The Adoption of Multi-Generational Platforms in the Presence of Intergenerational Services

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Abstract

We investigate the impact of intergenerational services on the adoption of multi-generational platforms. We consider mobile Internet platform generations for which users download complementary services from third party providers. These services are often intergenerational: newer platforms are backward compatible with respect to services released under older platform generations. In this paper, we develop a model to identify the main drivers of adoption of subsequent generations of mobile Internet platforms, including (i) the migration from older to newer platform generations, (ii) the indirect network effect between platform users and services, and (iii) the effect of intergenerational services on platform adoption. Using data on mobile Internet platform adoption and services consumption from a major wireless carrier in an Asian country for the time period of 2001 – 2007, we estimate the three effects noted above. We show that both the migration from older to newer platform generations and the indirect network effect 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 older generation platforms due to the continued use of older generation services on newer platform generations. This 'shot in the arm' effect for older generation platforms is due to the users who adopt an older generation platform instead of adopting a newer one.

Keywords: Platforms, multi-generation diffusion, backward compatibility of services, lease on life, network economics

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1. Introduction

Many IT products and services such as IBM mainframe systems (Mahajan and Muller 1996) and wireless telecommunication services (Kim et al. 2000) evolve over several generations.[1] The academic literature on multi-generation products has treated their adoption 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 product gradually migrate to the new generation product over time. In this paper we are exploring in more depth the dynamics of this generation handover, with a particular focus on platforms.

We frame our study in the context of mobile Internet platforms offered by a major wireless carrier. The wireless carrier categorizes platforms into different generations depending on the functionality of services that each platform supports. As a platform provider, the wireless carrier designs and provides the mobile Internet platform, and its supporting services are provided by third-party providers. A newer generation platform is *backward compatible* with the services originated with earlier generation platforms. The supporting services along with backward compatibility of a platform play important roles in platform adoption decisions. The value of a platform to users highly depends on the value of its supporting services (Gawer and Cusumano 2002) and backward compatibility carries over the value of supporting services originated with earlier generation platforms to the new platform (Gandal et al. 2000; Claussen et al. 2012).[2] Our focus in this study is the intergenerational nature of many services which link users of platforms of different generations. For example, two users who have different generations of smart phones can talk to each other via Skype. This offers new externalities which hitherto have not been considered in depth; while intergenerational services can foster the migration to newer platforms, they can, at the same time, *lengthen the lifecycle of the older platforms*.

[1] Other examples include Dynamic Random Access Memory (Norton and Bass 1987) and mobile Internet platforms (Chu and Pan 2008).
[2] In the handheld video-game industry, it has been discussed that the new generation console (e.g., Game Boy Advance) was adopted more rapidly because of backward compatibility (Calussen et al. 2012). Game Boy Advance was backward compatible with the games that were originally written for the earlier generation console, Game Boy Color.

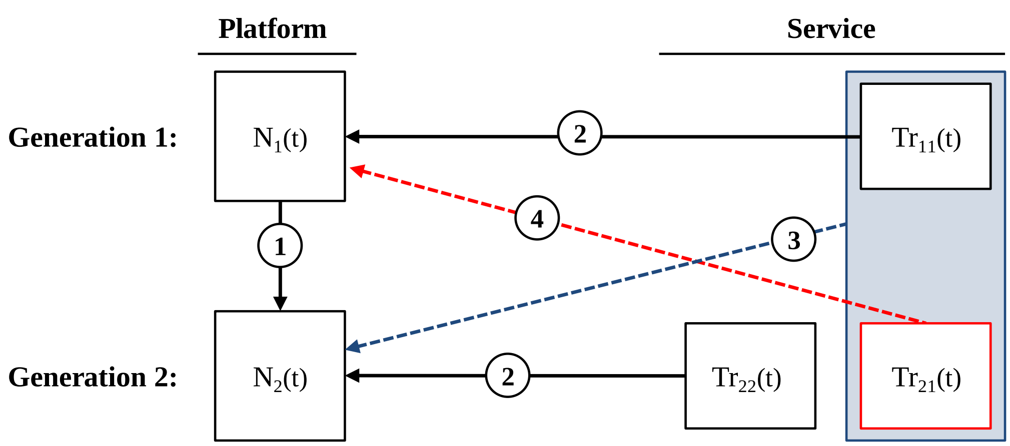
To identify and measure the aforementioned effects, we build a multi-generation diffusion model following extant models in the literature (Blackman 1974; Norton and Bass 1987; Mahajan and Muller 1996; Islam and Meade 1997; Jun and Park 1999; Kim et al. 2000; Danaher et al. 2001; Chu and Pan 2008; Bohlin et al. 2010; Jiang and Jain 2012). However, our approach differs from the previous literature in the following ways:

- We incorporate (i) the indirect network effect induced by complementary value-adding services and (ii) the migration from the earlier to new platform generations together in one model. Most multi-generation diffusion literature focuses on the migration and does not explicitly model the indirect network effect. Danaher et al. (2001) and Jiang and Jain (2012) incorporate the impact of marketing mix variables on the diffusion of multi-generation products but they assume that the marketing mix variables are exogenous to the model. Furthermore, their models do not include the dynamics between the diffusion of multi-generation platforms and intergenerational services. 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 effect but do not explore interactions between generations in depth.
- We include the effects of intergenerational services in our model. We identify two separate effects of intergenerational services: (i) a forward effect that fosters migration to the subsequent platform generation and (ii) a lease on life effect for the old generation platform. Clements and Ohashi (2005) incorporate backward compatibility in their model and examine the indirect network effect in video-game industry, but they do not investigate interactions between generations.

The rest of the paper is organized as follows. In Section 2, we discuss the conceptual model and assumptions. We describe the research context and data in Section 3, and empirical specification, methodology, and estimation results in Section 4. In Section 5, we discuss the detailed economics of backward compatibility and managerial implication, and conclude with the summary and discussion in Section 6.

2. The Conceptual Model and Assumptions

For expositional clarity, we first introduce the model and build the theory using a hypothetical market that has two platform generations (platform 1 and 2) and new complementary services released for each of them (service 1 and 2). Platform 1 and service 1 are introduced in the market before platform 2 and service 2. The parameterization for the full model is discussed in Section 4.1. Platform 2 (the new platform) exhibits backward compatibility in that platform 2 users can consume both service 1 and 2, but platform 1 (the old platform) users can consume only service 1. Let $N_i(t)$ be the cumulative number of adopters of platform i by time t, and $Tr_{ij}(t)$ be the cumulative traffic volume of service j consumed by platform i users by time t. Figure 1 illustrates the relationship between platforms and services.



Note: 1. Migration; 2. Indirect network effect; 3. Forward effect of backward compatibility; 4. Lease on life (Backward effect of backward compatibility)

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

Effect 1: Migration. Platform 1 adopters gradually migrate to platform 2 over time once platform 2 becomes available. As such, at any given time, adopters of platform 2 consist of new adopters and those adopters who have migrated from platform 1.

Effect 2: Indirect network effect. The value of a platform, and thereby, the number of adopters of the platform increases as more users consume its supporting services (Katz and Shapiro 1994).

Effect 3: Forward effect of backward compatibility. Since Platform 2 is backward compatible with service 1, the value of platform 2 is associated with the value of not only service 2 but also service 1. As more users consume service 1, the number of platform 2 adopters increases. This can be perceived as the forward effect of backward compatibility. By providing backward compatibility, the platform provider carries over the associated value of service 1 to platform 2, and motivates potential adopters to adopt the new platform, platform 2.

Effect 4: Lease on life (Backward effect of backward compatibility). Platform 2 users can consume both service 1 and 2, and hence, as more of platform 2 users consume service 1, platform 1 gets additional value in the following ways. First, service 1 does not get discontinued due to the continued demand, which allows platform 1 users to continue to derive value. Second, through continued service 1, platform 1 users can interact with platform 2 users, and it pushes further in the future the obsolescence of platform 1. As such, through backward compatibility, platform 1 gets a lease on life which can be perceived as 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:

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

$$N_2(t) = \hat{N}_2(t) + Mig_1(t), \tag{2}$$

where $\hat{N}_i(t)$ is the estimated number of adopters of platform i by time t in the absence of migration or lease on life, $Mig_1(t)$ is the number of platform 1 adopters who have migrated to platform 2 by time t, and $Lol_i(t)$ is the lease on life of platform 1 by time t (measured as the number of additional adopters of platform 1 due to platform 2 users' consumption of service 1).

