Co-Diffusion of Wireless Voice and Data Services: The Case of the Japanese Market

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Wireless telecommunications became over time a ubiquitous tool that not only sustains our increasing need for flexibility and efficiency, but also provides new ways to access and experience both utilitarian and hedonic information goods and services. This paper explores the parallel market evolution of the two main categories of wireless services - *voice* and *data* - in leading technology markets, inspecting the differences and complex interactions between the associated adoption processes. We propose a model that addresses specific individual characteristics of these two services and the *stand-alone/add-on* relationship between them. In particular, we acknowledge the distinction between the non-overlapping classes of *basic consumers*, who only subscribe to voice plans, and *sophisticated consumers*, who adopt both services. We also account for the fact that, unlike voice services, data services rapidly evolved over time due to factors such as interface improvement, gradual technological advances in data transmission speed and security, and the increase in volume and diversity of the content and services ported to mobile Internet. Moreover, we consider the time gap between the market introduction of these services and allow for different corresponding consumer learning curves. We test our model on the Japanese wireless market. The empirical analysis reveals several interesting results. In addition to an expected one-way effect of voice on data adoption at the market potential level, we do find two-way co-diffusion effects at the speed of adoption level. Counterintuitively, we observe that basic consumers impact the adoption of wireless voice services in a stronger way compared to sophisticated consumers. This, in turn, leads to a decreasing average marginal network effect of voice subscribers on the adoption of wireless voice services. Furthermore, we find that the willingness of voice consumers to consider adopting data services is positively related to both time and penetration of 3G-capable handsets among voice subscribers.

Key words: wireless telecommunication markets; mobile Internet; stand-alone and add-on services; network and imitation effects; co-diffusion of contingent IT products and services.

1. Introduction

Over time, the functioning of our society grew increasingly dependant on information exchange. Mobile telecommunications represent a fairly recent and widely adopted media that facilitates distant and location-independent human interaction and information transfer. At present, there exist over four billion mobile voice subscriptions worldwide (Global mobile Suppliers Association 2009). The wireless infrastructure, now completely digital, has recently transitioned to high-speed data-transfer technologies such as *EDGE*[1], *W-CDMA*[2], or others, thereby facilitating the birth of a market-inside-market for wireless *data* services on mobile devices. This sub-market covers Internet access, text messaging (SMS[3] or e-mail), m-commerce (e.g., maps, games, ring-tones, audio and video streaming and downloads, banking, purchases, payments), etc. According to Global mobile Supplier's Association, as of September 2009, *EDGE* was implemented in 181 countries (443 networks), while the significantly faster *W-CDMA* was implemented in 126 countries (300 networks).

In leading technology markets, such as Japan, the wireless sector is competitive, dynamic, and well developed. After the introduction of data services, an oversimplifying analysis of the market identifies four participating players: (i) wireless carriers, (ii) handset and accessories manufacturers/distributors, (iii) independent (third party) data services/content providers, and (iv) consumers. For market players in the first three groups, given the aggressive competition within each category, it is crucial to coordinate across categories so that they can improve their profit levels and also better serve the consumers. Therefore, it is very important for all these involved parties to understand how the adoption curves for voice and data services jointly evolve over time. Prior research (Grzybowski and Pereira 2008, Andersson et al. 2009, and Kim et al. 2009) links the two services solely at consumption level, focusing primarily on the complementarity or substitution effects between voice and SMS communication, conditional on preexistent adoption of a voice plan. However, as mentioned above, in technologically advanced countries, wireless data services have

[1] Enhanced Data rates for GSM Evolution (*EDGE*), represents an early 3G (third generation) technology, sometimes unofficially classified as 2.75G due to slower transfer rates compared to other 3G technologies.

[2] Wideband Code Division Multiple Access (*W-CDMA*) represents a 3G technology, considerably faster than *EDGE*.

[3] Short message service.

grown far beyond just being an alternative inter-personal communication channel. In the case of NTT DoCoMo, the leading wireless carrier in Japan, as of December 2006, the wireless data traffic in terms of the number of packets transmitted was massively dominated by web access (98% - including m-commerce consumption) with only a small fraction (2%) captured by email communication. The diversity of content and services ported to the mobile Internet space increases the versatility of wireless platforms and makes them more attractive to consumers. Given this, it is important to broaden our understanding of the joint diffusion of wireless voice and data services by accounting for consumer learning, technological progress, consumption patterns, and evolution of mobile Internet content variety.

In wireless telecommunication markets, most of the data transfer capabilities are offered as an *add-on service* to an existing *voice* plan (the *stand-alone service*). One important characteristic of the adoption of the add-on is its critical dependence on the adoption of the stand-alone product: a customer needs the latter in order to use the add-on, but not vice versa. Pertaining specifically to wireless markets, in addition to the above-mentioned one-way dependance, there are three very important dimensions along which voice and data services can be differentiated. First, in every technologically advanced region, there is a considerable time lag between the introduction of these two services. Second, in such markets, voice services have been commoditized for a very long time, initially through analog land lines, complemented later by mobile and VoIP (Voice over IP) technologies. However, the gist of the consumer experience is almost unchanged: dial a number and speak. Nowadays, in developed or developing countries, a negligible number of people can be assumed not to have made a phone call ever. Wireless voice services simply provide an upgraded way to experience a familiar service, voice telephony, allowing the user mobility within a wide coverage area. Given the already-mentioned introduction gap between wireless voice and data services, by the time the latter hit the market, the population has been exposed long enough to the new voice communication media and wireless voice subscription prices decreased to widely accessible levels. At that moment, potentially new adopters of voice services experience a very fast learning curve for this basic product. On the other hand, wireless data services represent a true novelty in terms of interface, user experience, and content, and, for that reason, they initially impose a significantly flatter (slower) learning curve on potential consumers. Third, while, as mentioned before, voice communication remained intrinsically unchanged as a service over a long time, data services evolved dramatically even over short periods, as increasingly more content was ported to mobile platforms. This is due, on one hand, to the gradual improvement in speed and security of data transmission, and, on the other hand, to the opportunistic behavior of firms already operating on other platforms who identify this communication media as an additional consumer channel to tap into.

Given the many differences between the two services, the following questions arise: how is the *adoption* of wireless data services different from that of wireless voice services, and what are the dynamic interactions (i.e., *co-diffusion* effects) between the two? In this paper, we approach these research questions in the context of leading technology markets by proposing a multiproduct adoption model that accounts for bi-directional co-diffusion effects, while incorporating some of the above mentioned characteristics of wireless voice and data services. First, we do account for the *stand-alone/add-on* relationship between the two services by modeling the market potential for data as a dynamic fraction of the installed base for voice. Second, we acknowledge the distinction between the non-overlapping classes of *basic consumers*, who only subscribe to voice plans, and *sophisticated consumers*, who adopt both services. Third, we also account for the fact that, unlike voice services, data services rapidly evolved over time due to factors such as gradual technological advances as well as the increase in volume and diversity of the content and services ported to the mobile Internet space. Moreover, we consider the time gap between the market introduction of these two services and allow for different corresponding consumer learning curves. We test our model on the Japanese mobile telecommunications market. The empirical analysis reveals several interesting results. While we do anticipate a one-way influences of voice on data adoption at the market potential level, we also observe two-way co-diffusion effects at the speed of adoption level. Counterintuitively, we find that basic consumers impact the adoption of wireless voice services in a stronger way compared to sophisticated consumers. Given the patterns of data adoption, this leads to a decreasing average marginal network effect of voice subscribers on the adoption of wireless voice services in parallel with the increase in overall voice installed base. Furthermore, we show that the willingness of voice consumers to consider adopting data services is positively related to both time and penetration of 3G-capable phones among voice services adopters.

The rest of the paper is organized as follows. In §2, we present a brief literature review of relevant research. In §3, we introduce our co-diffusion model and discuss in detail the theoretical assumptions behind it. In §4, we elaborate on the econometric methodology employed in this paper. In §5, we discuss the source and contents of our data sets. In §6, using our model, we present an empirical analysis of the Japanese wireless telecommunications market. The last section is reserved for conclusions and suggestions for further research. The Appendix contains a brief history of wireless voice services market in Japan, as well as various descriptive sections on data gathering and missing-value estimation.

2. Literature Review

In this section, we briefly describe the relevant literature on multiproduct growth models and wireless telecommunication markets, and elaborate on the modeling and theoretical contributions of our work.

