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**Giving the Old Platform a New Lease on Life:
The Unintended Effect of Backward Compatibility on Platform Adoption Decisions**

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We investigate the impact of backward compatibility on the adoption of multi-generation platforms. Our context is a mobile platform where platform users download services from third party providers. For each hardware platform generations, the services depend greatly on the embedded functionality. Newer handsets are backward compatible with respect to services. We develop a model to identify several drivers of adoption of subsequent generations of handsets, which include (i) the migration from older to newer generations of handsets, (ii) the relationship between services and handset users, and (iii) backward compatibility effect of handsets with respect to older generation services. Our main finding is that the backward compatibility effect has a perhaps unintended consequence; the continued use of older generation services on newer generation handsets provides a fresh lease on life for older generation handsets. This 'shot in the arm' for older generation handsets effect is due to the users who remain on or adopt an older generation platform instead of adopting a newer generation platform.

Keywords: Multi-generation diffusion, technology platform ecosystems, lease on life, network economics, backward compatibility.

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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 Like these services and products, demand for a new generation platform comes partly from older generations (migration), and partly from customers new to the platform altogether. When a new technology is incompatible with the previous generation and its associated ecosystem, this raises a barrier to migration to the new version since previous generation adopters might be heavily vested in deploying solutions or using complementary resources on the top of the old platform (Bresnahan and Greenstein, 1999). Moreover, in the case of cross-generational incompatibility, an ecosystem for an older generation might be more mature and diverse in what it offers compared to an incipient ecosystem for a new platform, at least in the beginning, thus potentially deterring even first-time adopters from embracing the newer generation. Lastly, in the presence of network effects, the new generation has to play catch in the beginning in building an installed base to boost these effects under incompatibility. Farrell and Saloner (1986) claim that in such cases, “early adopters [of the new generation] bear a disproportionate share of transient incompatibility costs” which may lead to “excess inertia”. To overcome these barriers, many platform providers embed backward compatibility in their newer generations, allowing them to replicate capabilities of the older systems. For example, certain versions of Microsoft Windows 7 operating system allow users to run older applications developed for Windows XP in a virtualized environment called “XP mode” (McDougall 2009).

The academic literature on multi-generation products (Bass 1995) has treated the introduction of a new generation as a generational handover; a technological substitution of the earlier generation by the new generation. Once the next iteration of the product or service is introduced, the adopters of the old generation migrate to the new generation over time. Given its ability to lower barriers to adoption of a new generation, backward compatibility has been argued to be a catalyst to the adoption of subsequent

¹ Other examples include Dynamic Random Access Memory (Norton and Bass 1987) and mobile Internet platforms (Chu and Pan 2008).

generations (Claussen et al. 2012). One side of the story would be that under backward compatibility, all capabilities are retained and thus there are fewer drawbacks from an upgrade. However, for some users, new features carry small value and thus they adopt an old generation and forgo the new generation. Of course, one factor that influences the adoption of older generation platforms once the new ones are released is the price markdown associated with the older generation. In this paper, in addition to the price effect, we attempt to identify and test another effect that may extend the value of an older generation during the time when it coexists along with newer generations in the market, namely the *lease on life* for old generations due to backward compatibility of newer generations. To the best of our knowledge, this effect has not been widely explored in the existing literature. In the presence of backward compatibility, we conjecture (and set out to test empirically), that complementary services/products can connect users even if they operate on different platform generations. For example, two cell phone users, even if they use different handset generations, may be able to exchange text messages, play the same old game and upload scores to community ranking boards, or contribute content to the same online social network. For users of older platforms who value the associated older services a lot and do not derive a lot of benefit from services designed explicitly to take advantage of the new features introduced in subsequent platform generations, backward compatibility can actually increase the value of the older generation due to network externalities. On services that matter to them, these adopters of the older platform can communicate with all other users, and the value of older services increases or these services endure longer as a result of more traffic (some of it coming from newer generations). As such, this lease on life may slow down the migration process to newer generations.