The (single-generation) diffusion literature defines different functional forms for $\hat{N}_i(t)$ for different contexts (see the reviews of the diffusion models in Mahajan and Muller 1979, Mahajan et al. 1990, and Meade and Islam 2006). Most of those functional forms, however, 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 the adoption penetration rate follows a probability curve (e.g., modified exponential, logistic, or Gompertz). Following the same underlying structure for the diffusion process, we define $\hat{N}_i(t)$ as:

$$\hat{N}_i(t) = m_i F_i(t - \tau_i), \tag{3}$$

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), $F_i(t)$ is the cumulative adoption probability of platform i by time t, and τ_i is the time at which platform i and service i were introduced in the market. Without loss of generality, we adjust the timeline such that $\tau_1 = 0$. Building on the generalized Bass model (Bass et al. 1994), we parameterize $F_i(t)$ as:

$$F_i(t) = \frac{1 - \exp\left[-[p_i + q_i]\left[t + \beta_i \log[1 + Tr_{ii}(t) - Tr_{ii}(t-1)] + I(t) \cdot \gamma_i \log\left[1 + \sum_{k<i}[Tr_k(t) - Tr_k(t-1)]\right]\right]\right]}{1 + \frac{q_i}{p_i}\exp\left[-[p_i + q_i]\left[t + \beta_i \log[1 + Tr_{ii}(t) - Tr_{ii}(t-1)] + I(t) \cdot \gamma_i \log\left[1 + \sum_{k<i}[Tr_k(t) - Tr_k(t-1)]\right]\right]\right]}, \tag{4}$$

if $t \geq 0$; and 0 otherwise.[3] $I(t) = 1$ if $t \geq 0$; and 0 otherwise. Consistent with the diffusion literature, we name p_i the coefficient of innovation and q_i the coefficient of imitation. β_i measures the effect of change in platform i users' consumption of service i (i.e., $Tr_{ii}(t) - Tr_{ii}(t-1)$) on the diffusion rate of platform i which is the indirect network effect. Similarly, γ_i measures the effect of change in the

[3] The derivation of $F_i(t)$ from the hazard rate function in general form is available in Bass et al. (1994).

popularity of old generation services (i.e., $\sum_{k<i}\left[Tr_k(t)-Tr_k(t-1)\right]$) on the diffusion rate of the new generation platform (platform i) which is the forward effect of backward compatibility.

As we mentioned above, the number of adopters of a platform increases as more users consume its supporting services. At the same time, as more people adopt a platform, each user of the platform consumes more of its supporting services due to the network effect. Thus, $Tr_{ii}(t)$ and $\sum_{k<i} Tr_k(t)$ in equation (4) are endogenous to the model. To control for this endogeneity, along with the rest of the model, we jointly estimate the following equations parameterizing traffic:

$$Tr_{ii}(t) = I(t)\cdot\left[a_i t + b_i \sum_{s=\tau_i}^{t} N_i(s)\right] \tag{5}$$

$$Tr_i(t) - Tr_{ii}(t) = \sum_{l>i} Tr_{li}(t) = I(t)\cdot\left[c_i t + d_i \sum_{l>i}\sum_{s=\tau_l}^{t} N_l(s)\right] \tag{6}$$

b_i and d_i capture the network effects, and a_i and c_i capture the time effects on the consumption of services for platform i. Equation (5) captures the traffic consumption in period t for service i, originating with the users of platform i, as being correlated with the current install base for that respective platform at time t (i.e., $Tr_{ii}(t)-Tr_{ii}(t-1)=a_i+b_iN_i(t)$). Similarly, equation (6) captures the fact that the traffic consumption in period t for service i can also be due to newer platform generations and average per user per time unit consumption for this user population stabilizes at d_i if there are sufficiently many adopters (i.e., $\sum_{l>i} Tr_{li}(t)-\sum_{l>i} Tr_{li}(t-1)=c_i+d_i\sum_{l>i} N_l(t)$). Note that, in the context of the simplified illustrative model with two platform generations and two services, equation (6) only describes $Tr_{21}(t)$. However, in the full model, as described in Section 4.1, this equation will apply in the more general sense.

The multi-generation 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 diffusion models by adding parameters to capture user migration to subsequent generations (similar to $Mig_1(t)$ in equation (3)). These models generally assume that (i) adopters migrate from earlier to later 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:

$$Mig_1(t) = m_1 F_1(t) F_2(t - \tau_2). \tag{7}$$

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

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

$$Lol_1(t) = \alpha_1 Tr_{21}(t) + \varsigma_1 e^{-I(t-\tau_2)\cdot\eta[t-\tau_2]} \sum_t \Delta P_1(t-1). \tag{8}$$

As mentioned earlier, the fact that service 1 is not discontinued in platform 2 (or not replaced by a backward-incompatible service) gives one less reason for users to choose platform 2 over platform 1. Moreover, if a lot of users of platform 2 consume service 1, this gives users of platform 1 a channel to interact with users of platform 2 that may impact the appeal of platform 1 contingent on how much that service is consumed (for utilitarian or hedonic purposes). Note that the interaction does not have to be direct (we are not talking necessarily about a social network hub). The lease on life can be due to an imitation effect as well - the more users see other users consuming service 1 they want a platform capable of running that service. We call α_1 is the coefficient of the lease on life. Note that, as time passes, usually in the industry we see older platform generations being marked down. In order to make sure that what we identify as lease on life due to backward compatibility is identified separately from the lease on life due to price effects, we control for the latter by including $\Delta P_1(t)$ in equation (8). $\Delta P_1(t)$ represents the price advantage of platform 1 over its successive platform, platform 2 (i.e., $\Delta P_1(t) = P_2(t) - P_1(t)$ if $P_2(t) \neq 0$; and 0 otherwise). A firm often cuts prices of the earlier platform after it launches a new platform and some adopters choose the earlier platform because of this price advantage. It has been discussed that the effects of marketing activities (e.g., price promotion) dissipate over time (Hanssens et al. 2001). Hence, we assume that the effect of price advantage on lease on life diminishes over time. The relationship between the lease on life and price is likely endogenous. To control for this endogeneity, we use one-period lagged price in equation (8).

3. Mobile Internet Market and Data

3.1. Description of the Mobile Internet Platform

We obtained monthly data on mobile Internet platform adoption and services consumption from a major wireless carrier in an Asian country with a highly developed mobile telecommunication infrastructure for the time period of 2001 – 2007. During this time period, the wireless carrier sequentially introduced four generations of mobile Internet platforms with backward compatibility.[4] Complementary services supporting each platform have been introduced by third-party providers via the wireless carrier's distribution channels. Here backward compatibility is unidimensional, covering only the platform side. In other words, the newer platforms were backward compatible with older generation services, but newer services introduced with the new platform were not backward compatible with older platforms. Table 1 summarizes each of these platforms and services.

Table 1. Summary of each platform and service

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

[4] Since 4th generation platform had been introduced in February 2003, no new platform was introduced until 2008 when the smartphone platform was released.

3.2. Data Description

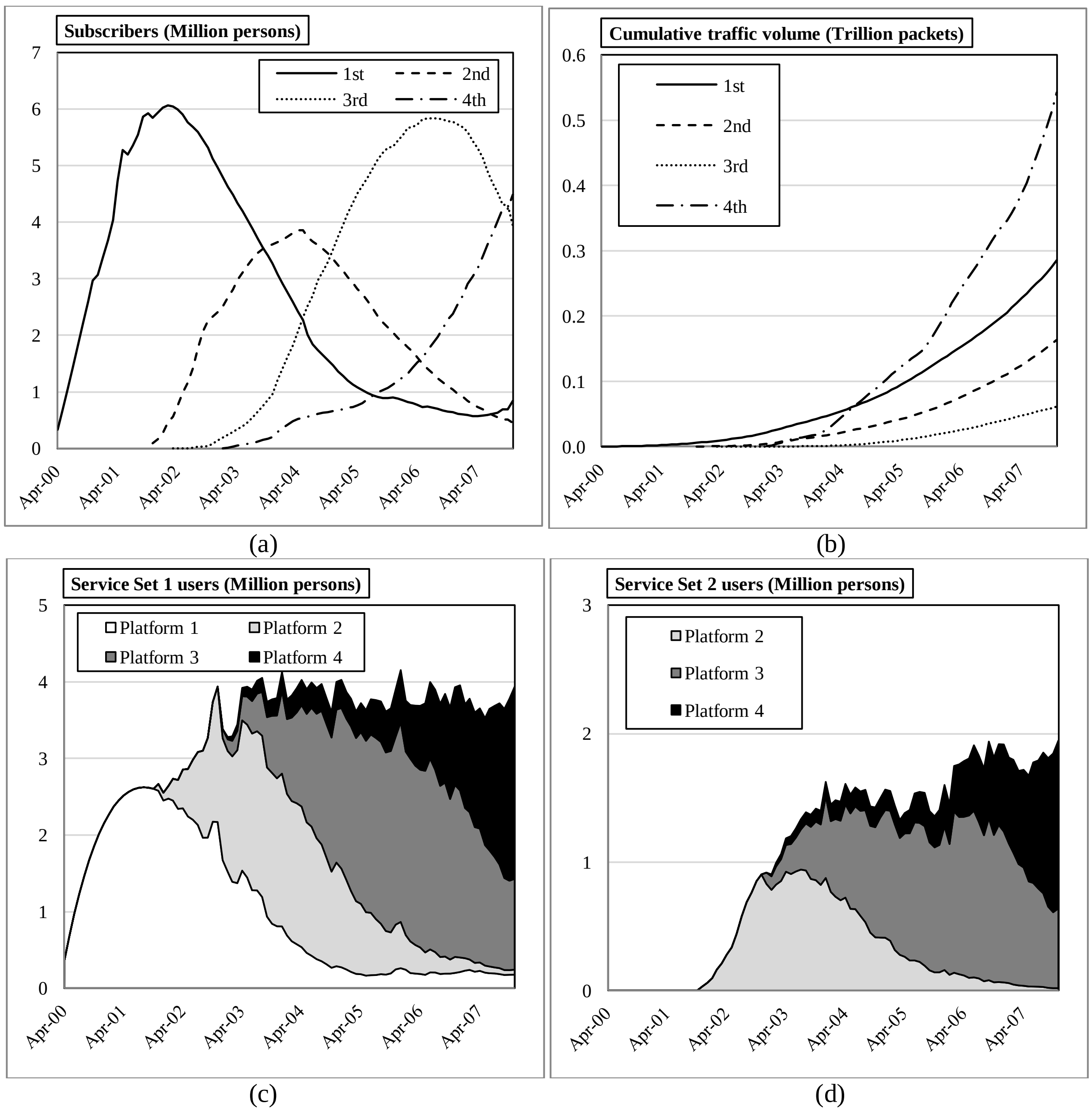
In our dataset, we have (i) the number of platform i subscribers ($N_i(t)$), (ii) the traffic volume of service j ($Tr_j(t)$), and (iii) the number of platform i users who consume service j ($N_{ij}(t)$) on a monthly basis for the time period 2001 – 2007. However, some data for the early time period is missing. There are a few alternative ways to estimate the model when there is missing data (see Grover and Vriens 2006). The simplest approach among those would be 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 the data from when the product/service was released is not available (Jiang et al. 2006). Therefore, following a regression substitution approach, we first interpolate the missing data using available data and estimate the model.[5] Table 2 summarizes the available data and interpolated time period for each variable.