At a high level, the general focus of our paper is on the analysis of the parallel adoption of wireless voice and data services, which exhibit a *contingent stand-alone/add-on* relationship. Two products are contingent if at least for one of them consumption is contingent on having adopted the other. If the relationship is symmetric, i.e., the products cannot be used without one another, we call them *captive* (e.g. coffee makers and paper filters, razor blades and blade holders, computers and operating systems). When the relationship is asymmetric, one product is a stand-alone product while the other is optional (add-on or complementary good - e.g. TV sets and DVD/VCR players) and cannot be consumed without prior adoption of the former. By virtue of this relationship, at any given moment, the market potential for the add-on product is a subset of the market potential for the stand-alone product. Mahajan and Peterson (1978) are among the first researchers to formally propose a hazard rate co-diffusion model for contingent products that accounts for direct network effects:

$$MP1: \qquad \dot{F}_1(t) = (a_1 + b_1 F_1(t))(\bar{F}_1 - F_1(t)),$$

$$\dot{F}_2(t) = (a_2 + b_2 F_2(t))(F_1(t) - F_2(t)),$$

where $F_i(t)$ denotes the cumulative proportion of adopters at time t for product i, $\bar{F}_i$ the ceiling on $F_i(t)$, and $\dot{F}_i(t)$ the derivative in continuous time or the change in $F_i(t)$ between two consecutive periods in discrete time. This is a simple theoretical model with no cross-product effects at the adoption speed level (i.e., inside the hazard rate function). Model $MP1$ captures, albeit in a rigid way, the fact that adopters of the add-on come from among adopters of the stand-alone product, and we use it as inspiration for our model. We point out that very little research has been done on the co-diffusion of contingent IT products and services, with primary focus on synergies between hardware and software. Diverse hardware platforms or products have been considered, such as compact disk players (Bayus 1987 and Gandal et al. 2000), Personal Digital Assistants (Nair et al. 2004), or video game consoles (Clements and Ohashi 2005). Instead of pairing one hardware platform with one software product, these studies tend to consider the evolution of the software offer variety over time for each specific platform. In these markets, each adopter of hardware can purchase multiple software titles. By contrast, in wireless markets, a voice plan subscription can be associated with only one data plan at a time.

In addition to accounting for the stand-alone/add-on relationship at the market potential level, we also intend to capture cross-product effects at the speed of adoption level. Such effects have been extensively studied in co-diffusion models for substitute or complementary products that are not necessarily contingent. We draw inspiration from one of the earliest co-diffusion models that consider cross-product effects at hazard rate level, also proposed by Mahajan and Peterson (1978):

$$\begin{aligned} MP2: \qquad & \dot{F}_1(t) = (a_1 + b_1 F_1(t) + c_1 F_2(t))(\bar{F}_1 - F_1(t)), \\ & \dot{F}_2(t) = (a_2 + b_2 F_2(t) + c_2 F_1(t))(\bar{F}_2 - F_2(t)). \end{aligned}$$

Here, the market potentials for the two products are not necessarily related, but co-diffusion occurs at the hazard function level, thus influencing solely the speed of adoption. Each product acts as a catalyst to the adoption of the other. Bucklin and Sengupta (1993) empirically test variants of model $MP2$ in the context of the parallel adoption of UPC[4] bar codes by product manufacturers

[4] Universal Product Code.

and laser scanners by retail stores. Teng and Thompson (1983, 1984) and Dockner and Jørgensen (1988) extend the theoretical co-diffusion framework by incorporating pricing and/or advertising controls into oligopolistic multiproduct competition. Givon et al. (1995, 1997), Prasad and Mahajan (2003), and Haruvy et al. (2004) explore the co-diffusion of legal and pirated software. Shankar and Bayus (2003) and Zhu and Iansiti (2007) study the competitive adoption of various technology platforms, with application to the video game console market. Recent co-diffusion models by Guevara et al. (2007) and Dewan et al. (2009) combine cross-product and cross-country effects to describe the parallel market growth for PCs and the Internet. In general, hardware *usage* and Internet *usage* are contingent actions because in order to access the Internet, a person needs access to hardware. Nevertheless, PC *adoption* and Internet *usage* are not necessarily contingent actions since Internet users do not need to own the hardware. One computer in a household can allow all members of the household to be Internet users. Internet can also be accessed via cell phones or in Internet cafes. Relevant to our work, the models proposed by Guevara et al. implicitly assume different learning curves for the two products by internalizing diffusion endogeneity into the evolution of the market potential for each of the two products. In our model, we take a very different approach in specifying the parametrizations for the market potentials and the cross-product effects for the wireless voice and data services, capturing the specific characteristics mentioned in the Introduction. We also note that there exist several other multiproduct growth models that address the co-diffusion of overlapping generations of technological innovation[5] or the co-diffusion of the same product across multiple countries[6]. However, these models are not directly relevant to our research questions. For further reading on multiproduct growth models, we direct interested readers to the recent survey paper by Bayus et al. (2000).

[5] Norton and Bass (1987) and Mahajan and Muller (1996) propose substitution models for the diffusion of overlapping generations of technological innovation, and apply them to the adoption of DRAM (Dynamic random access memory) and IBM mainframe computers, respectively.

[6] Different demographic characteristics, cultures, and release times play an important role in shaping the adoption paths. Past work (Takada and Jain 1991, Eliashberg and Helsen 1995, Kalish et al. 1995, Ganesh and Kumar 1996, Ganesh et al. 1997, Kumar et al. 1998, Kumar and Krishnan 2002) explores diffusion of adoption in the presence of a lead-lag effect: some countries are leaders in adopting the product, while others take additional time to acquire information (usage, benefits, technology) about the product and prepare an adoption process that would better fit their national characteristics.

With respect to our specific industry and product choices, there exists a fast-growing empirical research literature on diffusion in the wireless telecommunications markets. Frank (2000) and Gruber and Verboven (2001) use logistic models to analyze the diffusion of wireless voice services in Finland (a first-mover country) and in the European Union, respectively. Kim et al. (2000) explore the co-diffusion of cell phones, pagers, and CT2[7] devices over multiple product generations in Hong Kong and Korea. Madden and Coble-Neal (2004) consider price, income, and network size as significant determinants of wireless voice market growth in 59 countries, and they also highlight the existence of a substitution effect between landline and mobile telephony. Their analysis is based on a utility model for rational consumers. Massini (2004) employs two epidemic models (based on the logistic and Gompertz curves) to compare the diffusion of mobile telephony in Italy and the UK. Jang et al. (2005) inspect the pattern of diffusion of wireless voice services among 29 OECD countries and Taiwan. Doganoglu and Grzybowski (2007) employ a microeconomic model to explore network effects in the adoption of wireless voice services in Germany. Sawng and Han (2007) directly apply the well known Bass (1969) model to analyze the diffusion of the DMB[8] service in the Korean next-generation mobile communications market. To the best of our knowledge, there are no studies that explore the parallel diffusion of wireless voice and data services. A series of very recent papers by Grzybowski and Pereira (2008), Andersson et al. (2009), and Kim et al. (2009) started to explore the interdependence between wireless voice and data services, but they only focus on complementarity or substitution relationship between voice and SMS services. SMS messaging represents just one dimension of overall data services. More importantly, these studies do not explore adoption but rather the interaction between the consumption levels for the two services, conditional on consumers having adopted voice services in the past.

We complement the existing relevant literature at both modeling and theoretical levels. On the modeling side, we introduce a novel co-diffusion model for contingent stand-alone/add-on products. We combine features from models $MP1$ and $MP2$ in order to capture both contingency effects at

[7] Cordless Telephone 2 - wireless technology with cheaper call cost compared to cell phones, but with less functionality and much shorter coverage distance from transmitters/receivers.

[8] Digital multimedia broadcasting.

market potential level as well as cross-product effects at the speed of adoption level. We also account for technological progress, consumer learning, price, seasonal, and macroeconomic effects. One of our major modeling contributions lies in the parametrization of the complex relationship between the evolution of the market potential for the add-on and the evolution of the installed base for the stand-alone, extending the framework introduced by Mahajan and Peterson (1978). In particular, we acknowledge the fact that the two products exhibit different consumer learning curves and that data services rapidly evolved over time due to factors such as interface improvement, gradual technological advances in data transmission speed and security, and the increase in volume and diversity of the content and services ported to the mobile Internet space. Our modeling approach allows us to advance the theory on the co-diffusion of contingent IT stand-alone/add-on products by explaining how the willingness of the adopters of the stand-alone product to consider adopting the add-on is related to learning or technological progress. We further complement the literature on the co-diffusion of general contingent IT products (not necessarily characterized by a stand-alone/add-on relationship) by choosing a pair of products whereby only a single instance of the optional product can be associated with any adoption of the stand-alone one. This approach differentiates our work from the work on co-diffusion of hardware and software, since we abstract away from any offering variety in either wireless voice or data services.