In this study, we focus on mobile Internet platforms and the associated services and attempt to identify and measure the lease on life effect for older generation platforms due to backward compatibility of older platforms. Our study is motivated by observed adoption and consumption data from an Asian telecom carrier over a span of seven years (2000-2007). Over this window, the carrier introduced four distinct platform generations (with backward compatibility embedded in each new release) and third party providers built an ecosystem of services and apps around these platforms. Data is described in detail in

Section 3. As can be seen from Figure 2(a), for at least five years generation 1 platform (the oldest) coexisted in the market along newer generations and, towards the end of 2007, the decrease in installed base slowed down a lot indicating that this platform can still remain the preferred choice for some customers for some time to come.

Following 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), we model the lifecycle of multi-generation platforms from a multi-generation diffusion point of view. Our contribution to existing literature is twofold. First, on the modeling side, we advance one integrated framework that accounts for various factors that influence adoption dynamics in a multi-generation platform context: (i) the indirect network externality induced by complementary value-adding services, (ii) the migration from the old generation to the new generation, (iii) and the lease on life induced to an old generation due to consumption of older services by users running on newer platforms. Most multi-generation diffusion literature focuses on migration and does not explicitly model indirect network externality induced by the consumption of a complementary service. 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 effects of complements but do not explore in depth interactions between product generations.

Our empirical analysis reveals that, when controlling for the price difference effects (which can also lead to a prolonged life of older generations), backward compatibility is statistically significant. This finding has important managerial implications for ecosystems built around platforms. Depending on the industry, the lease on life for an old generation platform could cause significant amount of maintenance expenses to the firm, and to avoid these extra expenses, the firm may need to force migration to newer versions by deliberately shutting down the old platform or phase out backward compatibility for an older platform at some point in time.

2. A Simplified Model and Assumptions

For expositional clarity, we first introduce the model and build the theory based on a hypothetical market that has two platform generations (platform 1 and 2) and single service available for each (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 newer one) exhibits backward compatibility in that its adopters can access both service 1 and 2, but platform 1 adopters can access only service 1. Let $N_i(t)$ be the number of adopters of platform i by time t , and $Tr_{ij}(t)$ be the traffic volume of service j accessed by platform i users by time t . Figure 1 illustrates the relationship between platforms and services.

Note: 1. Migration; 2. Service consumption effects due to new features; 3. Lease on life

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

- 1) **Migration:** Adopters of platform 1 gradually migrate to platform 2 over time once platform 2 becomes available. As such, at any point in time, the installed base of platform 2 consists of new adopters and those adopters who have migrated from platform 1.
- 2) **Service consumption effect due to new features:** The value of a platform increases as its supporting service (built on new features introduced in the current platform) becomes popular. This can be perceived as an indirect network externality since one would expect that consumption of such services increases as more adopters join the platform.

3) *Lease on life*: Since a platform allows for backward compatibility with respect to services, the adopters of platform 2 can consume both services 1 and 2, and as more platform 2 users consume service 1, platform 1 and its supporting service become more valuable, as argued in the Introduction. As such platform 1 gets a lease on life due to the backward compatibility.

From the relationships illustrated in Figure 1, $N_1(t)$ and $N_2(t)$ can be written as:

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

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

$\hat{N}_i(t)$ is the estimated number of adopters of platform i by time t if there is neither migration nor lease on life, $Mig_i(t)$ 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 (i.e., the number of new adopters of platform 1 due to platform 2 adopters' access of service 1). Building on the generalized Bass model (GBM – introduced in Bass et al. 1994), we define the underlying adoption pattern net of migration and lease-on-life effects as $\hat{N}_i(t)$ as:

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

where m_i is the market growth (increase in market potential) for platform i and $F_i(t)$ is the cumulative adoption probability of platform i by time t . Similar to Bass et al. (1994) to we parameterize $F_i(t)$ as:²

$$F_i(t) = \frac{1 - \exp(-(p_i + q_i)(t + \beta_i \log(Tr_{ii}(t) - Tr_{ii}(t-1))))}{1 + \frac{q_i}{p_i} \exp(-(p_i + q_i)(t + \beta_i \log(Tr_{ii}(t) - Tr_{ii}(t-1))))} \quad (4)$$

where

$$Tr_{ii}(t) = a_i t + b_i \sum_t N_i(t) \quad (5)$$

Let τ_i be the time at which platform i was introduced in the market. Then, $F_i(t) = 0$ for $t < \tau_i$.

