dec. 2007	May 2000 - Dec. 2002
$Tr_2(t)$	Jan. 2003 - Dec. 2007	Dec. 2001 - Dec. 2002
$Tr_3(t)$	Apr. 2003 - Dec. 2007	Apr. 2002 - Mar. 2003
$Tr_4(t)$	Apr. 2003 - Dec. 2007	Feb. & Mar. 2003
$S_{11}(t)$	Jan. 2002 - Dec. 2007	May 2000 - Dec. 2001
$S_{21}(t), S_{22}(t)$	Jan. 2002 - Dec. 2007	Dec. 2001
$S_{31}(t), S_{32}(t)$	Jan. 2003 - Dec. 2007	Apr. 2002 - Dec. 2002
$S_{33}(t)$	Apr. 2003 - Dec. 2007	Apr. 2002 - Mar. 2003
$S_{42}(t), S_{42}(t), S_{43}(t), S_{44}(t)$	Feb. 2004 - Dec. 2007	Feb. 2003 - Jan. 2004

We interpolate missing data for each variable using a polynomial trend function (i.e.,  $Y(t) = \sum_k \lambda_k t^k$ , where  $Y(t) \in \{N_i(t), Tr_j(t), S_{ij}(t)\}$ ). For interpolation, we use  $N_i(t) = Tr_j(t) = S_{ij}(t) = 0$  for  $i \geq j$  when  $t < \tau_i$  and  $\tau_j$ . For  $N_i(t)$ ,  $Tr_i(t)$ , and most of  $S_{ij}(t)$ , we choose  $k$  that gives the highest adjusted R-square while keeping all  $\lambda_k$  significant.

For  $S_{31}(t)$ ,  $S_{32}(t)$ , and  $S_{33}(t)$ , given the very slow start in the adoption of platform 3 followed by a relatively rapid increase in adoption afterwards, polynomial approximations using all the existing data lead to negative estimates around introduction time. As such we employed a different approach for these particular sets of missing data points. We assumed that  $S_{31}(t)$ ,  $S_{32}(t)$ , and  $S_{33}(t)$  follow an accelerating trajectory in the early adoption stages similar to traditional S-curve models such as the Bass model. As such, until the (first) inflection point, adoption usually displays a convex increasing pattern. Hence, we used a quadratic polynomial trend fitted on data points only up until the first inflexion point. With this approach, most of the estimates of missing early data points came positive. There were still 3 points that came with negative estimates ( $S_{31}(\tau_3 + 1)$ ,  $S_{33}(\tau_3 + 1)$ , and  $S_{33}(\tau_3 + 2)$ ). To generate non-negative estimates for these points, we used linear interpolation between  $S_{31}(\tau_3) = 0 < S_{32}(\tau_3 + 2)$  and  $S_{33}(\tau_3) = 0 < S_{33}(\tau_3 + 3)$ . We also imposed a constraint  $S_{ij}(t) \leq N_i(t)$  for all  $i, j$  with  $i \geq j$  because  $S_{ij}(t)$  is always a subset of the installed base for platform  $i$ .

In all, across 18 main variables of our study, we interpolated 10 percent of data (167 out of 1,674 observations). There is no clear guideline in the literature regarding the acceptable amount of missing observations for valid statistical inferences; however, the literature (Little and Rubin 2002, Saunders, et al. 2006) suggests that 20 percent or less would be acceptable.

## **B.2. Prices of Handsets**

We impute the missing data by employing the following strategy. It is often observed that the prices of new technologies decrease at a constant rate over time (Bass et al. 1994). Accordingly, using the collected data, we first test if there is an evidence to believe that the average handset prices of each platform generation also decrease at a constant rate in the context of this study by estimating the following equation

$$p_i^n(t) = \omega_i \cdot p_i^n(t - 1), \quad (\text{B.1})$$

where  $i \in \{1,2,3,4\}$  and  $p_i^n(t)$  is the average nominal price of platform  $i$  in time period  $t$ . If  $\omega_i$  parameters are estimated to be statistically significant, then it would be plausible to expect that the price pattern of handsets is consistent with the observed price pattern of new technologies in the literature, and thereby,