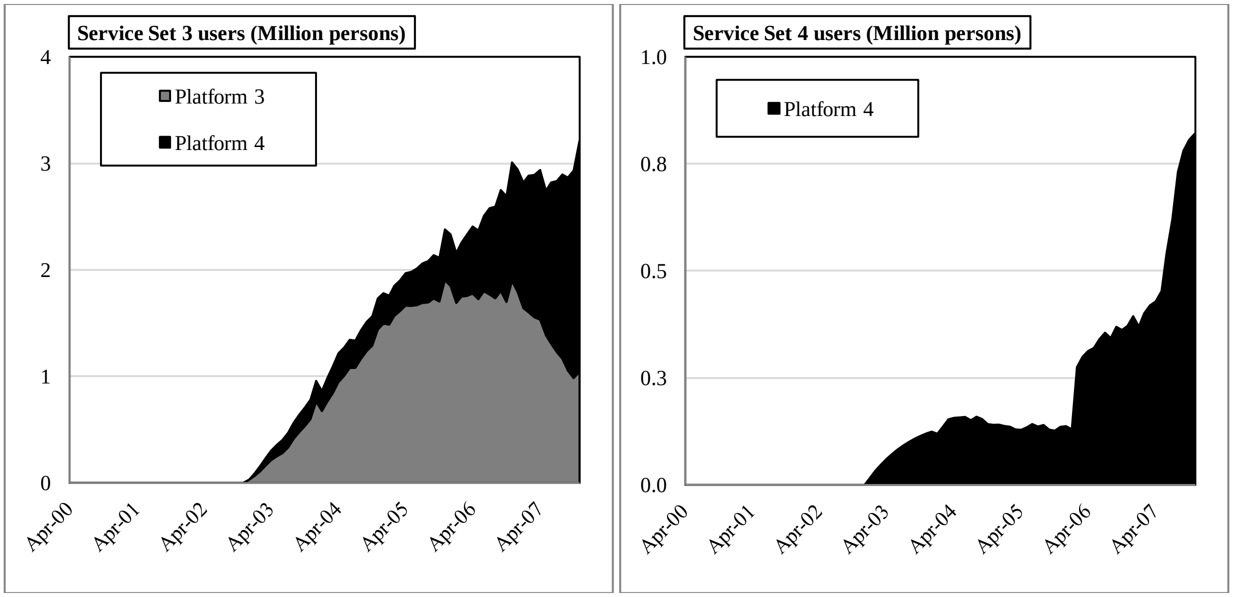
Table 2. Available data and interpolated time period for each variable

Variable		Available data	Interpolated time period
$N_i(t)$	1st	Jan. 2001 - Dec. 2007	May 2000 - Dec. 2000
	2nd	Dec. 2001 - Dec. 2007	None
	3rd	Apr. 2002 - Dec. 2007	None
	4th	Feb. 2003 - Dec. 2007	None
$Tr_j(t)$	1st	Jan. 2003 - Dec. 2007	May 2000 - Dec. 2002
	2nd	Jan. 2003 - Dec. 2007	Dec. 2001 - Dec. 2002
	3rd	Apr. 2002 - Dec. 2007	None
	4th	Feb. 2003 - Dec. 2007	None
$N_{ij}(t)$	1st	Jan. 2002 - Dec. 2007	May 2000 - Dec. 2001
	2nd	Jan. 2002 - Dec. 2007	Dec. 2001
	3rd	Jan. 2003 - Dec. 2007	Apr. 2002 - Dec. 2002
	4th	Feb. 2004 - Dec. 2007	Feb. 2003 - Jan. 2004

[5] For interpolation, we use $N_i(t)=0$, $Tr_j(t)=0$, and $N_{ij}(t)=0$ for $t<\tau_i$ and τ_j, where τ_i and τ_j are the time at which platform i and service j was released respectively.

We interpolate missing data for each variable using a polynomial trend function (i.e., $Y(t)=\sum_k \lambda_k t^k$, where $Y(t)\in\{N_i(t), Tr_j(t), N_{ij}(t)\}$). We choose k that gives the highest adjusted R-square while keeping all λ_k significant. We provide the details of how we interpolate the missing data - parameter estimates and model fits - in the Appendix. Figure 2 shows the time series of each variable including the data we interpolate.





(e) (f)

Figure 2. (a) the number of subscribers of each platform, (b) the cumulative traffic volume of each service, and (c) – (f) the breakdown of the number of each service users by platform generation

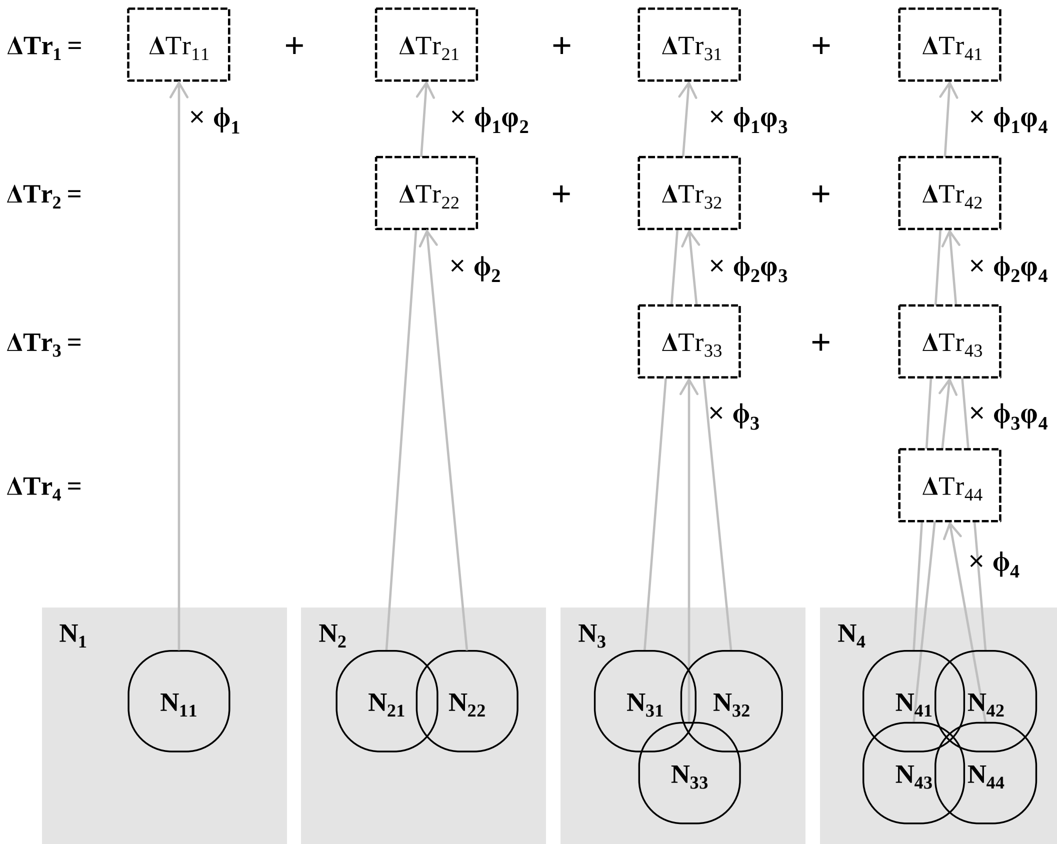
3.3. Breakdown of the Consumption of Each Service by Corresponding Platform Generation

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

$$Tr_{ij}(t) - Tr_{ij}(t-1) = \begin{cases} \phi_j \cdot N_{ij}(t) & \text{if } i = j \\ \phi_j \cdot \varphi_i \cdot N_{ij}(t) & \text{if } i \neq j \end{cases}, \tag{9}$$

where ϕ_j is the service multiplier (average user consumption volume for services introduced for that respective platform) and φ_i is the platform (or backward compatibility) multiplier (i.e., $\phi_j \cdot \varphi_i$ represents the platform-service-dependent average consumption volume by users of platform i with respect to older generation services introduced for platform j). In our model, we account for the fact that users might consume at different rates the services dedicated to older platforms compared to the services introduced for the current platform. Then, using (9), from $Tr_j(t) - Tr_j(t-1) = \sum_i [Tr_{ij}(t) - Tr_{ij}(t-1)]$, we have:

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



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

Figure 3. The relationship between $Tr_j(t)$ and $N_{ij}(t)$

Figure 3 illustrates the relationship between $Tr_j(t)$ and $N_{ij}(t)$ defined in equation (10). We estimate the parameters - ϕ_j and φ_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 and/or time 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 3. The rates for text, application, and multimedia packets were reduced by 30% in February 2007.