Without loss of generality we adjust the timeline such that $\tau_1 = 1$. Consistent with the diffusion literature,

² $F_i(t)$ is derived from the hazard rate function. The derivation of $F_i(t)$ from the hazard rate function in general form is available in Bass et al. (1994).

we call p_i the coefficient of innovation and q_i the coefficient of imitation (i.e., direct network effects). Parameter β_i quantifies consumption effect due to services specific to i . In order to control for the fact that $Tr_{ii}(t)$ is endogenous in our model we estimate equations (4) and (5) simultaneously.

The multi-generation diffusion literature (Blackman 1974; Norton and Bass 1987; Mahajan and Muller 1996; Jun and Park 1999) extends diffusion models by adding $Mig_1(t)$ in equation (3). Although each of these studies defines different functional forms of $Mig_1(t)$, they are typically built based on similar assumptions. They assume that platform users move from earlier to later (but not from later to earlier) generations and that the number of adopters of the earlier generation decreases monotonically once it starts decreasing. Following the same assumptions, we define $Mig_1(t)$ as:

$$Mig_1(t) = m_1 F_1(t) F_2(t) \quad (6)$$

The adopters of platform 1 migrate to platform 2 with the same rate that the new adopters adopt platform 2 and the number of platform 1 adopters becomes zero when platform 2 reaches the market potential. This assumption is more likely to hold true when there are low switching costs (e.g., no stringent lock-in mechanisms such as long-term contracts) from one platform to another. We confirm that our data correspond to a carrier for whom most wireless contracts are short term (a couple of months).

We stipulate that lease on life for platform 1 is in direct proportion of the traffic volume of service 1 accessed by platform 2 users. Thus, we define $LoL_1(t)$ as:

$$LoL_1(t) = \alpha_1 Tr_{21}(t) + \varsigma_1 Z_1(t) \quad (7)$$

where

$$Tr_{21}(t) = c_1 t + d_1 \sum_i N_2(t) \quad (8)$$

α_1 is the coefficient of lease on life and $Z_1(t)$ represents the set of control variables for platform 1 such as the price advantage of platform 1. A firm often cuts prices of the previous platform after it launches a new one, and some consumers choose to adopt the older platform due to this price advantage. α_1 and ς_1

are assumed to be non-negative; that is, there is no negative lease on life. $Tr_{21}(t)$ is endogenous to the model. Thus, we control endogeneity by estimating (7) and (8) simultaneously.

3. Mobile Internet Platform: Research Context and Data Description

3.1. Research Context: 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 introduced four subsequent generations of mobile Internet platforms with backward compatibility.³ Complementary services building on the capabilities of each platform have also been introduced by third-party providers. Table 1 summarizes each of these platforms and services.

Table 1. Summary of each platform and service

Platform Generation	Platform Generation Release date	Novel Characteristics of Platform Generation	New 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 services.	Live TV and Video on demand (VOD)

³ 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) traffic volume of service j ($Tr_j(t)$), (iii) the number of platform i subscribers who access 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. It has been discussed that the diffusion model parameter 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, using available data, we interpolated the missing data.⁴ Table 2 summarizes the available and interpolated time periods for each variable.

Table 2. Available and interpolated time period for each variable

Variable		Available data	Interpolated data
$N_i(t)$	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

We interpolated missing date of each variable ($Y(t) \in \{N_i(t), Tr_j(t), N_{ij}(t)\}$) using a polynomial trend function (i.e., $Y(t) = \sum_k \lambda_k t^k$). We choose k that gives the highest adjusted R-square while keeping all λ_k significant. We provide the details of how we interpolated the missing data (e.g., parameter

⁴ Please note that $N_i(t) = 0$, $Tr_j(t) = 0$, 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 were released.

estimates and model fits) in the Appendix. Figure 2 shows the time series of each variable including the data that we interpolated.