We also advance the literature on the adoption of wireless services by providing the first (to the best of our knowledge) study of the parallel adoption of voice and data services. As described above, relationships between the two services have been explored before only at consumption level (voice vs SMS), conditional on voice services having already been adopted. Text messaging (SMS or email) represents just one dimension of overall data services. In particular, SMS usage does not even require a subscription to a comprehensive data plan with access to mobile Internet. As discussed in the Introduction, in Japan, wireless data services encompass a large array of services that are not related to interpersonal communication and this segment dominates data consumption in terms of transferred packets and exhibits strong hedonic characteristics. Therefore, it is important to understand how the overall adoption of data services evolves over time. In the past, one barrier in running such studies was the compilation of a price measure per unit of consumption for data services, since information on the overall average packet traffic volume per customer was scarce, leading to challenges in filtering consumption out of average revenue. We propose in §3.2.1 a method for getting around that issue by deriving a proxy for the price for data services. Moreover, by splitting voice adopters into basic and sophisticated consumers, we further advance the theory behind the adoption of wireless services by exploring how each of these consumer classes affects the adoption of each service. In particular, our study reveals that, in leading technological markets such as Japan, basic consumers have a stronger impact on voice services adoption compared to sophisticated consumers. Furthermore, since both basic and sophisticated consumer are voice subscribers, as will be further detailed in §6, our model predicts a decreasing average marginal network effect of overall voice installed base on voice adoption, which cannot be captured by many simple reduced-form diffusion models that do not account for differences between subscriber groups or time-dynamic coefficients of imitation.

3. Co-Diffusion Model

In this section, we introduce a discrete-time multiproduct model that accounts for co-diffusion effects, dynamic evolution of the market size for each service, technological progress, consumer learning, consumption patterns, price elasticity, macroeconomic conditions, and seasonality. Our modeling approach is general enough and can be applied to many stand-alone/add-on settings. Along the presentation, we introduce various parametric specifications and supporting arguments related to wireless telecommunication markets and, in particular, to technology leaders such as Japan. For expositional flow we continue to use the wireless voice/data services paradigm throughout the entire paper.

3.1. General Model

We focus on the analysis and forecast of monthly sales. Our model assumes aggregate industry-level data, and, for that reason, migration of subscribers across individual carriers does not influence total sales.

Let m_t denote the market potential for voice plan subscriptions at the end of month t. We restrict our analysis to the period where the two services coexist on the market, after the introduction of the data add-on. Therefore, on top of the implicit right censorship of diffusion data (since the adoption of the two studied services - wireless voice and data - is still undergoing everywhere in the world), we have extensive left censorship of voice subscription behavior. In particular, in the case of Japan, the gap between the introduction of wireless voice and data services was of two decades. Chronological details are included in §3.2.2, §5, and Appendix A. For that reason, we favor an exogenous dynamic parametric specification of m_t based on demographic and market data. The use of exogenous data to estimate the market potential is also advocated by Mahajan et al. (1990) and van den Bulte and Lilien (1997). An underlying assumption of our general model is that a buyer who purchases additional plans uses the same reasoning as in the case of an initial adoption (i.e. we do not distinguish between the two). We postpone the specific details of estimating m_t in the context of the Japanese wireless market until §3.2.2.

We account for the effect of price on the adoption of wireless services by incorporating a multiplicative price function at sales level, as detailed below in equations (1) and (2). We use a negative exponential form, following the model proposed by Robinson and Lakhani (1975). Multiplicatively separable price effects have been widely used in the literature on the diffusion of adoption (e.g., Dolan and Jeuland 1981, Kalish 1983, Thompson and Teng 1984, Bass et al. 1994, Mesak and Clark 1998, Krishnan et al. 1999, Sethi and Bass 2003, Dockner and Fruchter 2004). We include a detailed explanation and derivation of our price measures for wireless voice and data services ($p_{V,t}$ and $p_{D,t}$) in §3.2.1.

Since our analysis covers co-diffusion over a considerable time span, similar to Guevara et al. (2007), we also account for the adoption sensitivity with respect to the evolution of macroeconomic conditions. We capture these conditions using a moving average over last four quarters for the quarter-to-quarter percentage change in GDP ($MAPCGDP_t$). Furthermore, since our adoption data is at monthly granularity, it is important to account for seasonality. Given the usually limited number of monthly data points, it is not recommended to use 11 dummies for each of the voice and data diffusion equations because that will add 22 new coefficients in addition to the other parameters. Therefore, to reduce the number of parameters, we restrict our attention to events such as the end and the beginning of the fiscal year, the peak of the holiday sales season, the end of fiscal quarters, and other relevant product-related periods. Let RM denote the *reduced* set of months including these periods and $d_{i,t} = 1_{\{t\text{-th month is } i\}}$ the corresponding monthly dummies for $i \in RM$. In the particular case of the Japanese wireless market, we explain our choice of months in RM in §3.2.3. Both macroeconomic and seasonal effects manifest solely on the potential consumers who have not adopted yet, and, for that matter, they must affect sales according to the evolution of the market. To stay consistent with the parametrization of the price effect, we incorporate them in multiplicative exponential form as part of the hazard rate function as well.

Let V_t and D_t respectively denote the subscription installed bases for wireless *voice* and *data* services at the end of month t. For each service, the sales during month $t+1$ equal the difference between the installed bases at the end of month $t+1$ and at the end of month t (i.e., $V_{t+1} - V_t$ and $D_{t+1} - D_t$ for voice and data, respectively). Consequently, we associate with these sales the price, percentage change in GDP, seasonality dummies, and error term corresponding to period $t+1$. Let t_V and t_D represent the market release times for the two services, with $t_D > t_V$ (the add-on is released later). For $t \geq t_D$, we assume that the monthly sales of wireless voice plans evolve as follows:

$$V: \quad V_{t+1} - V_t = (m_{t+1} - V_t) \times (a + b(V_t - D_t) + cD_t) \\ \times\, e^{\,-\beta_p p_{V,t+1}} \times e^{\beta_{GDP} MAPCGDP_{t+1}} \times e^{\sum_{i \in RM} \beta_i d_{i,t+1}} + \epsilon_{t+1}. \qquad (1)$$

Parameter a captures static exogenous influences on the adoption of voice services, and, in line with the existing literature on the diffusion of adoption, we call it the *coefficient of innovation.* Voice subscribers are of two types: *basic* consumers (who subscribe only to voice services, $V_t - D_t$) and *sophisticated* consumers (who subscribe to both voice and data services, D_t). Since data subscribers represent a subset of the voice subscribers, by splitting the voice installed base into two disjoint subsets we avoid dealing with overlapping effects. We call $b(V_t - D_t)$ the *basic (wireless) consumption effect* and cD_t the *sophisticated (wireless) consumption effect* on the adoption of voice services. Since both basic and sophisticated consumers are voice subscribers, the two consumption effects are intrinsically direct network effects of potentially different marginal intensities, capturing the fact that a larger network of subscribers yields a higher communication benefit for a prospective adopter. In this way we dynamically account for the temporal change in the ratio between sophisticated and basic users. It is an observed phenomenon in leading wireless markets that voice usage volume has been under pressure from cheaper data communication such as mobile e-mail and text messaging (MobileMonday 2006). An advantage of these substitutes is that they facilitate communication even in situations when the recipient is not available for a direct voice conversation. Given the choice, sophisticated consumers use less voice and more data even in one-on-one communication, which leads to a reduced interaction with basic consumers. Therefore, a customer who adopts voice for the first time is more likely to be influenced more by basic consumers, until she adopts data as well. In other words, *the influence of voice subscribers on voice adoption depends on their sophistication level*.

Since data services on cell phones represent an add-on to voice services, all the subscribers to the former *must* have adopted the latter earlier or at the same time. Thus, it is reasonable to assume that, at every moment t, the market potential for data plans is a fraction $0 \leq s_t \leq 1$ of the current installed base of voice plan subscribers. This quantity describes the fact that there might be voice plan subscribers who do not purchase data plans. Examples include elderly people, who are not comfortable with using data services but want to stay in touch with the rest of their family and need a means to communicate in case of health emergencies, or young children whose parents, while seeing the benefit of being in touch with their kids, are worried about them being exposed to Internet-related addictive and potentially inappropriate communication and information access. We discuss the parametric specification for s_t after introducing the adoption model for data services.