Table 3. 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

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 4 shows the parameter estimates and model fit. All parameters are significant and adjusted R-square values are considerably high.

Table 4. Parameter estimates and model fits for the service and platform multipliers

	Traffic volume			
	1st generation (j = 1)	**2nd generation (j = 2)**	**3rd generation (j = 3)**	**4th generation (j = 4)**
ϕ_j	0.26*** (0.02)	0.34*** (0.03)	0.11*** (0.01)	34.21*** (0.92)
φ_2	1.43*** (0.92)	-	-	-
φ_3	3.58*** (0.36)		-	-
φ_4	12.62*** (1.15)			-
n	93			
Adj R-Sq.	0.9786	0.9872	0.8550	0.8912

Note: φ_3 and φ_4 are simultaneously estimated from multiple equations; *** p<0.01; ** p<0.05; * p<0.1; Approx. standard errors in parentheses

3.4. Price of Handheld Devices

We collected from an online forum the store prices of 73 handsets in November 2007 that were locked on the network of the wireless carrier that we study.[6] On the online forum, the release store prices of 16 handsets, among 73, were also available.[7] The average release store price of 16 handsets is $558 and the average store price of handsets for each mobile Internet platform (generation) in November 2007 is as summarized in Table 5.

Table 5. The average store price of handsets for each mobile Internet platform in November 2007

Mobile Internet platform (Generation)	Count (Percentage)	Average store price (Unit: converted to US$)
1st	3 (4.11%)	299
2nd	11 (15.07%)	308
3rd	2 (2.74%)	366
4th	57 (78.08%)	479

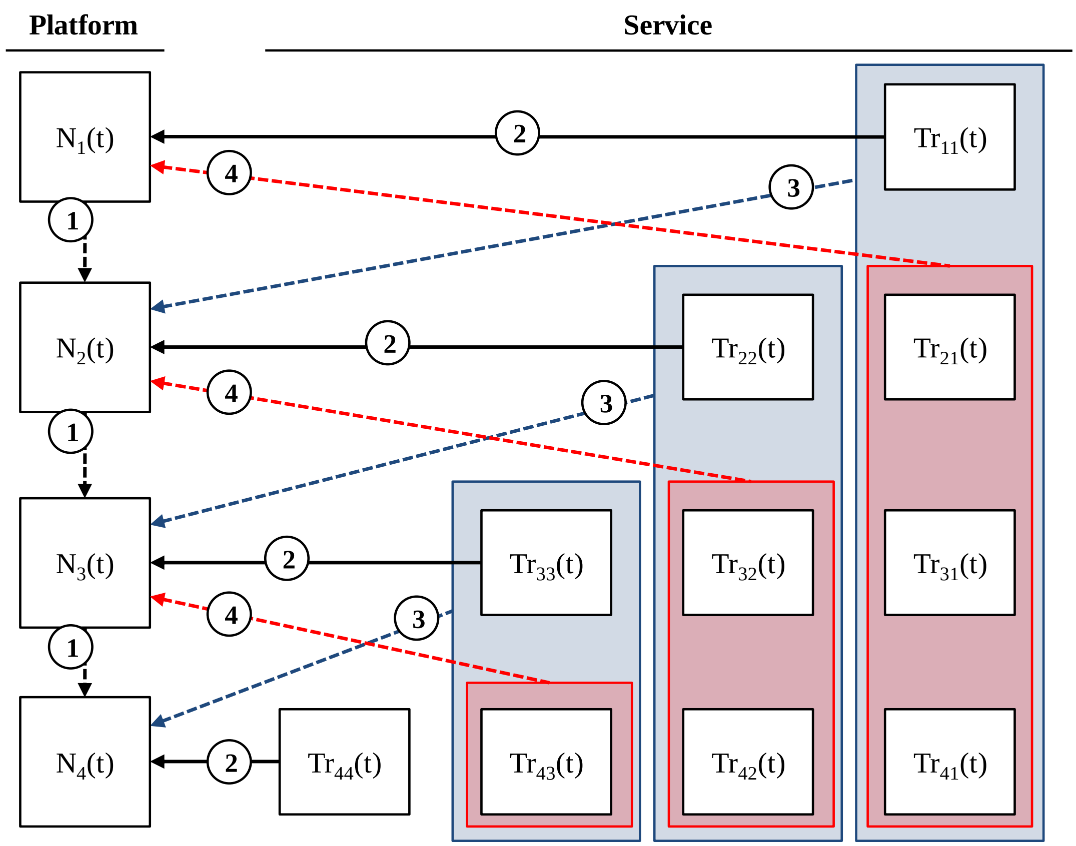
Comprehensive time series of price data for handsets are not readily available due to the large number of available handsets at any given time and relatively short lifecycle of each of them. Thus, we interpolate average price of handsets for each mobile Internet platform using the average release store price and the average store price of handsets for each platform in November 2007. To interpolate the data, we make the following two assumptions. First, we assume that average release prices of handsets for all mobile Internet platforms (generations) are identical. This is a common practice in IT industry. The release price of new version of many IT products is identical to that of earlier version. Second, we assume that the average price of handsets for each platform decreases over time at a constant percent rate.

[6] In the Asian country that we study, each handset could be used only on the network of the locked wireless carrier. Further, marketing promotions were regulated by the government and fixed-term contracts were restrictively allowed. Therefore, the store price fairly represents what each consumer really paid.
[7] The release prices are available only for those handsets released before early 2006.

4. The Impact of Backward Compatibility on Platform Adoption Decisions

4.1. Empirical Specification

In this section, extending the model in Section 2 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. The relationship between platforms and services when there are four generations of platforms and services is illustrated in Figure 5.



Note: 1. Migration; 2. Indirect network effect 3. Forward effect of backward compatibility; 4. Lease on life (Backward effect of backward compatibility)

Figure 5. The relationship between platforms and services – four generations case

From the relationship illustrated in Figure 5, the model can be extended as:

$$N_1(t) = m_1 F_1(t)\left(1 - F_2(t-\tau_2)\right) + \alpha_1 \sum_{l>1} Tr_{l1}(t) + \varsigma_1 e^{-I(t-\tau_2)\cdot\eta[t-\tau_2]} \sum_t \Delta P_1(t-1), \qquad (11)$$

$$N_2(t)=(m_2+m_1F_1(t))F_2(t-\tau_2)(1-F_3(t-\tau_3))+\alpha_2\sum_{l>2}Tr_{l2}(t)+\varsigma_2 e^{-I(t-\tau_3)\cdot\eta[t-\tau_3]}\sum_t \Delta P_2(t-1), \tag{12}$$

$$N_3(t)=(m_3+(m_2+m_1F_1(t))F_2(t-\tau_2))F_3(t-\tau_3)(1-F_4(t-\tau_4))$$
$$+\alpha_3\sum_{l>3}Tr_{l3}(t)+\varsigma_3 e^{-I(t-\tau_4)\cdot\eta[t-\tau_4]}\sum_t \Delta P_3(t-1), \tag{13}$$

$$N_4(t)=(m_4+(m_3+(m_2+m_1F_1(t))F_2(t-\tau_2))F_3(t-\tau_3))F_4(t-\tau_4), \tag{14}$$

where $F_i(t)$, $Tr_{ii}(t)$, and $Tr_i(t)$ satisfy equations (3) – (5) for all $1 \le i \le 4$.

4.2. Model Estimation

To account for endeogeneity, we estimate equations (3) – (5) and (11) – (14) simultaneously using non-linear system Generalized Method of Moments (GMM). The benefit of using non-linear system GMM is that it controls for endeogeneity as well as serial correlation in the error terms and heteroskedasticity of unknown forms.[8] GMM estimation, however, requires instruments that are correlated to the endogenous variables but not to the error terms, and valid instruments are often not readily available. Lagged regressors are commonly used as instruments for time series and panel data analysis, though there has been discussion about the validity of using lagged regressors as instruments since the lagged regressors can be correlated to the error terms (Angrist and Krueger 2001). We therefore use a two-pronged approach: Following the commonly used instrumentation strategy, we first estimate the model by instrumenting one-period lag of regressors (i.e., one period lag of age of each generation $t-\tau_i-1$, and one-period lag of cumulative number of adopters of each platform $\sum_{s=\tau_i}^{t} N_i(s-1)$) (Model A). We then follow Suarez et al.'s (2013) approach to estimate the model by including non-GMM exogenous variables as instruments (Model B).