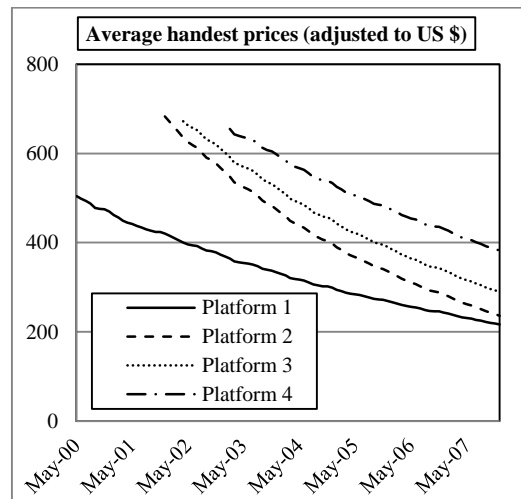
equation (B.5) could be used to reasonably impute the missing data. The following table reports the parameter estimates and model fit.

**Table B.2.** Parameter estimates and model fits for the price pattern of each platform generation

	Platform generation			
	1 <sup>st</sup>	2 <sup>nd</sup>	3 <sup>rd</sup>	4 <sup>th</sup>
$\omega_i$	0.9934 <sup>***</sup> (0.0072)	0.9879 <sup>***</sup> (0.0045)	0.9900 <sup>***</sup> (0.0076)	0.9931 <sup>***</sup> (0.0017)
$n$	22 <sup>†</sup>	24	24	24
<i>Adj R-Sq.</i>	0.9988	0.9995	0.9986	0.9999

Note: <sup>\*\*\*</sup>  $p < 0.01$ ; <sup>\*\*</sup>  $p < 0.05$ ; <sup>\*</sup>  $p < 0.1$ ; Approx. standard errors in parentheses; <sup>†</sup> The price of generation 1 handset for February 2007 was unavailable.

Adjusted R-squares are noticeably high and all  $\omega_i$  parameter estimates are statistically significant at the 0.01 percent confidence level. This result suggests that the average nominal handset prices of each platform generation indeed have decreased at a constant rate. Therefore, using equation (B.1), we obtain the average nominal handset prices of each platform generation. We then derive the real average prices of platform  $i$  handsets  $p_i(t)$  by adjusting the observed and estimated nominal average handset prices using the consumer price index using April 2000 as base, as illustrated in the following figure.



**Figure B.1.** Average handset prices, adjusted to US \$.

### C. Leapfrogging and Switching

Several studies (Danaher et al. 2001, Jiang and Jain 2012) separate the migration into *leapfrogging* and *switching* by defining multipliers for each. We illustrate here how we can also achieve this separation in the context of our model by employing the multiplier-based approach in Jiang and Jain (2012) which retains the underlying diffusion structure in the Norton and Bass (1987) model intact. In our paper, the initial adoption and migration corresponding to the Norton and Bass (1987) model are coupled in the first terms in equations (11)-(14). We define platform *switching* as moving from being an adopter of platform  $i$  to being an adopter of platform  $i + 1$  (existing users who upgrade to the very next generation). Different from switching, we say that a customer *leapfrogs* over platform  $i$  if she would have got platform  $i$  in the absence of any newer generation but, when facing multiple available options that co-exist in the market, chooses a platform  $k > i$ . Note that each generation expands the market introducing new adopters. However, these are not leapfroggers as they never considered prior generations when these existed in the market.

Abstracting from the lease on life effect, let us consider the following notation for the instantaneous rates of adoption, switching, and leapfrogging (corresponding to a continuous-time version of the Norton and Bass model):

- $\hat{n}_i(t) = m_i f_i(t)$  – the rate of adoption for platform  $i$  at time  $t$  due to the market expansion induced by this platform generation in the absence of newer generations, where  $\hat{n}_i(t) = \frac{\partial \hat{N}_i(t)}{\partial t}$ .
- $lpf_{i,none-to-k}(t)$  – the rate of leapfrogging into platform  $k \geq 2$  for consumers who were not adopters before *but had considered the product starting with platform  $i < k$*  (i.e., being part of  $m_i$ ).
- $lpf_{i-to-k}(t)$  – the rate of leapfrogging from being a user of platform  $i$  (regardless of how the consumer ended up adopting  $i$ ) directly to being a user of platform  $k \geq i + 2$ , skipping all the generations in between.



- $s_{i,i+1}(t)$  - the rate of switching from being a user of platform  $i$  to being a user of platform  $i + 1$  (upgrading to the immediately subsequent generation)
- $nin_i(t)$  – the consumer *net* inflow rate into platform  $i$  at time  $t$ . If the net inflow is negative, that means the installed base of the platform is shrinking.