The adoption speed for the wireless data services is initially boosted by the fact that, at its release time, there were already many basic users of the stand-alone product and some of them moved fast to embrace the add-on. In the particular case of Japan, when wireless data services were introduced in February 1999, there were approximately 40 million wireless voice subscribers. While this *catching-up effect* loses strength in time, as more users subscribe to both services and the number of basic consumers shrinks, the data adoption speed is also assisted by an increasingly stronger direct network/immitation effect of its own installed base. Thus, we again consider the disjoint classes of basic and sophisticated voice consumers. For $t \geq t_D$, the sales of wireless data services are modeled as follows:

$$D: \qquad D_{t+1} - D_t = (s_{t+1}V_{t+1} - D_t) \times (\alpha + \delta D_t + \tau(V_t - D_t)) \\ \times\, e^{\,-\gamma_p p_{D,t+1}} \;\times\; e^{\gamma_{GDP} MAPCGDP_{t+1}} \;\times\; e^{\sum_{i \in RM} \gamma_i d_{i,t+1}} \;+\; \xi_{t+1}. \qquad (2)$$

Price effects, macroeconomic effects, seasonality, and noise are modeled in a similar way as for voice sales. Note that we are using V_{t+1} instead of V_t at the market potential level. It is important to understand that data adopters during month $t+1$ may come from *both* past voice subscribers (V_t) as well as current month voice subscribers ($V_{t+1} - V_t$). Failing to account for the latter would add bias to our parameter estimates since we would ignore people who subscribe to both services from the very beginning. In the empirical analysis, we are careful to use methodology that accounts for simultaneous equations (details in §4). Nevertheless, within the same time period, we assume that adoption speed is influenced by the information available at the end of the previous month $\{V_t, D_t\}$. For consistency with the wireless voice adoption parametrization, we name α, τ, and δ the coefficients of innovation, basic consumption effect, and sophisticated consumption effect. In the case of data services, $\tau(V_t - D_t)$ represents a catching-up effect while δD_t captures a combination between direct network effects and imitation effects. The fact that data adopters can communicate with each other via text (SMS or email) messages on top of voice calls implies that the benefit of data services to a user increases with a larger data subscriber network. On the other hand, there are hedonic dimensions of data services that involve access to digital entertainment content such as ring tones, music, video clips, or games. There we can talk about imitation effects based on word of mouth.

While wireless voice services bring an intuitive technological upgrade to fixed telephony, a widely adopted communication method, wireless data services impose a significantly slower (flatter) learning curve on the consumers due to their novelty and recent introduction to the market. We assume that s_t increases in time due to multiple factors. First, there is a learning curve associated with this novel service. With time, people become more used to it. In addition, the variety of accessible data content and consumer activity through such a communication medium increase over time, making it more appealing and relevant to a broader group of voice users. Moreover, the demographic composition of the market potential for wireless data might change over time. Some elderly and less technology-savvy adopters of voice may never consider data. As time goes on, they leave the market as new young generations that embrace technology enter it. Furthermore, people learn how to use the service in time. Therefore, it is important to account for a time influence on the evolution of the market potential for data. In parallel, technological progress improves the user interface (e.g., upgrade from monochrome to color to touchscreen displays) and transmission speed (e.g., upgrade from 2G to 3G technology), increasing the market potential over time as well. We do account for the latter by considering the gradual transition of the wireless market towards 3G-capable phones. These effects diminish with time, as the market matures, and, for that reason, we capture them through a negative exponential parametric specification:

$$s_t = s\left(1 - e^{-(t-t_D+1)\lambda_{time} - \frac{V_{3G,t}}{V_t}\lambda_{3G}}\right), \text{ and } s \in [0,1],\ \lambda_{time}, \lambda_{3G} > 0, \tag{3}$$

where $V_{3G,t}$ represents the number of voice subscribers who have 3G-capable phones.

It is also important to point out that, as of August 2009, wireless data and voice services were not bundled in general in the major wireless markets including Japan. The majority of users have an option not to purchase data services. If mandatory bundling will occur in the future, such a marketing shock will push s_t to 1 in time, since technology obsolescence and the advent of newer and better plans eventually compels all voice users to renew their handsets and voice plan contracts, automatically adopting data as well.

3.2. Parametric Specifications for the Japanese Wireless Market

While in §3.1 we introduced the model at a more general level, in this section we discuss some of the parametric choices that are specific to the Japanese wireless market.

3.2.1. Derivation of Adjusted Price Measures. In this section, we show how to construct the time series of adjusted price measures per unit of consumption for wireless voice and data services. These values are not reported directly by the firms. Instead, we retrieve them by filtering consumption volume out of the average revenue per user (ARPU), which is a *joint measure* *of both price and consumption of the service* in telecommunication markets such as Japan where some of the wireless services are offered under multi-part tariff pricing schemes.[9] ARPU by itself cannot be used directly as a proxy for price. For example, an increase in ARPU is not synonymous to an increase in price, since it can be also caused by a strong increase in consumption due to a moderate decrease in price.

For wireless voice services, the derivation is straightforward for the average actual price per minute of communication:

$$p_{V,t} = \frac{ARPU_{V,t}}{MOU_t}, \tag{4}$$

where MOU_t represents the average number of minutes of voice communication during month t per adopter of voice services. This ratio is widely used in industry reports.

For wireless data services, the derivation is more complex. Ideally, we would like to use the average actual price per packet (128 bytes) transferred $p_{PAC,t}$. However, firm- or industry-level information on the average number of packets transferred per user per month is generally not available. Nevertheless, there is a way to derive a proxy for it. In Japan, the traffic generated by data services consumption is broken into email and web access, with m-commerce services predominantly delivered via mobile Internet. Japanese wireless services subscribers prefer email usage over SMS (Eurotechnology 2009). Let $PAC_{e,t}$ and $PAC_{w,t}$ denote the average number of packets of data that are transmitted on per one email (sent or received) and per one web page accessed during month t while using wireless data services. $PAC_{w,t}$ also accounts for any content downloading. We assume that, over time, the average number of packets per email is relatively constant, i.e. $PAC_{e,t} = PAC_e$. This reasonable and benign assumption allows for $PAC_{w,t}$ to fluctuate over time, accounting for the evolution of complexity of websites and services for the mobile Internet space. We were unable to retrieve real data for PAC_e and $PAC_{w,t}$. However, under the assumption of constant average email size, the *average price per one email* (sent or received) $p_{email,t} = p_{PAC,t} \times PAC_e$ is directly

[9] In Japan, for all data services (i-mode, EZweb, and Yahoo!Keitai), as of January2007, there exists a flat subscription fee of ¥300, on top of which consumers pay for communications charges (per packet, through various quota-tiered flat-fee packet plans, or through an unlimited plan) and, if applicable, for site subscriptions and downloadable content.

proportional to the packet transfer price, and we are going to use it as a *proxy for the price of data services*. Thus, in our analysis we employ $p_{D,t} = p_{email,t}$.

In order to estimate $p_{email,t}$, we need to break down $ARPU_{D,t}$ into revenue from email communication and revenue from web access consumption. Let $TPAC_{e,t}$ and $TPAC_{w,t}$ denote the average total number of packets transferred per user during month t for email usage and web access, respectively. Then we have:

$$ARPU_{D,t} = (TPAC_{e,t} + TPAC_{w,t})\ p_{PAC,t} = \left(\frac{TPAC_{e,t}}{PAC_e} + \frac{TPAC_{w,t}}{TPAC_{e,t}} \times \frac{TPAC_{e,t}}{PAC_e}\right) p_{email,t}. \quad (5)$$

Note that in equation (5) we consider $p_{PAC,t}$ to absorb any service or site subscription fees. If, for example, the subscription to mobile Internet is ¥300 per month, on average users pay ¥300 per month in premium content fees, and the price per transferred packet is ¥0.3, then the actual real price per packet corresponding to an average consumption of 1000 packets per month is ¥0.9/packet, while the value corresponding to an average consumption of 2000 packets per month is ¥0.6/packet. Therefore, $p_{email,t}$ is an upward-adjusted average email price that reflects subscription and consumption patterns for all data services.

For month t, we denote by $k_{e,t}$ the average number of emails sent and received per user and by $r_{web/email,t}$ the ratio between the number of packets transferred during web sites access and the number of packets transferred during email usage. The following relationships hold true:

$$k_{e,t} = \frac{TPAC_{e,t}}{PAC_e} \qquad \text{and} \qquad r_{web/email,t} = \frac{TPAC_{w,t}}{TPAC_{e,t}}. \quad (6)$$

Using (5) and (6), we obtain:

$$p_{email,t} = \frac{ARPU_{D,t}}{k_{e,t}\left(1 + r_{web/email,t}\right)}\ . \quad (7)$$

We were able to retrieve $ARPU_{V,t}$, $ARPU_{D,t}$, MOU_t, $k_{e,t}$, and $r_{web/mail,t}$ historical data for NTT DoCoMo, the dominant player on the Japanese wireless services market. This data is discussed in more detail in §5 and in Appendix C. We assume that these numbers are representative for the entire market and use them to derive adjusted price measures $p_{V,t}$ and $p_{D,t} = p_{email,t}$.