Figure 2. (a) number of subscribers of each platform, (b) cumulative traffic volume of each service, and (c) – (f) the number of each platform subscribers who access each service

3.3. The traffic volume of service j accessed by platform i users

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

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

where ϕ_j is the service multiplier and ϕ_i is the platform (or backward compatibility) multiplier. Then,

using (14), from $Tr_j(t) - Tr_j(t-1) = \sum_i (Tr_{ij}(t) - Tr_{ij}(t-1))$, we have:

$$Tr_j(t) - Tr_j(t-1) = \phi_j \left(N_{jj}(t) + \sum_{i \neq j} \phi_i N_{ij}(t) \right) \quad (10)$$

Note: $dTr_i = Tr_i(t) - Tr_i(t-1)$; 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 this equation using non-linear least square (NLS) regression methods and obtain estimates for ϕ_j and φ_i . Our estimation can be biased if there are price and time effects. However, there was little change in per-packet traffic fees over the time window of our study, and 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 were reduced by 30% in February 2007.

Table 3. Traffic fee rates

Service/Application type	Rate (US\$ per packet/message)	
	Before Feb. 2007	After Feb. 2007
Text	0.0065	0.00455
Application	0.0025	0.00175
Multimedia Message	0 – 100 packets: 0.2 101 – 300 packets: 0.5	
Multimedia	0.0013	0.00091

We considered a more complex parameterization of traffic including also learning effects in equation (15) but those turned out not significant. Thus, we dropped those parameters. Table 4 shows the parameter estimates and model fits. 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	2nd generation	3rd generation	4th generation
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)	3.58*** (0.36)	-	-
φ_4	12.62*** (1.15)	12.62*** (1.15)	12.62*** (1.15)	-
n	93			
Adj R-Sq.	0.9786	0.9872	0.8550	0.8912

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

3.4. Price of handheld devices

In the Asian country that we study, each handheld device could be used only on the network of the locked wireless carrier. We collected from an online forum the store prices of 73 handheld devices in November 2007 that were locked on the network of the wireless carrier that we study. The release prices of 16 devices, among 73, those were released in either 2005 or early 2006, were also available from the forum.⁵ The average release store price of 16 devices is \$558 and the average store price of handheld devices in November 2007 by each mobile Internet platform is as summarized in Table 5.

Table 5. The average store price of handheld devices by mobile Internet platform in November 2007

Mobile Internet platform (Generation)	Count (Percentage)	Average store price (US\$)
1st	3 (4.11%)	299
2nd	11 (15.07%)	308
3rd	2 (2.74%)	366
4th	57 (78.08%)	479
Total/Average	73 (100%)	442

Comprehensive time series of price data for mobile handheld devices due to scarce historical data on the many different devices (with short lifecycles) available on carriers at various points in time, along with their associated price trend from introduction until discontinuation. We interpolate time series of average prices of handheld devices for each mobile Internet platform using the average release store price and the average store price for each mobile internet platform in November 2007. To interpolate the date, we make the following two assumptions. First, we assume that on average, the release price point for handheld devices is relatively the same for all generations. It is fairly common practice especially in IT industry. The release prices of new versions of many IT products are identical to those of earlier versions. Second, we make the assumption that the average price of handheld devices for each mobile Internet

⁵ In contrast to other countries, marketing promotions were regulated by the government and fixed-term contracts were not allowed. Therefore, the store price represents what a consumer really paid.

platform decreases with a constant percentage change over time. Figure 4 illustrates the interpolated time series of average price of handheld devices for each mobile internet platform.

Figure 4. The time series of average price of handheld devices

4. The Impact of Backward Compatibility on Platform Adoption Decisions

4.1. Empirical specification

In this section, extending the model in Section 2 to four generations, we investigate the impact of backward compatibility on platform adoption decisions. In the general case, there can be multiple services associated with each platform and variable $Tr_{ij}(t)$ accounts for service consumption (packet traffic) from all users of a specific platform generation i with respect to services specific to platform generation j , where $i \geq j$. The relationships between platforms and services when there are four generations of platforms and services are illustrated in Figure 5 and can be summarized via the following multi-generation diffusion model

Note: 1. Migration; 2. Service consumption effects due to new features 3. Lease on life