All the above adoption “streams” capture customer flow rates into given platform installed bases and they all depend on which platform generations are in the market at a given time. Following the model in Jiang and Jain (2012), we detail below these rates in the context of 4 generations.

i.  $\tau_1 \leq t < \tau_2$ .

Platform 1:

$$nin_1(t) = \hat{n}_1(t),$$

- $\hat{n}_1(t) = m_1 f_1(t)$ .

ii.  $\tau_2 \leq t < \tau_3$ .

Platform 1:

$$nin_1(t) = \hat{n}_1(t) - lpf_{1,none-to-2}(t) - s_{1,2}(t),$$

- $\hat{n}_1(t) = m_1 f_1(t)$ .
- $lpf_{1,none-to-2}(t) = m_1 f_1(t) F_2(t)$ .
- $s_{1,2}(t) = m_1 F_1(t) f_2(t)$ .

Platform 2:

$$nin_2(t) = \hat{n}_2(t) + lpf_{1,none-to-2}(t) + s_{1,2}(t),$$

- $\hat{n}_2(t) = m_2 f_2(t)$ .
- $lpf_{1,none-to-2}(t) = m_1 f_1(t) F_2(t)$ .
- $s_{1,2}(t) = m_1 F_1(t) f_2(t)$ .

iii.  $\tau_3 \leq t < \tau_4$ .

Platform 1:

$$nin_1(t) = \hat{n}_1(t) - lpf_{1,none-to-2}(t) - lpf_{1,none-to-3}(t) - lpf_{1-to-3}(t) - s_{1,2}(t)$$

- $\hat{n}_1(t) = m_1 f_1(t)$ .
- $lpf_{1,none-to-2}(t) = m_1 f_1(t) F_2(t) [1 - F_3(t)]$
- $lpf_{1,none-to-3}(t) = m_1 f_1(t) F_2(t) F_3(t)$
- $lpf_{1-to-3}(t) = m_1 F_1(t) f_2(t) F_3(t)$
- $s_{1,2}(t) = m_1 F_1(t) f_2(t) [1 - F_3(t)]$

Platform 2:

$$nin_2(t) = \hat{n}_2(t) + lpf_{1,none-to-2}(t) + s_{1,2}(t) - lpf_{2,none-to-3}(t) - s_{2,3}(t),$$

- $\hat{n}_2(t) = m_2 f_2(t)$ .
- $lpf_{1,none-to-2}(t) = m_1 f_1(t) F_2(t) [1 - F_3(t)]$
- $s_{1,2}(t) = m_1 F_1(t) f_2(t) [1 - F_3(t)]$
- $lpf_{2,none-to-3}(t) = m_2 f_2(t) F_3(t)$
- $s_{2,3}(t) = [m_2 + m_1 F_1(t)] F_2(t) f_3(t)$

Platform 3:

$$nin_3(t) = \hat{n}_3(t) + lpf_{1,none-to-3}(t) + lpf_{2,none-to-3}(t) + lpf_{1-to-3}(t) + s_{2,3}(t)$$

- $\hat{n}_3(t) = m_3 f_3(t)$ .
- $lpf_{1,none-to-3}(t) = m_1 f_1(t) F_2(t) F_3(t)$
- $lpf_{2,none-to-3}(t) = m_2 f_2(t) F_3(t)$
- $lpf_{1-to-3}(t) = m_1 F_1(t) f_2(t) F_3(t)$
- $s_{2,3}(t) = [m_2 + m_1 F_1(t)] F_2(t) f_3(t)$

iv.  $\tau_4 \leq t$ .