3.2.2. Wireless Voice Market Potential m_t. We define *market penetration* for wireless voice services in a given country as the ratio between the installed base and the population size. In mature wireless markets, high penetration rates (over 100%) are usually attributed to the *multiple connections* phenomenon (also known as *multiple SIM* phenomenon - subscribers with multiple plans or cards). A recent market study by GSM Asia Pacific (2006) argues that the magnitude of the *multiple connections* phenomenon in a country is linked to the penetration of *prepaid* wireless services in that region. High levels of prepaid services lead to more connections per user due to low associated costs of entry, whereas low levels of prepaid services are observed in association with a small number of multiple connections. By virtue of these arguments, the same study identifies Japan as a country with a very low prevalence of the multiple connections phenomenon. Real data supports this argument. According to GSM Asia Pacific (2008), at the end of December 2007, in Japan, the market penetration rate was 77.54%, and prepaid services represented only 2.49% of the market. By contrast, at the same point in time, in Singapore, the market penetration was 146.11%, partly due to the high penetration of prepaid services, representing 44.19% of the wireless market. Given the above arguments, for the purposes of this empirical analysis, we consider the multiple connections phenomenon negligible in Japan.

This, in turn, allows us to derive an estimate of the market potential based on demographic data. In estimating m_t, we emphasize the fact that, at any point in time, the market potential represents the total number of potential users expected during the entire product lifetime, in the absence of future structural changes in the models. In our study, we assume that the Japanese population *above age 6* will eventually achieve *full* wireless voice services penetration. We based our estimate on four reasons. First, a survey study by Analytica1st (2006) documents that wireless voice adoption has penetrated age groups starting as early as elementary school freshmen (usually six year old pupils). According to MSNBC (2008), a recent approach by the Japanese government in order to lower youngsters' addiction to Internet-enabled cell phones was to request the handset manufacturers to offer devices that only allow for voice communication and GPS functionality. This will likely boost the adoption of voice plans among school students since parents want to keep in touch with their children, without having to worry about their exposure to problematic and potentially inappropriate content and interactions possible via an Internet environment. Second, from high school students to young professionals, the penetration rate is already high (according to Web Japan 2005, as of November 2004, more than 80% of the people in their twenties and thirties owned a cell phone). Over time, people age and they move to older age groups, in turn increasing the penetration rate of the groups at the senior end of the age spectrum. Third, wireless voice adoption also took off in the senior age groups (with adoption rates of 26.4% for the 65-69 age group, 11.4% for 70-79 age group, and 4.7% for the 80+ age group, as of November 2004), and carriers are making an active push to win these clients through phones with simplified interfaces (Web Japan 2005). Fourth, according to the same study, people who do not own a cell phone have continuously decreasing options of communicating outside of their home because public pay phones are being discontinued at a very fast rate (from over 820000 at the end of March 2003, to 503000 at the end of March 2004). Thus, we consider the following estimate for the market potential for wireless voice services at the end of month t:

$$\begin{aligned} m_t &= Pop\,^{Japan}_{age\geq 6,\ t} \\ &\sim Pop\,^{Japan}_{total,\ t} - Pop\,^{Japan}_{0\leq age\leq 4,\ t} - \frac{1}{5} Pop\,^{Japan}_{5\leq age\leq 9,\ t}, \end{aligned} \tag{8}$$

where we assumed that population is evenly split inside the 5-9 age group. We use this formula because we have demographic breakdown by five-year age groups, as described in §5.

3.2.3. Seasonality. Our choice for the reduced set of months to account for fixed effects is $RM^{Japan} = \{March,\ April,\ June,\ July,\ September,\ December\}$. As mentioned before, in the interest of keeping the number of parameters within reasonable limits, we choose months associated with known economic effects or anticipated consumer behavior. First, it is important to account for the seasonality effect corresponding to the end of the fiscal year since it captures both consumer behavior and aggressive firm-related fiscal marketing and operating practices (Oyer 1998, Larkin 2006, Lai 2008). Fiscal year targets or fiscal year performance-related bonuses might represent incentives for the managers to offer extraordinary promotions in order to move sales from the next fiscal year into the present one and/or dispose of aging stock. March represents the end of the fiscal year for the companies in the Japanese wireless market. Second, the Japanese school year starts in April and ends in March of the next year (Foreign Press Center Japan, 2006). We speculate that wireless voice and data commodities are very popular among the school age demographic group (from elementary school to university level). Sales to this group might come in the form of graduation packages or back-to-school packages, and, in addition, might also be accompanied by discounts (e.g., KDDI offers a 50%-off student discount plan - KDDI 2007). Two traditional midyear and end-of-year social obligation gift-giving periods are in July (Ochugen) and in December (Oseibo). While wireless plans (voice or data or both) are not traditional gifts on these occasions, we still do expect their adoption to be somewhat influenced by the gift purchasing mood in the population. Many department stores in Japan also offer significant discounts in July and we would expect to see various promotions on wireless services and handsets during that month. Furthermore, mainly based on commercial influences from the rest of the world, Christmas became a very popular shopping and gift-giving period in Japan in the recent decades (Larke 1994). Last, since we included March and December, we also consider June and September in order to capture additional potential end-of-quarter spikes in adoption (albeit of a smaller magnitude than the end-of-fiscal-year effect).

3.2.4. Evolution of Wireless Services Adoption as the Market Matures. As of August 2009, there was no mandatory bundling of voice and data services in Japan. As we later elaborate in §4, we employ an instrumental variable method for our empirical analysis. Recent historical data on some of our relevant instruments is not available and we truncate our time series at January 2007 to include eight full years of sales. In Figure 1, it seems that new subscriptions to voice and data services are almost identical between January 2005 and January 2007. However, that period actually only depicts the interval when data sales intersect voice sales from above. While not captured in Figure 1, after May 2007, the ratio between new subscriptions to data and voice services $\frac{D_{t+1}-D_t}{V_{t+1}-V_t}$ drops significantly below 1 (0.60, 0.51, 0.50, 0.35 in December 2007, June 2008, December 2008, June 2009). We speculate that, by 2007, as the wireless voice market approaches saturation, the great majority of the existing voice adopters who also wanted to subscribe to wireless data services already did it and the catching-up effect fades in strength. Recent adoption numbers indicate that sales of voice and data services do not have the same structural parametrization after 2005 and thus we consider it reasonable to explore a model with different but inter-related voice and data adoption patterns throughout the entire time interval of our empirical study.

4. Methodology

Note that the adoption processes for wireless voice and data services run in parallel since 1999. Moreover, given that the data service is an add-on to the voice service, we expect the two adoption processes to interact with each other. For that reason, it is necessary to *jointly* estimate the parameters. For consistency, it is important to account for serial autocorrelation, heteroscedasticity, and simultaneity of equations. For efficiency, we need to allow for the errors to be correlated across equations.

Since the forms of autocorrelation and heteroscedasticity are not known, in order to account for all these effects and obtain efficient estimates, we employ an *iterated GMM* (Generalized Method of Moments) estimation. Iterations are used to improve the efficiency of the estimates. The HAC[10] covariance matrix and corresponding HAC parameter estimates and standard errors are computed according to the method proposed by Newey and West (1987), using the Bartlett density kernel. Asymptotically, iterated GMM is equivalent to two-step efficient GMM. However, various papers (e.g., Ferson and Foerster 1994) uncover superior finite-sample results when using iterated GMM. An added benefit from using a GMM approach is that we do not impose any distribution assumption on the errors. For a detailed presentation of GMM methods, we direct interested readers to Wooldridge (2002) and Hall (2005).

Since iterated GMM is an instrumental variable method, we need to provide exogenous instruments. For the sales in month $t+1$, in addition to a constant, we use instruments based on exogenous regressors and their lagged values ($d_{mar,t+1}$, $d_{apr,t+1}$, $d_{jun,t+1}$, $d_{jul,t+1}$, $d_{sep,t+1}$, $d_{dec,t+1}$, m_{t+1}, m_{t+1-3}, m_{t+1-12}, $MAPCGDP_{t+1}$, $MAPCGDP_{t+1-3}$), inflation-adjusted R&D expenditure for the entire Japan ($R\&D_{t+1}$, $R\&D_{t+1-6}$, $R\&D_{t+1-12}$), number of researchers in Japan ($N_{R,t+1}$, $N_{R,t+1-3}$,

[10] Heteroscedastic autocorrelation consistent.