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

$$N_1(t) = m_1 F_1(t) (1 - F_2(t)) + \alpha_1 \sum_{j>1} Tr_{j1}(t) + \varsigma_1 Z_1(t) \quad (16)$$

$$N_2(t) = (m_2 + m_1 F_1(t)) F_2(t) (1 - F_3(t)) + \alpha_2 \sum_{j>2} Tr_{j2}(t) + \varsigma_2 Z_2(t) \quad (17)$$

$$N_3(t) = (m_3 + (m_2 + m_1 F_1(t)) F_2(t)) F_3(t) (1 - F_4(t)) + \alpha_3 \sum_{j>3} Tr_{j3}(t) + \varsigma_3 Z_3(t) \quad (18)$$

$$N_4(t) = (m_4 + (m_3 + (m_2 + m_1 F_1(t)) F_2(t)) F_3(t)) F_4(t) \quad (19)$$

where

$$F_i(t) = \frac{1 - \exp(-(p_i + q_i)(t + \beta_i \log(Tr_{ii}(t) - Tr_{ii}(t-1))))}{1 + \frac{q_i}{p_i} \exp(-(p_i + q_i)(t + \beta_i \log(Tr_{ii}(t) - Tr_{ii}(t-1))))} \quad (20)$$

$$Tr_{ii}(t) = a_i t + b_i \sum_t N_i(t) \quad (21)$$

$$\sum_{i>j} Tr_{ij}(t) = c_j t + d_j \sum_{i>j} \sum_t N_i(t) \quad (22)$$

Further, we define the price advantage of an earlier generation platform over its successive generation platforms as $\Delta P_i(t) = \min_{j>i} \{P_j(t)\} - P_i(t)$ if $\min_{j>i} \{P_j(t)\} \neq 0$ and 0 otherwise, and control possible price effects on lease on life by designating $Z_i(t) = e^{-\eta t} \sum_i \Delta P_i(t)$. We assume (i) the number of adopters of platform i due to the price advantage is positively influenced by the price difference between the price of the least expensive alternative newer option and the price of platform i , and (ii) the effect of price advantage on lease on life diminishes over time.⁶

4.2. Model estimation and results

Following prior literature (Kim et al. 2000; Dewan et al. 2010), we estimate the model using nonlinear seemingly unrelated (NLSUR) regression methodology with boundary conditions. We include the non-negativity assumptions that we discussed in Section 2. (i.e., $\alpha_i \geq 0$ and $\varsigma_1 \geq 0$) as boundary conditions in our model. Estimation results and model fits are reported in Table 6 and Figure 6.

Table 6. Parameter estimates and model fits

		Estimates	Significance	Approx. Std. Err.
Market potential	m_1	8.4269	***	0.3386
	m_2	0.4942		0.3533
	m_3	0.0522		0.4009
	m_4	1.0649	***	0.2662
Innovation effects	p_1	0.0071	***	0.0009
	p_2	0.0107	***	0.0014
	p_3	0.0054	***	0.0005
	p_4	0.0009	***	6.9E-5
Imitation effects	q_1	0.0873	***	0.0058
	q_2	0.0899	***	0.0044
	q_3	0.0741	***	0.0024
	q_4	0.0570	***	0.0017
Service consumption effect due to new features	β_1	38.2850	***	3.0399
	β_2	6.5924	***	2.5256
	β_3	22.0100	***	7.2982

⁶ We assume a consumer compares the price of an old generation platform and the least expense alternative option since she is likely a price sensitive consumer.