Suarez et al. follow the instrumentation strategy of Berry et al. (1995). Berry et al. suggest that the instruments for endogenous variables (e.g., price and demand) of a product of a firm can be developed

[8] The White test (White 1980) rejects the null hypothesis of homoscedasticity. It has been discussed that when there is heteroskedasticity of unknown form, the estimation results of GMM is more efficient than seemingly unrelated (SUR) regression and other IV (Instrumental variable) methods (Baum et al. 2003).

from the characteristics (e.g., size) of all other products of the firm and characteristics of products of its rival firms. Following the same strategy, we include (i) the cumulative number of adopters of all other platforms (i.e., $\sum_{j \neq i} \sum_{s=\tau_i}^{t} N_j(s-1)$) and (ii) the cumulative number of adopters across all platform generations of its competitor $c = \{1,2\}$ as instruments.[9]

Table 6 shows the parameter estimates, model fit, and Hansen's J Statistic for Model A and B. For both models, the adjusted R-squares are noticeably high and the insignificant Hansen's J statistic suggests that the instruments are valid. The estimation results of Model A and B are qualitatively identical – no difference in the sign of the estimates and significance, and thereby, no difference in the interpretation of the results. However, estimates for some parameters are slightly different. In the following sections, we discuss the estimation results regarding the market potential, innovation and imitation effects, indirect network effects, forward effects of backward compatibility, and lease on life (backward effects of backward compatibility) based on parameter estimates of model B, and discuss the difference in parameter estimates of model A and model B if there is any.

Table 6. Parameter estimates and model fit

		Model A		Model B	
		Estimates (Std. Err.)	Significance	Estimates (Std. Err.)	Significance
Market potential	m_1	8.0863 (0.2487)	***	8.6493 (0.1658)	***
	m_2	1.0234 (0.2429)	***	0.4100 (0.0332)	**
	m_3	0 (0)		0.0634 (0.0977)	
	m_4	0.5162 (0.0920)	***	0.5246 (0.1212)	***
Innovation effect	p_1	0.0069 (0.0007)	***	0.0064 (0.0005)	***
	p_2	0.0047 (0.0008)	***	0.0059 (0.0006)	***
	p_3	0.0047 (0.0001)	***	0.0046 (0.0002)	***
	p_4	0.0002	**	0.0005	***

[9] Three wireless carriers (including the one that we analyze) provide mobile Internet services in the Asian country during the time period that we study. The aggregate number of subscribers across all platform generations at each time t of each of those two competing wireless carriers is publicly available on its website.

		(9.6E-5)		(0.0001)	
Imitation effect	q_1	0.0929 (0.0040)	***	0.0874 (0.0026)	***
	q_2	0.0861 (0.0010)	***	0.0842 (0.0008)	***
	q_3	0.0670 (0.0003)	***	0.0680 (0.0009)	***
	q_4	0.0284 (0.0051)	***	0.0443 (0.0034)	***
Indirect network effect	β_1	34.1237 (1.5348)	***	34.5692 (1.6117)	***
	β_2	8.8342 (2.2373)	***	6.7708 (1.7174)	***
	β_3	52.2947 (0.9126)	***	49.0487 (1.1897)	***
	β_4	29.5188 (5.3959)	***	9.7820 (0.9660)	***
Forward effect of backward compatibility	γ_2	7.7666 (1.7083)	***	6.9646 (0.7926)	***
	γ_3	0.3371 (0.2056)		0.3454 (0.5105)	
	γ_4	4.9664 (8.0453)		3.6593 (4.2257)	
Lease on life (Backward effect of backward compatibility)	α_1	0.0028 (1.3E-5)	***	0.0028 (1.4E-5)	***
	α_2	-75E-12 (0)		-75E-12 (0)	
	α_3	0.0021 (0.0009)	**	0.0028 (0.0011)	**
Price effect on lease on life	ζ_1	0.0636 (0.0801)		0.0098 (0.0498)	
	ζ_2	1.6895 (0.4094)	***	1.4789 (0.3235)	***
	ζ_3	0.0221 (0.0300)		0.0156 (0.0245)	
Time control on price effect	η	0.2808 (0.0436)	***	0.2636 (0.0269)	***
Network effect	b_1	0.1379 (4.2E-5)	***	0.1379 (0.0001)	***
	b_2	0.0613 (0.0001)	***	0.0612 (0.0003)	***
	b_3	0.0323 (9.6E-6)	***	0.0323 (1.5E-5)	***
	b_4	5.2082 (0.0100)	***	5.2061 (0.0100)	***
	d_2	0.6696 (0.0002)	***	0.6695 (0.0004)	***
	d_3	0.4516 (6.8E-5)	***	0.4516 (9.8E-5)	***
	d_4	0.5444 (0.0002)	***	0.5444 (0.0002)	***

Time control on consumption of services	a_1	-0.1000 (0.0001)	***	-0.1001 (0.0003)	***
	a_2	0.0228 (0.0003)	***	0.0230 (0.0006)	***
	a_3	0.0159 (2.8E-5)	***	0.0159 (4.2E-5)	***
	a_4	2.9128 (0.0088)	***	2.9169 (0.0108)	***
	c_2	-0.8732 (0.0008)	***	-0.8723 (0.0023)	***
	c_3	0.1151 (0.0002)	***	0.1149 (0.0005)	***
	c_4	0.0595 (0.0001)	***	0.0594 (0.0002)	***
Adj. R-Square	N_1	0.9965		0.9966	
	N_2	0.9962		0.9967	
	N_3	0.9969		0.9984	
	N_4	0.9701		0.9797	
	Tr_{11}	0.9677		0.9677	
	Tr_{22}	0.9412		0.9412	
	Tr_{33}	0.9978		0.9978	
	Tr_{44}	0.9960		0.9960	
	ΣTr_{i1}	0.9735		0.9735	
	ΣTr_{i2}	0.9884		0.9884	
	ΣTr_{i3}	0.9992		0.9992	
Number of observations		91		91	
Number of instruments		8		14	
Hansen's J statistic		48.95		49.42	
Degree of freedom		59		125	
P-value		0.8216		1.0000	

*** $p<0.01$; ** $p<0.05$; * $p<0.1$

4.3. Market Potential

The market potential of platform 1 (m_1) is 8.65 million and it is increased by 0.41 million for platform 2 (m_2) and by 0.52 million for platform 4 (m_4). Compared to model B, model A overestimates m_2 (8.09 million) and underestimates m_1 (0.52 million), suggesting a smaller market size for platform 2 and a stronger migration from platform 1 to platform 2. m_3 is relatively small and not significant. It suggests that there is no significant increase in the market potential (i.e., no new adopters) for platform 3. This result is consistent with the observed actions of the wireless carrier. Platform 3 was launched only four months after platform 2, and the difference between platform 2 and 3 in terms of functionality and features was marginal (see Table 1). In contrast, platform 2 and 4 were launched, respectively, 19 months and 10 months after its previous generation, and new functionality and features were sufficiently different. These results suggest that a new generation platform may expand the market only if it provides significantly different functionality and features to users.

4.4. Innovation and Imitation Effects

All parameters for innovation (p_i) and imitation (q_i) effects are positive and significant. The average innovation effect for all four generations is 0.0044 (0.0041 in model A), and the average imitation effect is 0.0710 (0.0686 in model A). The diffusion literature has shown that the innovation and imitation effects vary widely across products (see Lilien and Rangaswamy (2006) for estimated values of the strength of innovation and imitation effects for various products), with the average coefficient of innovation being 0.03 and average coefficient of imitation being 0.38 (Sultan et al. 1990). For our context, the innovation effect is similar to the average, and the imitation effect is weaker than the average but resemble the one observed in cable TV industry (0.06).

4.5. Indirect Network Effects

Parameters for the indirect network effects (β_i) are all positive and significant, confirming that the value of a platform, and thereby, the number of adopters of a platform increase as the traffic volume of its supporting services increases. While the indirect network effect is relatively strong for service 1 (β_1 = 34.5692) and service 3 (β_3 = 49.0487), it is relatively weak for service 2 (β_2 = 6.7708) and service 4 (β_4 = 9.7820). Compared to model B, model A overestimates β_4 (β_4 = 29.5188) and underestimates q_4. Model A captures some of the imitation effects for platform 4 in model A as the indirect network effects.

Our result is consistent with the service offerings introduced for each platform. While service 3 (e.g., multimedia messaging service) and some portion of service 1 (e.g., short-text-based instant messengers) require extensive communication between users, a big portion of service 2 (e.g., mobile games, banking, and stock trading) and service 4 (e.g., Live TV and Video on demand) require relatively little communication between users. It suggests that the service that requires more communication between users has the stronger indirect network effect on the diffusion rate of a platform compared to other services that require less communication between users. Our finding provides an important implication for the platform provider. Consider a smart phone platform and its supporting services (e.g., games). While some of those popular services (e.g., Angry Birds) do not require much communication between users, others (e.g., FarmVille) do. The benefit to the platform provider in the diffusion rate of the platform from those services that require more communication between users is likely higher than other services that do not require much communication.

4.6. Forward Effect of Backward Compatibility

While γ_2 (= 6.9646) is significant, γ_3 and γ_4 are not. Via backward compatibility, service 1 adds significant value to platform 2, yet consumption of older generation services on platform 3 and 4 does not impact their adoption in a significant way. Given that the indirect network effect of service 2 (β_2) is relatively weaker than that of any other services, this result suggests that backward compatibility carries over the value of the earlier services to a new platform if the indirect network of its supporting services is not sufficiently strong. If the indirect network of supporting services is sufficiently strong, the additional value that the earlier services provide to a new platform is likely to be marginal and not significant.