Platform 1:

$$nin_1(t) = \hat{n}_1(t) - lpf_{1,none-to-2}(t) - lpf_{1,none-to-3}(t) - lpf_{1,none-to-4}(t) - lpf_{1-to-3}(t) \\ - lpf_{1-to-4}(t) - s_{1,2}(t)$$

- $\hat{n}_1(t) = m_1 f_1(t).$
- $lpf_{1,none-to-2}(t) = m_1 f_1(t) F_2(t) [1 - F_3(t)]$
- $lpf_{1,none-to-3}(t) = m_1 f_1(t) F_2(t) F_3(t) [1 - F_4(t)]$
- $lpf_{1,none-to-4}(t) = m_1 f_1(t) F_2(t) F_3(t) F_4(t)$
- $lpf_{1-to-3}(t) = m_1 F_1(t) f_2(t) F_3(t) [1 - F_4(t)]$
- $lpf_{1-to-4}(t) = m_1 F_1(t) f_2(t) F_3(t) F_4(t)$
- $s_{1,2}(t) = m_1 F_1(t) f_2(t) [1 - F_3(t)]$

Platform 2:

$$nin_2(t) = \hat{n}_2(t) + lpf_{1,none-to-2}(t) + s_{1,2}(t) - lpf_{2,none-to-3}(t) \\ - lpf_{2,none-to-4}(t) - lpf_{2-to-4}(t) - s_{2,3}(t),$$

- $\hat{n}_2(t) = m_2 f_2(t).$
- $lpf_{1,none-to-2}(t) = m_1 f_1(t) F_2(t) [1 - F_3(t)]$
- $s_{1,2}(t) = m_1 F_1(t) f_2(t) [1 - F_3(t)]$
- $lpf_{2,none-to-3}(t) = m_2 f_2(t) F_3(t) [1 - F_4(t)]$
- $lpf_{2,none-to-4}(t) = m_2 f_2(t) F_3(t) F_4(t)$
- $lpf_{2-to-4}(t) = [m_2 + m_1 F_1(t)] F_2(t) f_3(t) F_4(t)$
- $s_{2,3}(t) = [m_2 + m_1 F_1(t)] F_2(t) f_3(t) [1 - F_4(t)]$

Platform 3:

$$nin_3(t) = \hat{n}_3(t) + lpf_{1,none-to-3}(t) + lpf_{2,none-to-3}(t) + lpf_{1-to-3}(t) + \\ s_{2,3}(t) - lpf_{3,none-to-4}(t) - s_{3,4}(t)$$

- $\hat{n}_3(t) = m_3 f_3(t).$
- $lpf_{1,none-to-3}(t) = m_1 f_1(t) F_2(t) F_3(t) [1 - F_4(t)]$
- $lpf_{2,none-to-3}(t) = m_2 f_2(t) F_3(t) [1 - F_4(t)]$

- $lpf_{1-to-3}(t) = m_1 F_1(t) f_2(t) F_3(t) [1 - F_4(t)]$
- $s_{2,3}(t) = [m_2 + m_1 F_1(t)] F_2(t) f_3(t) [1 - F_4(t)]$
- $lpf_{3,none-to-4}(t) = m_3 f_3(t) F_4(t)$
- $s_{3,4}(t) = [m_3 + [m_2 + m_1 F_1(t)] F_2(t)] F_3(t) f_4(t)$

Platform 4:

$$nin_3(t) = \hat{n}_4(t) + lpf_{1,none-to-4}(t) + lpf_{2,none-to-4}(t) + lpf_{3,none-to-4}(t) \\ + lpf_{1-to-4}(t) + lpf_{2-to-4}(t) + s_{3,4}(t)$$

- $\hat{n}_4(t) = m_4 f_4(t)$ .
- $lpf_{1,none-to-4}(t) = m_1 f_1(t) F_2(t) F_3(t) F_4(t)$
- $lpf_{2,none-to-4}(t) = m_2 f_2(t) F_3(t) F_4(t)$
- $lpf_{3,none-to-4}(t) = m_3 f_3(t) F_4(t)$
- $lpf_{1-to-4}(t) = m_1 F_1(t) f_2(t) F_3(t) F_4(t)$
- $lpf_{2-to-4}(t) = [m_2 + m_1 F_1(t)] F_2(t) f_3(t) F_4(t)$
- $s_{3,4}(t) = [m_3 + [m_2 + m_1 F_1(t)] F_2(t)] F_3(t) f_4(t)$

Using the parameter estimates in Table 4, we can compute all the leapfrogging and switching rates above. To obtain the overall aggregate switchers or leapfroggers in one particular category over an interval of time, all we have to do is to integrate the particular rates over that period of time. For example, the overall leapfrogging from being a platform 1 adopter to being a platform 3 adopter, skipping platform 2, computed in the interval  $[t, T]$  such that  $\tau_3 \leq t < T$ , is given by  $\int_t^T lpf_{1-to-3}(r) dr$ .