	β_4	3.5429	***	0.4671
Lease on life	α_1	0.0027	***	0.0001
- Backward compatibility	α_2	0.0009	**	0.0004
	α_3	0		0
Lease on life	ζ_1	0		0
- Price advantage	ζ_2	5.2889	***	0.8833
	ζ_3	0		0
Time effects on price advantage	η	0.1730	***	0.0240
Marginal consumption	b_1	0.1400	***	0.0047
	b_2	0.0600	***	0.0061
	b_3	0.0325	***	0.0003
	b_4	4.8226	***	0.0665
	d_1	0.6608	***	0.0082
	d_2	0.4524	***	0.0037
	d_3	0.5452	***	0.0020
Time controls	a_1	-0.1047	***	0.0157
	a_2	0.0239	*	0.0142
	a_3	0.0149	***	0.0007
	a_4	2.6700	***	0.0624
	c_1	-0.8118	***	0.0420
	c_2	0.1123	***	0.0116
	c_3	0.0592	***	0.0020
Number of observations			93	
Adj. R-Square	N_1		0.9969	
	N_2		0.9979	
	N_3		0.9982	
	N_4		0.9812	
	Tr_{11}		0.9703	
	Tr_{22}		0.9429	
	Tr_{33}		0.9978	
	Tr_{44}		0.9966	
	ΣTr_{i1}		0.9735	
	ΣTr_{i2}		0.9885	
	ΣTr_{i3}		0.9992	

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

Figure 6. Model fit to the data

The model fits to the data very well and adjusted R-squares are noticeably high. We discuss the results regarding the market potential, innovation and imitation effects, service consumption effects due to new features, and lease on life in the following paragraphs.

4.3. Market potential

The market potential of platform 1 (m_1) is 8.43 million and it increased by 1.06 million for platform 4 (m_4). The market potential for platform 2 and platform 3, m_2 and m_3 respectively, are not significant.

This result is consistent with the observed actions of the wireless carrier, which launched platform 3 only four months after platform 2, and platform 4 10 months after platform 3. Overall, the wireless carrier launched three subsequent generations of platforms and services in 14 months.

4.4. Innovation and imitation effects

All parameters for innovation (p_i) and imitation (q_i) effects are positive and significant. Across four generations, the average innovation effect is 0.006 and the average imitation effect is 0.077. The diffusion literature has shown that the innovation and imitation effects vary widely across products (see Lilien and Rangaswamy (2006) for the list of innovation and imitation effects across products). For our context, it appears that the innovation effects are similar to the cellular phone industry (0.008) and the imitation effects resemble the one observed ones in the cable TV industry (0.060).

4.5. Service Consumption Effects due to New Features

Parameters for service consumption effects due to new features (β_i) are all positive and significant confirming that the value of a platform, and thereby, the number of adopters of a platform increases as its supporting services become more popular. While the consumption effects of services for generations 1 ($\beta_1 = 38.2850$) and 3 ($\beta_3 = 22.0100$) are relatively strong, the similar effects associated with services for generation 2 ($\beta_2 = 6.5924$) and 4 ($\beta_4 = 3.5429$) are relatively weak. This result is consistent with the service offerings introduced in each generation; while service 1 (e.g., short-text-based instant messengers) and 3 (e.g., multimedia messaging services) require extensive communications between users, a big portion of services for generation 2 (e.g., mobile games, banking, and stock trading) and 4 (e.g., live TV and video on demand) are stand-alone, and hence, require relatively little communication between users.

4.6. Lease on life

The estimation result confirms that there is a lease on life for platform 1 and 2 due to the backward compatibility. However, α_3 is constrained by the boundary condition and we are not able to identify a lease on life for platform 3. One potential explanation for this result might be that the time window that we study is not sufficiently long enough for platform 3. The market for platform 3 had grown until late 2006 and we have data till the end of 2007 (see Figure 2(a)). We might be able to identify a lease on life for platform 3 if more recent data were available.

The lease on life effect for platform 1 ($\alpha_1 = 0.0027$) appears three times stronger than that for platform 2 ($\alpha_2 = 0.0009$). However, please note that α_i measures lease on life per unit of traffic (i.e., packet) effect. While we do not have precise data about the size of each service/application, according to the industry experts, the average size of service/application of service 2 is two to three times larger than that of service 1 (Korea Database Agency 2005). Therefore, it is conceivable that the lease on life effects per service/application for platform 1 and 2 are not significantly different from each other.