4.7. Lease on Life (Backward Effect of Backward Compatibility)

The estimation results confirm that there is a lease on life for platform 1 (α_1 = 0.0028) and platform 3 (α_3 = 0.0028) but not for platform 2. α_2 is close to zero and not significant. This suggests that new platform users' consumption of the earlier services via backward compatibility gives the earlier platform a lease on life unless the indirect network effect of supporting services for the platform is sufficiently weak. The low indirect network effect implies a weak association between the value of a platform and the value of its supporting services. Therefore, given that the indirect network effect of service 2 (β_2) is relatively weak, it is conceivable that platform 3 and 4 users' consumption of service 2 does not add significant value to platform 2, and thereby, there is no lease on life for platform 2.

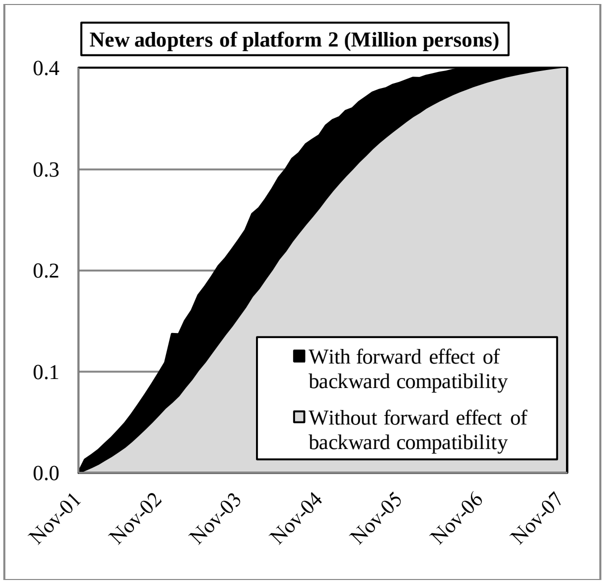
On the other hand, ς_2 (= 1.4789) is positive and significant, but ς_1 and ς_3 are not. While the price advantage of platform 2 handsets over handsets of a successive generation induces some adopters to choose platform 2, the price advantages of platform 1 and 3 over their successive generations were not playing a significant role in the adoption process. Given that the cannibalization is more severe when the difference between product line is not sufficiently large (Kim and Chhajed 2000), this result was somewhat expected. As we mentioned, platform 3 was released only 4 months after platform 2 and the marginal difference between platform 2 and 3, in terms of its supports for services, was not significant.

5. The Economic Effects of Intergenerational Services

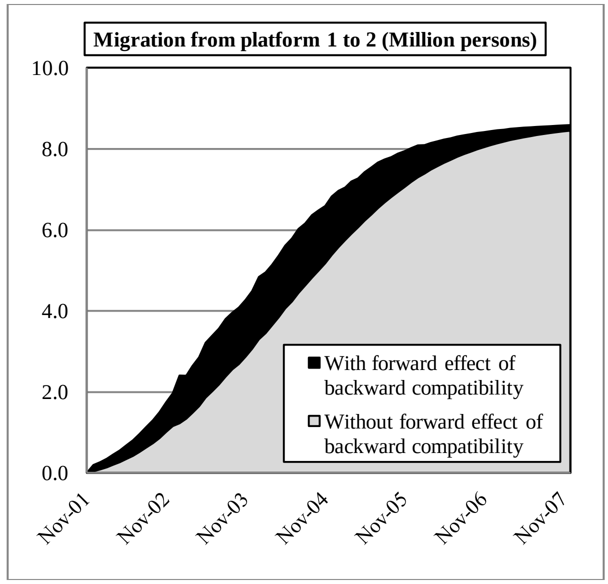
In this section, we focus on the economic impact of backward compatibility of services in the platform market. We distinguish between the forward effect and the lease on life effect of intergenerational services.

5.1. Forward Effect of Intergenerational Services

By carrying over a service from platform 1 to platform 2 via backward compatibility, the platform provider motivates more potential adopters and existing adopters of platform 1 to choose platform 2 (see Figure 6). Our results indicate that, compared to a scenario without backward compatibility, in the month when platform 2 was lunched (December 2001), 0.01 million more people adopted platform 2 and 0.15 million more adopters of platform 1 migrated to platform 2. Within one year (by end of December 2002), an additional 0.04 million people adopted platform 2 and an additional 0.81 million people migrated from platform 1 to platform 2. This represents an about 70% faster diffusion and migration compared to the case without backward compatibility.



(a)



(b)

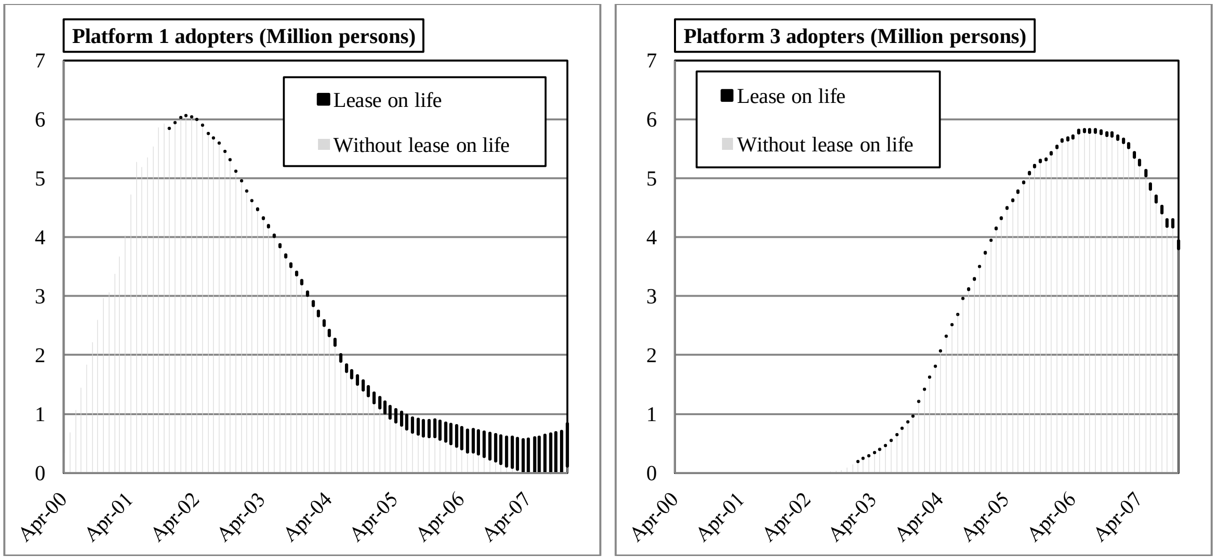
Figure 6. The impact of forward effect of intergenerational services on (a) new adoption of platform 2 and (b) migration from platform 1 to platform 2

5.2. Lease on Life Effect of Intergenerational Services

The newer platforms adopters' consumption of intergenerational services that were originally introduced with earlier generation platforms creates value not only to the new platforms but also to the old platforms. We find that this boon to the earlier generation platforms is significant. Our result suggests that on average every 1 million packets of service 1 consumed on platforms 2, 3, or 4, created 2.8 new users on platform 1. Similarly, every 1 million packets of service 3 consumed on platform 4 created 2.8 new adopters of platform 3.[10]

By December 2007, the lease on life effect allowed platform 1 to gain 0.74 million new (or retained) users and allowed platform 3 to gain 0.13 million new users (see figure 7). Compared to the market potential, this represents about 8.5% and 1.5% size of the market for platform 1 and platform 3 respectively.

[10] An average content/app size of service 1 is 100 – 150 packets, and hence, 1 million packets of first generation services consumption is equivalent to 6,500 – 10,000 content/app downloads. The traffic of third generation services consists mainly multimedia messages (MMS) sent and received. Our data shows that the average size of one MMS during the time window of our study is 61 packets. Thus, 1 million packets of third generation services consumption is equivalent to about 16,000 MMS sent and received.



(a) (b)

Figure 7. Lease on life for (a) platform 1 and (b) platform 3

5.3. Managerial Implication of Intergenerational Services

Our results confirm that backward compatibility of services has both forward and backward effects. From the time since platform 2 was launched and before platform 3 came out (approximately for four months), platform 2 gained 0.25 million additional adopters from platform 1 because of forward effect of backward compatibility of intergenerational services. During the same time period, platform 1 also added 670 additional adopters because of the lease on life effect of backward compatibility of intergenerational services (i.e., platform 2 users' consumption of service 1). If there are both forward and backward effects of backward compatibility, it appears that the forward effect is stronger than the backward effect.[11]

It is not clear whether the lease on life is an intended and ideal consequence of backward compatible services for the platform owner because the lease on life could induce additional costs. In order to serve new users of the earlier platforms, the wireless carrier needs to continue to maintain the infrastructure (e.gg, the mobile network) and the distribution channels for the supporting services. Therefore, the net profit from the lease on life can be either positive or negative. In fact, in January 2008,

[11]This may change in the later stage of lifecycle. The forward effect of backward compatibility reduces over time and becomes zero (see Figure 6), whereas the lease on life effects depends on the new platform users' consumption of the earlier generation services.

the wireless carrier that we study merged the distribution channels for services 1 and 4 into one, and in early 2012, it terminated 2G mobile network that supported the earlier platforms.