$N_{R,t+1-6}$), and population composition variables ($Pop_{total,t+1}$, $Pop_{total,t+1-12}$, $Pop_{total,t+1-24}$, $Pop_{0\leq age\leq 4,t+1}$, $Pop_{0\leq age\leq 4,t+1-12}$). We consider $MAPCGDP_{t+1}$ and $MAPCGDP_{t+1-3}$ to be exogenous to wireless services adoption in period $t+1$. According to OECD (2009), in 2007 in Japan, revenue from wireless services accounted for 71% of telecommunications revenue, but, in turn, telecommunications revenue accounted for only 3.07% of GDP. Furthermore, shifts in wireless revenues are not only due to new subscribers but also to old subscribers who change consumption habits in response to price and product variety changes. For example, $ARPU_{D,t+1}$ has been consistently increasing over time as more content is ported to mobile Internet. On the other hand, $ARPU_{V,t+1}$ has been decreasing due to lower usage of voice minutes. Thus, we consider that the impact of the number of new wireless subscriptions in month $t+1$ on $MAPCGDP_{t+1}$ is negligible. The chosen population instruments are influencing sales indirectly, by influencing the market size. The number of researchers and the R&D expenditure in Japan show an increasing trend over time. We expect these variables to be correlated with $p_{V,t+1}$, and $p_{D,t+1}$. Technological progress drives down the marginal costs of providing wireless services. Since the Japanese wireless market is competitive, we would expect the cost reduction to put a downward pressure on price as well. Indeed, we observed that the adjusted prices have a decreasing trend for most of the time frame of our study. Furthermore, since these instruments cover the entire spectrum of Japanese industrial and academic research, we do not expect them to be influenced in a significant way by the monthly sales of wireless services. In total, we have 23 instruments. In order to test for the validity of the instruments, we use the *overidentifying restriction test* (J-test) proposed by Hansen (1982).[11]

In terms of measures of performance, we report MAD (mean absolute deviation), MSE (mean squared error), and adjusted R^2. We favor these measures because they handle rather well canceling-out effects. Note that we can obtain identical parameter estimates in two ways, by either regressing sales $V_{t+1} - V_t$ and $D_{t+1} - D_t$ (as in equations (1) and (2)) or regressing solely installed bases V_{t+1} and D_{t+1} (moving the lagged term on the right hand side). While both approaches provide

[11] If n is the sample size, r the number of moment conditions, and k the number of parameters to be estimated, then the J-statistic ($n \times$ GMM objective function), converges in distribution to a χ^2_{r-k}. The null hypothesis *H0* states that the necessary orthogonality implied by the moment conditions is satisfied. For that matter, we need large p-values for this test, in order not to reject *H0*.

the same MAD and MSE values, they produce significantly different adjusted R^2 values.[12] We are careful to report adjusted R^2 values using the sales approach in order to observe how well our sales estimates fit the data.

Due to the implied optimization in the estimation process, we are aware that our results may be influenced by initial (starting) parameter values. For that matter, we looked at potential starting parameters on a multidimensional grid.

5. Data Description

We briefly describe the composition of the Japanese wireless telecommunications market, as well as the control variables and instruments used in our regressions. We elaborate on the estimation of missing values, the time span, and the sources of our data points. For a recent, well-documented, and detailed chronological evolution of the Japanese wireless market, we direct interested readers to Haas (2006). Our time series contain monthly observations between January 1999 and January 2007.

We collected monthly voice subscriber data for all telecom companies in Japan (NTT DoCoMo[13], KDDI[14], and SoftBank Mobile[15] - more companies existed in the past, but consolidation took place reducing the number to three as of January 2007), and for the entire market on aggregate.[16] The data for total cellular subscriptions is publicly available from the Japanese Telecommunications Carrier Association (2009), to which all Japanese mobile carriers report monthly. However, total cellular subscriptions also include subscriptions for data-only plans that operate on certain wireless

[12] For a model $y = h(x;\theta)$, the formula for adjusted R^2 is $1 - \frac{n-1}{n-k-1}\frac{SSE}{SST}$ where $SSE = \sum_{i=1}^{n}(y_i - \hat{y}_i)^2$, $SST = \sum_{i=1}^{n}(y_i - \bar{y})^2$, where $\hat{\theta}$ represents the vector of parameter estimates, $\hat{y}_i = h(x_i;\hat{\theta})$, $\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i$, and n and k were introduced in the previous paragraph. Note that SSE is the same under sales or installed base approach since the parameter estimates will be the same. However, SST numbers differ and they are independent of the parameter estimates. If we use notations SST_s and SST_{ib} for the sales ($y_t = x_t - x_{t-1}$, where $x \in \{V, D\}$) and installed base ($y_t = x_t$, where $x \in \{V, D\}$) approaches, then, by a simple visual inspection of Figure 1, we see can easily see that $SST_{ib} \gg SST_s$. Consequently, the R^2 and adjusted R^2 values will likely be very large in the installed base approach, in spite of a potentially poor fit of the model at the sales level.

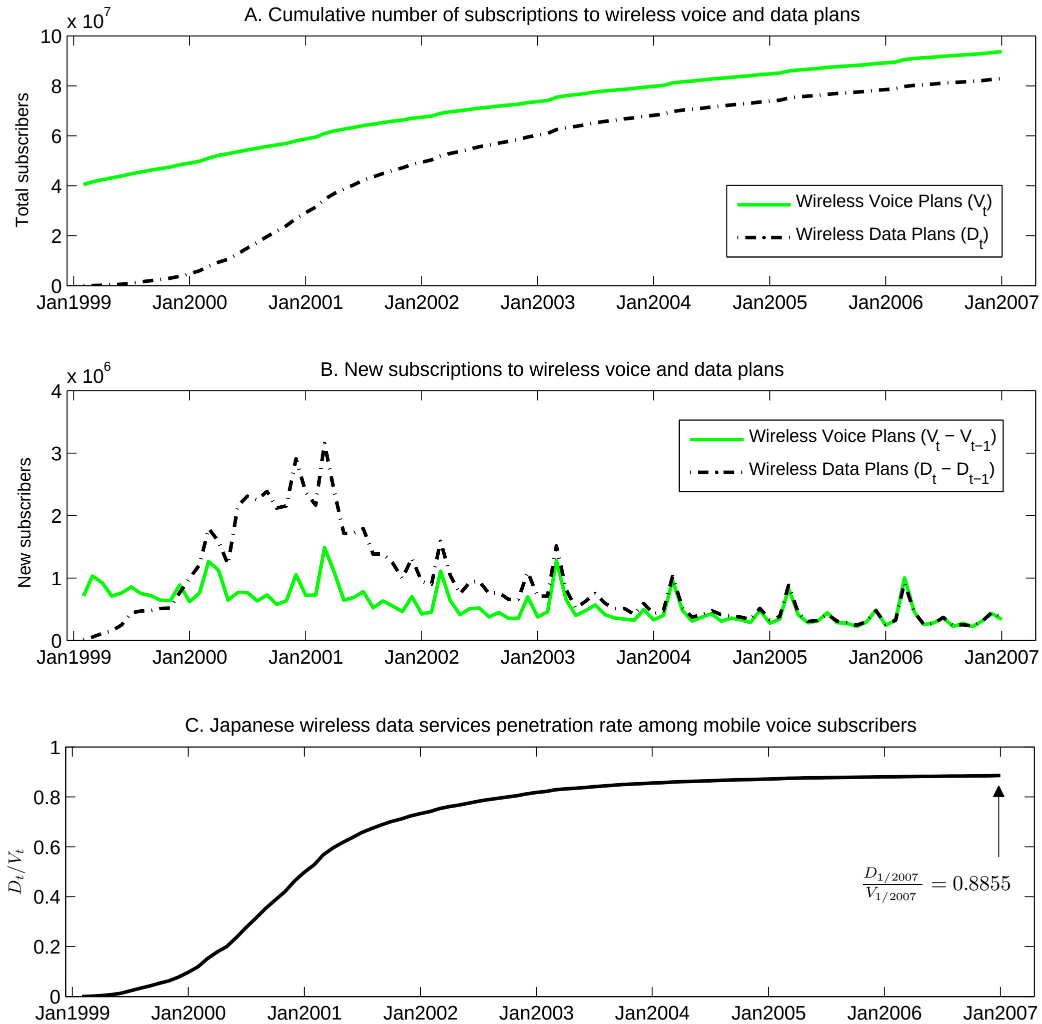
[13] The wireless telecommunications division of Nippon Telegraph and Telephone.

[14] Formed in October 2000, by the merger between DDI, KDD and IDO.

[15] Vodafone bought a majority share in J-Phone in October 2001, and changed the company and brand name to Vodafone in October 2003. In March 2006, Vodafone sold its participation to SoftBank. The company name officially changed to SoftBank Mobile Corp. in October 2006.

[16] We do not include in our analysis PHS (Personal Handyphone Services - a precursor to regular mobile phones) subscriber data.