While ς_2 is significant, ς_1 and ς_3 are not significant; that is, while discounted prices of platform 2 handsets induce some consumers to choose platform 2 over its successive platforms, discounted prices

of platform 1 and 3 handsets are not attractive enough to a consumer. This result was somewhat expected because of the following two reasons. First, as of November 2011, about 15% of available handsets have platform 2, whereas only 4% and 3% of them have platform 1 and 3 respectively (see Table 5). It shows that in the presence of all four platforms, while the demand for platform 2 was still relatively strong, the demand for platform 1 and 3 was weak. Second, platform 3 was released only 4 months after platform 2 was introduced and the marginal difference between platform 2 and 3, in terms of its supports for services, was not significant (see Table 1). It has been discussed that if the difference between two product-lines is not sufficiently large cannibalization is more severe (Kim and Chhajed 2000).

5. The Economics of Backward Compatibility

In this section, we focus on and discuss the economic impact of backward compatibility on the platform market. Our results suggest that on average every 1 million packets of service 1 consumptions by newer platforms (platform 2 – 4) users via backward compatibility create 2.7 new or retained subscribers (lease on life) of platform 1. Similarly, every 1 million packets of service 2 consumptions by platform 3 and 4 users create 0.9 new or retained subscribers of platform 2.⁷

Due to such a lease on life effect from backward compatibility, by December 2007, compared to when the market reached the peak, platform 1 has gained about 12% (0.70 million) and platform 2 has gained about 4% (0.14 million) of new or retained users (see Figure 7). That is, if platforms were not backward compatible, platform 1 would have been disappeared by early 2007 and the market for platform 2 in December 2007 would have been smaller by about 30%.

⁷ Average service/application size of service 1 is 100 – 150 packets and service 2 is 200 - 300 packets (Korea Database Agency 2005). Thus, 1 million packets are equivalent to about 7,000 – 10,000 and 3,000 – 5,000 downloads of platform 1 and 2 services/applications respectively.

Figure 7. Lease on life of (a) platform 1 and (b) platform 2

There are users who might not have adopted a mobile Internet platform if the platforms were not backward compatible. Clearly backward compatibility creates a new lease on life, and thereby, additional revenue for the wireless carrier. However, whether this is an intended and ideal consequence of backward compatibility for the carrier could be arguable because the lease on life (i.e., the extended life span of an old platform) induces additional costs. To serve new users of the old platform, the carrier needs to continue to maintain the infrastructure such as the mobile network and distribution channels for its supporting services, and hence, net profit from lease on life can be either positive or negative. In fact, in January 2008, the wireless carrier that we study merged the distribution channels for services for generations 1 and 4 into one, and in early 2012, it terminated 2G mobile network that supported old platforms. Similarly, in a related industry example, only the first three models of Sony PlayStation 3 are fully backward compatible with PlayStation 2 games, and Sony is gradually shutting down channels for PlayStation 2 online games. Microsoft also recently announced that it would stop supports for its old Windows versions.⁸

⁸ <http://windows.microsoft.com/en-US/windows/help/end-support>

6. Discussion and Conclusion

We model the lifecycle of multi-generation platforms from a diffusion point of view and investigate the impact of backward compatibility on the adoption of older generations using the data we collected from a major wireless carrier in an Asian country. Our approach complements the previous literature that mostly focuses on the positive effect of backward compatibility on the subsequent generations.

Our main finding is that the backward compatibility has a perhaps unintended consequence: the continued use of old generation services on new generation platforms provides a fresh lease on life for old generation platforms. This finding has important managerial implications for ecosystems built around platforms. Depending on the industry, the lease on life for an old generation platform could cause significant amount of maintenance expenses to the firm, and to avoid these extra expenses, the firm may need to force migration to newer versions by deliberately shutting down the old platform or phase out backward compatibility for an older platform at some point in time. .

Our study presents many 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 intensity 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 impact of each of these classes on the lease on life phenomenon. 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 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*** (0.0020)	0.0153*** (0.0015)	0.0268*** (0.0020)	0.0183*** (0.0021)
λ_2	-0.0012*** (9.98E-05)	-0.0006*** (7.65E-05)	-0.0011*** (0.0001)	-0.0008*** (0.0001)
λ_3	2.39E-05*** (1.21E-06)	1.28E-05*** (9.29E-07)	2.20E-05*** (1.25E-06)	1.24E-05*** (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