6. Summary and Discussion

We model the adoption dynamics of multi-generation platforms from a diffusion point of view and investigate the impact of intergenerational services on the platform adoption decisions using data from a major wireless carrier in an Asian country. Our approach complements two streams of literature. We complement the diffusion literature by incorporating both the indirect network effects of complementary products/services and the migration in one model. Most prior literature focuses on either of those but not both. We also complement the literature that studies backward compatibility by investigating both forward and backward effects of backward compatibility. In contrast, many earlier models include only the forward effects of backward compatibility.

Our main finding is that for intergenerational services, backward compatibility can have two effects; it can carry over the value of an earlier generation service to a new platform. However, backward compatibility has also a perhaps unintended consequence; the continued use of the earlier generation services on a new generation platform provides a shot in the arm for the earlier generation platforms. Therefore, backward compatibility may not induce more adopters to choose new platform but instead may give an earlier generation a second wind. This finding has important managerial implications for the platform owner. In addition to delaying the adoption of the new generation platform, the lease on life for the earlier generation platforms could also cause significant amount of additional maintenance and operational expenses. In order to avoid these additional expenses and to 'encourage' the adoption of the new platform, the platform owner may need to deliberately shut down the earlier generation platforms or phase out backward compatibility at some point in time. We have observed such moves in industry. For example, in the gaming console industry Sony designed its gaming consoles such that, only the first three models of PlayStation 3 have been fully backward compatible with PlayStation 2 games and Sony has gradually shut down channels for PlayStation 2 online. Microsoft has also used such practice in its operating system division; it recently announced that it would stop in 2014 supports for its old Windows versions.[12] These steps do not have to be as drastic.

Our study presents several research directions in which it can be extended. For example, 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). Also, one could 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.

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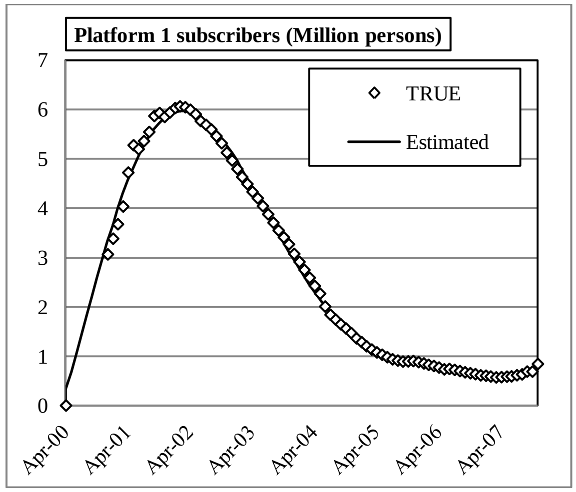
Appendix.

The following is the parameter estimates and model fits for each variable that we interpolated:

1. *The number of platform 1 subscribers* ($N_1(t)$):

	Estimate	Std. Error
λ_1	0.3194^{***}	0.0176
λ_2	0.0153^{***}	0.0021
λ_3	-0.0013^{***}	9.29E-05
λ_4	2.95E-05***	1.89E-06
λ_5	-2.74E-07***	1.80E-08
λ_6	9.36E-10***	6.51E-11
n	84	
Adj. R-Square	0.9860	

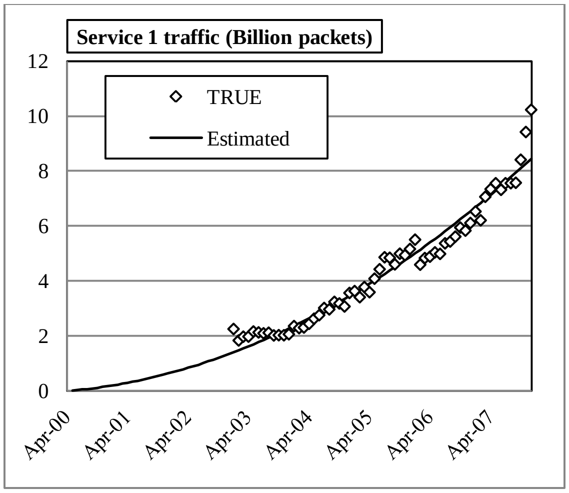


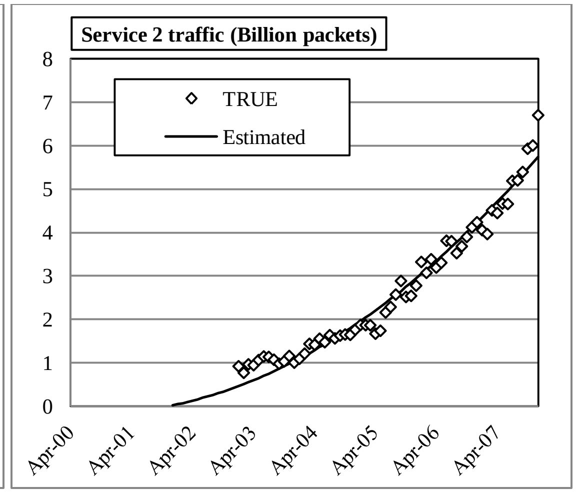
*** p<0.01; ** p<0.05; * p<0.1

2. *The traffic volume of service 1 and 2* ($Tr_1(t), Tr_2(t)$):

	Service 1		Service 2	
	Estimate	Std. Error	Estimate	Std. Error
λ_1	0.0152^{***}	0.0042	0.0219^{***}	0.0032
λ_2	0.0008^{***}	5.73E-05	0.0008^{***}	5.60E-05
n	60		60	
Adj. R-Square	0.9748		0.9747	

*** p<0.01; ** p<0.05; * p<0.1

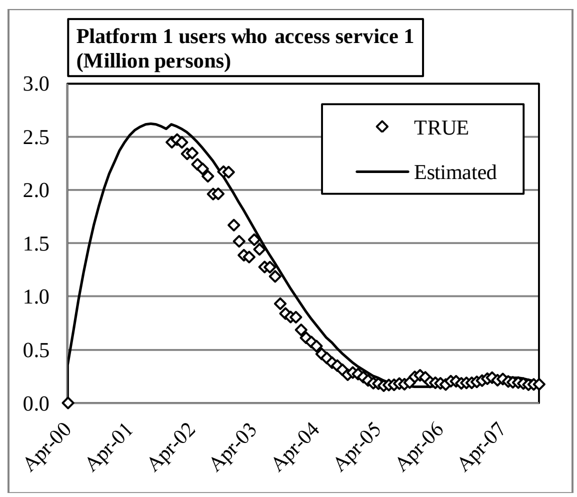




3. *The number of platform i subscribers who access service j* ($N_{ij}(t_i)$):

3.1. Platform 1

	Platform 1 access Service 1	
	Estimate	Std. Error
λ_1	0.9707***	0.0145
λ_2	-0.0170***	0.0011
λ_3	0.0003***	3.09E-05
λ_4	-1.99E-06***	3.58E-07
λ_5	4.82E-09***	1.49E-09
n	72	
Adj. R-Square	0.9797	



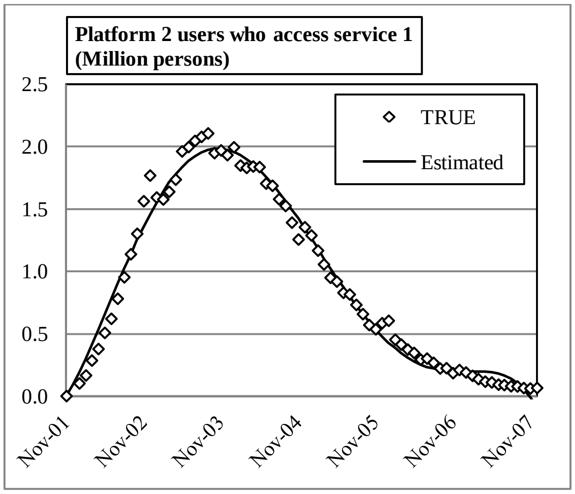
*** p<0.01; ** p<0.05; * p<0.1

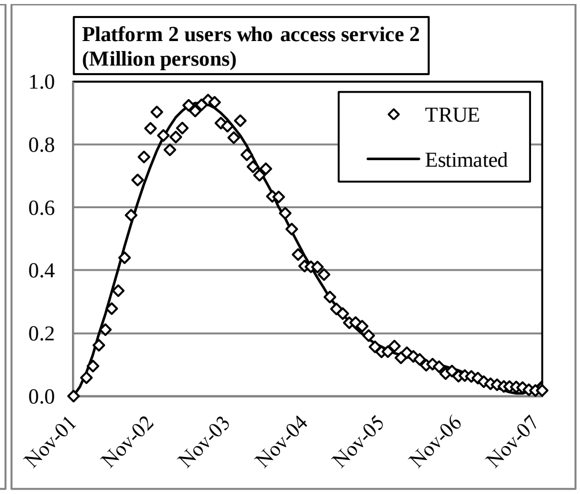
3.2. Platform 2

	Platform 2 access service 1		Platform 2 access service 2	
	Estimate	Std. Error	Estimate	Std. Error
λ_1	0.0814***	0.0089	0.0214***	0.0058
λ_2	0.0070***	0.0010	0.0091***	0.0009
λ_3	-0.0005***	3.90E-05	-0.0007***	5.31E-05
λ_4	7.89E-06***	6.24E-07	1.71E-05***	1.40E-06
λ_5	-4.37E-08***	3.52E-09	-1.95E-07***	1.73E-08