Figure 1 **Japanese wireless services market 1/1999 - 1/2007**



devices that include data communication modules (e.g., G-Book telematics subscription service offered by Toyota in some of its vehicles using a data communications module provided by KDDI, DoPa single plan offered by NTT DoCoMo, etc.). We eliminate from our cellular subscription data all the subscriptions to data-only communication module services in order to obtain voice subscriber data. Moreover, it is reasonable to assume that whoever uses a data-only communication module service also owns a separate cell phone and subscribes at least to voice plans. As a side note, wireless telephony was introduced in Japan in 1979, and, as of 1996, the market was competitive, liberalized, and deregulated (see Appendix A for a brief history of the Japanese wireless voice services market prior to 1999).

Wireless data services on mobile phones were first introduced by NTT DoCoMo in February 1999 (i-mode), followed shortly by KDDI in April 1999 (EZweb[17]), and J-phone (now Softbank) in December 1999 (J-sky, which turned into Vodafone Live in October 2003, and, upon SoftBank takeover, into Yahoo!Keitai in October 2006). These services cover Internet and email access and represent an add-on to voice services on mobile phones. Similar to the voice subscriber case, we do not incorporate any data-only communication module subscriptions in our wireless data subscriber numbers and assume that if a customer subscribes to a data-only communication module service, that will not affect in any way her decision whether to subscribe or not to data services on her cell phone. The installed bases beyond April 2000[18] are available online from Japanese Telecommunications Carrier Association (2009) for all companies. For i-mode, NTT DoCoMo USA (2000) contains the subscriber data prior to April 2000. For EZweb, we were able to retrieve similar early subscriber data from the annual report of KDDI Corporation (2000). However, we were unable to retrieve early J-sky adoption data (four months: December 1999-March 2000). Therefore, we estimated it based on observed market patterns. Details are presented in Appendix B.

While i-mode and EZweb numbers reflect the actual installed bases for these services, Haas (2007) points out that J-phone reported the number of J-sky-enabled handsets in the market, without reporting the number of customers who actually use the service. However, as of January 2007, Softbank's voice services installed base is larger than data services installed base, indicating the existence of unbundled offers. In the absence of more precise historical data, we assume that the majority of customers that purchased the initial J-sky-enabled sets made that decision in the context of available unbundled options, and ended up using the J-sky functionality of they phones. Thus, in this paper, we consider the J-sky numbers to be equivalent to a subscriber installed base.

In order to compute adjusted price measures, as described in §3.2.1, we retrieved monthly values $ARPU_{V,t}$, $ARPU_{D,t}$, MOU_t, $k_{e,t}$, and $r_{web/email,t}$ for NTT DoCoMo. This data is publicly available

[17] In the beginning, EZweb was offered by DDI (and towards the end of 1999 also by TU-KA group, which became a subsidiary of KDDI), and EZaccess was offered by IDO. The two platforms were very similar, and, upon the formation of the KDDI corporation, they got unified under the EZweb brand.

[18] Officially, on its web site, the Japanese Telecommunication Carriers Association reports data service subscriber numbers starting from May 2000, but each report also contains the installed base at the end of the previous month.

online on the carrier's corporate website. Details for the estimation of missing data points for each of these time series are included in Appendix C. Comprehensive historical data for the other companies is not available.

For the estimation of the voice services market potential m_t and the construction of demographic instrumental variables, we gathered monthly Japanese population estimates, reported by five-year age groups ($Pop^{Japan}_{0\leq age\leq 4,t}$, $Pop^{Japan}_{5\leq age\leq 9,t}$, ..., $Pop^{Japan}_{70\leq age\leq 74,t}$, $Pop^{Japan}_{75\leq age,t}$). We also retrieved the number of researchers and the R&D expenditure in Japan in order to use them as additional exogenous instruments. The data is publicly available online from the Japanese Ministry of Internal Affairs and Communications (2009a, 2009b). Missing data points are estimated through linear interpolation.

Historical data on the 2000-base seasonally-adjusted quarterly GDP deflator and percentage change in quarterly GDP is available from the Cabinet Office of the Government of Japan (2009). $MAPCGDP_t$ represents the moving average of the percentage change in quarterly GDP over the last four quarters. We consider this value the same for all three months in any given quarter. We adjust our ARPU and R&D expenditure values for inflation using the GDP deflator.

6. Discussion of Results

We present in Table 1 the parameter estimates for our model. The simultaneous regressions are run using the aggregate market monthly sales. The J-test does not reject the null hypothesis that our instruments are valid. We remind the reader that we use end-of-month installed bases for voice and data services from January 1999 till January 2007. These translate into $n = 96$ monthly sales points, or eight full years (discarding January 1999 due to subtractions). Fitted versus real values are plotted in Figure 2. Visually, our proposed model fits reasonably well the Japanese wireless market.

Since one of the objectives of this empirical study is to the existence, dimensions, and magnitude the co-diffusion effects, we start by discussing these effects. For both voice and data, the estimates for the coefficients of basic and sophisticated wireless consumption effects $\hat{b}$, $\hat{c}$, $\hat{\delta}$, and $\hat{\tau}$ are positive and statistically significant. Thus, *both basic and sophisticated consumers positively affect the speed of adoption of both wireless voice and data services, indicating the presence of two-way co-diffusion effects.*

Table 1 Iterated GMM - Parameter estimates

		Estimates		Std. Err.
VOICE	a	0.0068		(0.0078)
	b	4.22E-10	**	(2.06E-10)
	c	1.12E-10	*	(6.28E-11)
	β_p	0.0219	**	(0.0104)
	β_{GDP}	-7.3120		(4.5530)
	β_{mar}	0.8029	****	(0.0750)
	β_{apr}	0.4638	****	(0.0366)
	β_{jun}	0.1676	****	(0.0252)
	β_{jul}	0.2701	****	(0.0350)
	β_{sep}	0.1053	****	(0.0282)
	β_{dec}	0.4937	****	(0.0443)
	MAD	6.70E4		
	MSE	1.12E10		
	Adjusted R^2	0.8251		
DATA	s	0.8880	****	(0.0010)
	λ_{time}	0.0552	****	(0.0006)
	λ_{3G}	0.3428	*	(0.2035)
	α	-0.3221	*	(0.1634)
	δ	1.41E-8	***	(5.316E-9)
	τ	8.48E-9	*	(4.07E-9)
	γ_p	0.4206	*	(0.2186)
	γ_{GDP}	10.6788	*	(5.6794)
	γ_{mar}	0.2938	****	(0.0760)
	γ_{apr}	0.2068	****	(0.0475)
	γ_{jun}	0.0882	**	(0.0365)
	γ_{jul}	0.1142	**	(0.0455)
	γ_{sep}	0.0845	**	(0.0359)
	γ_{dec}	0.1958	****	(0.0559)
	MAD	9.12E4		
	MSE	1.86E10		
	Adjusted R^2	0.9553		
Hansen's overidentifying restrictions test	J-statistic	15.8683		
	p-value	0.7770		

Note: * ($p < 0.1$), ** ($p < 0.05$), *** ($p < 0.01$), **** ($p < 0.001$).

For each service, we further compare the *strength* between marginal basic and sophisticated consumption effects via a *one-sided paired difference t-test*, as shown in Table 2. Interestingly, *in the case of voice services, basic consumers impact adoption in a significantly stronger way compared to sophisticated consumers.* At first glance, one might expect a different outcome. With increased adoption of data services, better technology solutions are considered, leading to better integrated wireless capabilities within one device. This should make wireless communication more attractive

Table 2 One-sided paired difference t-test

Pair	$H0$	$H1$	p-value
$\{b, c\}$	$b \leq c$	$b > c$	0.036
$\{\delta, \tau\}$	$\delta \leq \tau$	$\delta > \tau$	< 0.001

altogether, positively influencing the adoption of voice plans. However, a simple argument can be made to support the opposite statement. As discussed in §3.1, wireless voice usage has been on decline in Japan, under pressure from cheaper data communication services such as mobile e-mail. Sophisticated wireless consumers use a combination of the available communication channels, with a decreasing share allocated to voice conversations, thus interacting less with basic consumers. Therefore, new voice adopters are influenced in a stronger way by existing basic consumers compared to sophisticated consumers, until they also adopt data. Such substitution effects between voice and data services (voice vs SMS) at consumption level are also identified by Kim et al. (2009). As discussed in §3.2.1, in Japan, consumers prefer to use mobile email over SMS and per-packet charges are the same for email usage and web access.