λ_6			8.22E-10***	8.02E-11
n	72		72	
Adj. R-Square	0.9789		0.9794	

*** p<0.01; ** p<0.05; * p<0.1

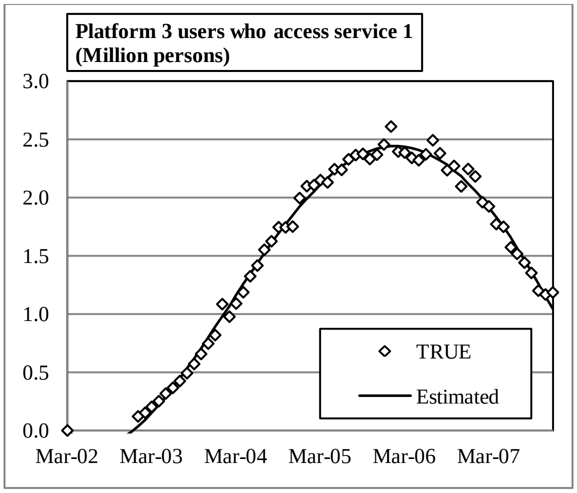


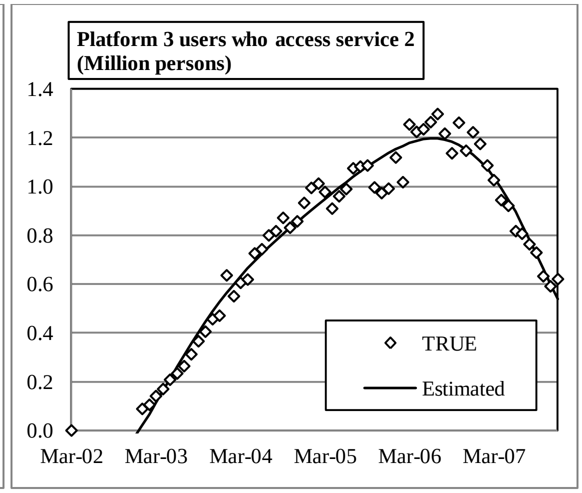


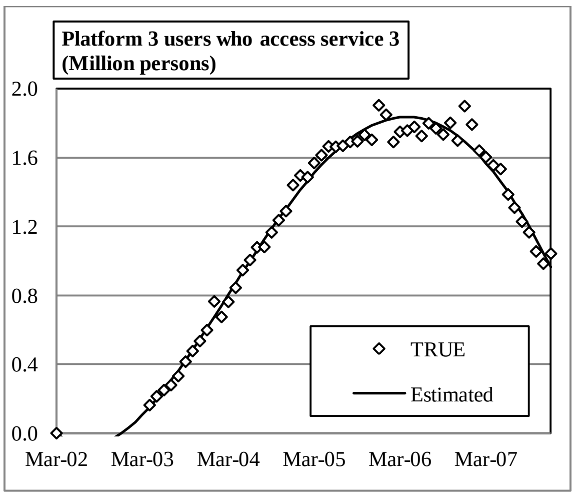
3.3. Platform 3

	Platform 3 access service 1		Platform 3 access service 2		Platform 3 access service 3	
	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
λ_1	-0.0565***	0.0049	-0.0803***	0.0209	-0.0356***	0.0053
λ_2	0.0073***	0.0004	0.0133***	0.0032	0.0046***	0.0004
λ_3	-0.0001***	8.96E-06	-0.0006***	0.0002	-8.28E-05***	9.23E-06
λ_4	7.12E-07***	6.69E-08	1.52E-05***	4.61E-06	3.74E-07***	6.79E-08
λ_5			-1.74E-07***	5.70E-08		
λ_6			7.60E-10***	2.69E-10		
n	60		60		60	
Adj. R-Square	0.9807		0.9765		0.9791	

*** p<0.01; ** p<0.05; * p<0.1



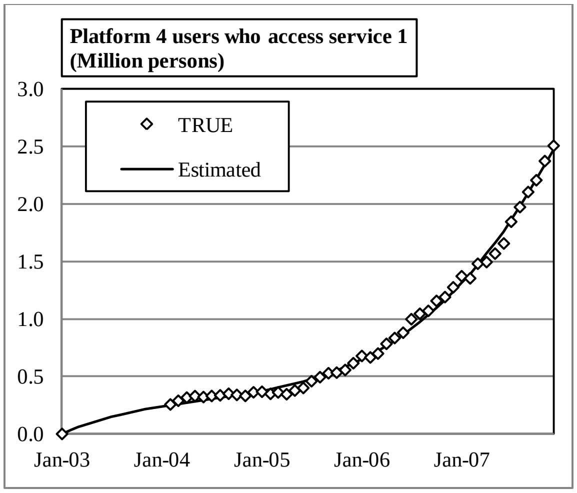


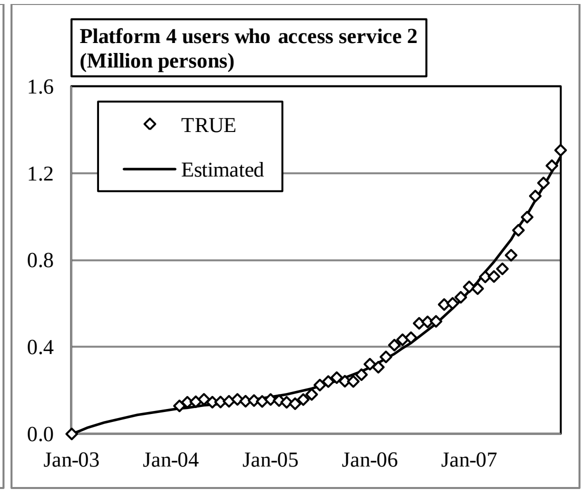


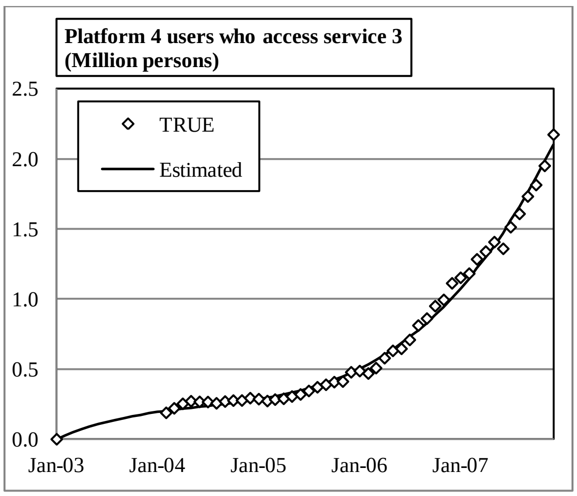
3.4. Platform 4

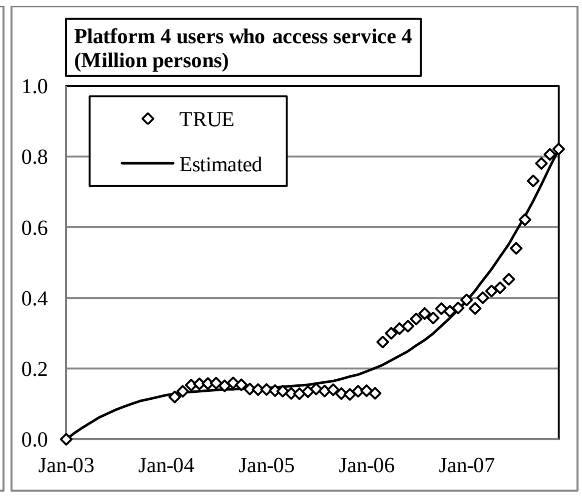
	Platform access service 1	Platform 4 access service 2	Platform 4 access service 3	Platform 4 access service 4
λ_1	0.0313***	0.0153***	0.0268***	0.0183***
	(0.0020)	(0.0015)	(0.0020)	(0.0021)
λ_2	-0.0012***	-0.0006***	-0.0011***	-0.0008***
	(9.98E-05)	(7.65E-05)	(0.0001)	(0.0001)
λ_3	2.39E-05***	1.28E-05***	2.20E-05***	1.24E-05***
	(1.21E-06)	(9.29E-07)	(1.25E-06)	(1.31E-06)
n	47	47	47	47
Adj. R-Square	0.9758	0.9739	0.9750	0.9604

*** p<0.01; ** p<0.05; * p<0.1; Approx. standard errors in parentheses


Platform 4 users who access service 1 (Million persons)
TRUE
Estimated
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Jan-03
Jan-04
Jan-05
Jan-06
Jan-07


Platform 4 users who access service 2 (Million persons)
TRUE
Estimated
1.6
1.2
0.8
0.4
0.0
Jan-03
Jan-04
Jan-05
Jan-06
Jan-07


Platform 4 users who access service 3 (Million persons)
TRUE
Estimated
2.5
2.0
1.5
1.0
0.5
0.0
Jan-03
Jan-04
Jan-05
Jan-06
Jan-07


Platform 4 users who access service 4 (Million persons)
TRUE
Estimated
1.0
0.8
0.6
0.4
0.2
0.0
Jan-03
Jan-04
Jan-05
Jan-06
Jan-07