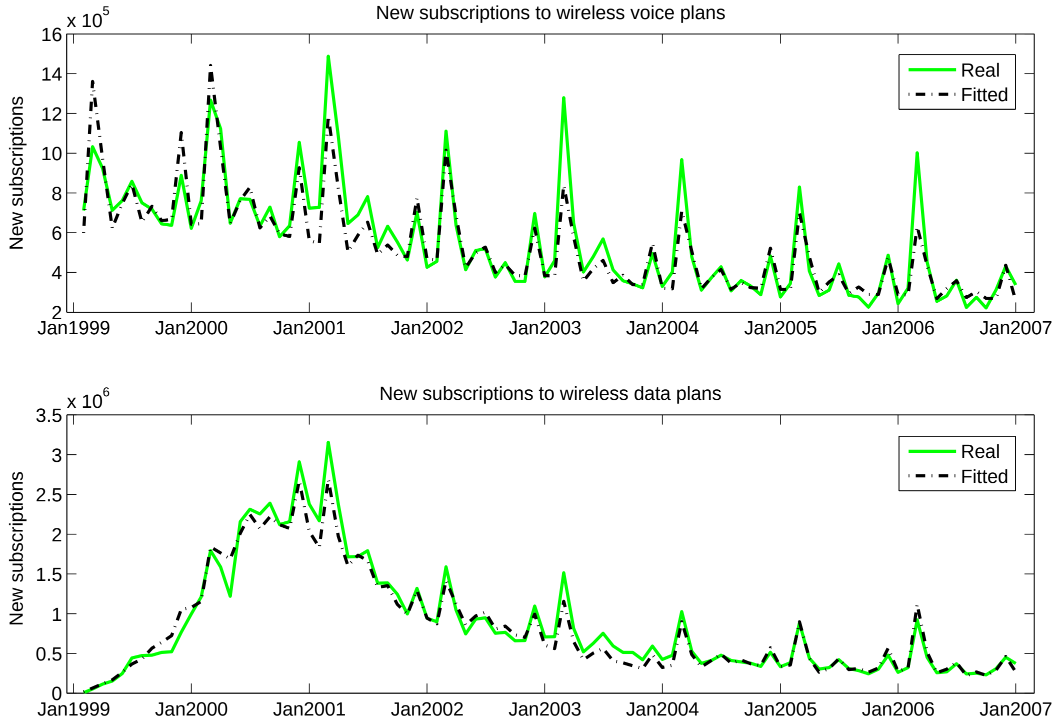
Another argument can be advanced based on consumer age and familiarity with wireless technology. Given the level of technological development in Japan, a person who has not upgraded to wireless voice communication would likely be either very young, elderly, and/or technologically unsophisticated. In the case of young children, as already discussed in §3.1 and §3.2.2, parents make the purchase decision and, while looking for a service that allows them to stay in touch with their kids, they may want to minimize or avoid the potentially harmful consequences of unsupervised web access by choosing very basic phones and plans, implicitly limiting the level of communication with other sophisticated users. On the other hand, moderately old people may see a benefit in having a handy but simple means of communication in case of a health emergency or in order to stay in touch with younger relatives. For the third group, that of technologically unsophisticated people (which may well overlap with the first two), data services are characterized by a much flatter (slower) learning curve than voice services, due to the considerable complexity and novelty of the add-on. In such cases, the adjustment necessary to understand and use the add-on may significantly drive down its benefits. Overall, for each of these three categories of consumers, an increase in the installed base of data subscribers is unlikely to impact their decision to adopt voice services in a positive way. In our model, this can be seen by rewriting $\hat{b}(V_t - D_t) + \hat{c}D_t = \hat{b}V_t - (\hat{b} - \hat{c})D_t$.

The estimated *average* marginal effect of all existing voice subscribers on the adoption of voice, $\frac{\hat{b}(V_t - D_t) + \hat{c}D_t}{V_t} = \hat{b} - (\hat{b} - \hat{c})\frac{D_t}{V_t}$, depends on the evolution of the *data services penetration rate among voice subscribers* $\frac{D_t}{V_t}$. By visual inspection, from Figure 1.C, we see that $\frac{D_t}{V_t}$ is increasing in the beginning, before stabilizing around the value of 0.886. Given that $\hat{b} > \hat{c} > 0$, this means that *the overall average marginal network effect is decreasing over time for voice services before reaching an equilibrium, approximately five years after the market release of the data services.* A simpler reduced-form diffusion model that does not distinguish between the two groups of voice subscribers and assumes an overall constant marginal network effect over time would miss this effect. Other co-diffusion models (e.g., Guevara et al. 2007) capture time dynamics of the average marginal network effects by directly specifying time-dependent parametrizations for the respective coefficients.

On the other hand, *in the case of data services, sophisticated consumers influence adoption in a significantly stronger way compared to basic consumers.* First, given that we already capture the overall impact of all voice subscribers on the adoption of data services at the market potential level, it is interesting to see a significant basic consumption effect also appear at the adoption speed level. Unlike in the case of voice services where both basic and sophisticated consumers are subscribers, in the case of data services, basic consumers represent people who did not experience the service. Nevertheless, $\tau(V_t - D_t)$ captures a catching-up effect based on the eagerness of basic consumers to adopt data and has an important contribution in the early diffusion of the add-on. As more people transition to data services and the number of basic consumers shrinks, the sophisticated consumption effect takes over. Since $\hat{\delta} > \hat{\tau}$, by rewriting $\hat{\delta}D_t + \hat{\tau}(V_t - D_t) = (\hat{\delta} - \hat{\tau})D_t + \hat{\tau}V_t$ we see that both a new voice subscriber or an existing voice subscriber switching from basic to sophisticated consumption have a positive impact on the adoption speed for data services.

So far we analyzed co-diffusion effects at the adoption speed level for both services. However, *voice also affects data adoption at the market potential level*, through parameter s_t, which depicts

Figure 2 **Real vs fitted new subscriptions to wireless services in Japan 1/1999 - 1/2007**



the dynamic *willingness* of voice subscribers to consider adopting data services. Given the structure of our model and the parameter estimates, under reasonable assumptions regarding the stability of the market size for voice (between 119.3 and 121.2 million during the eight years of our data set), future non-increasing trends for the adjusted price measures, and lack of future long-lasting catastrophic macroeconomic disruptions, it can be shown that $lim_{t\to\infty} \frac{D_t}{V_t} = s$. Thus, under a fairly stable wireless services market such as Japan, s represents the *asymptotic* penetration rate of data services among voice adopters. We notice from Figure 1.C that $\frac{D_t}{V_t}$ appears to exhibit an increasing pattern with asymptotic limit below 1 (the slope is very small at the right end and the most recent value is $\frac{D_{1/2007}}{V_{1/2007}} = 0.8855$). Our estimate for parameter s, 0.8880, is statistically significant, seems well aligned with reality, and captures the argument previously discussed in §3.1 that *not all voice subscribers are part of the market potential for data services.*

Furthermore, estimates $\hat{\lambda}_{time}$ and $\hat{\lambda}_{3G}$ are positive and statistically significant, indicating that *the willingness of voice subscribers to consider data services increases with time and gradual spread of technological advances.* In the first month after data services were introduced, $\hat{s}_{t_D} \approx 0.054\hat{s}$ as data adoption starts in a timid way. However, s_t grows rapidly ($\hat{s}_{t_D+12} \approx 0.51\hat{s}$, $\hat{s}_{t_D+24} \approx 0.75\hat{s}$, $\hat{s}_{t_D+36} \approx 0.87\hat{s}$, $\hat{s}_{t_D+48} \approx 0.94\hat{s}$, $\hat{s}_{t_D+60} \approx 0.97\hat{s}$, ...). In about 5-6 years after the introduction of wireless data services, the market starts to mature and voice users become more familiar with the wireless data content, interface, and services. The learning curve for this innovative add-on becomes much steeper with time. Technological progress, captured on the margin through parameter $\hat{\lambda}_{3G}$, further increases the willingness of voice subscribers to consider data services. Our model has an advantage over simpler models that consider a constant value $s_t = s$ (e.g., Mahajan and Peterson's model MP1) because it does not overestimate the market size for data services in the early stages of adoption.

We next discuss the estimates for the coefficients of innovation a and α. In the context of the diffusion of a single innovation, this coefficient captures some of the exogenous effects that influence the adoption. Assuming that the structure of the model stays unchanged over time, the coefficient of innovation must be strictly positive in order for the diffusion to be triggered at market release time, when there is no installed base. The problem becomes more complex for co-diffusion systems, especially when the related products are introduced on the market at different times. In particular, in the context of this paper, data services (the add-on) are released on the market much later than voice services (the stand-alone product), when the latter already has a significant established installed base (over 39 million voice subscriptions at the end of January 1999). Thus, if co-diffusion of voice on data exists at the hazard rate level ($\tau > 0$), a large-enough voice installed base could spark data adoption even in the presence of a negative coefficient of innovation. In that sense, α can be interpreted as a correction term for the catching-up effect. For that reason, we do not form any expectation for the sign of α. The estimate for this parameter is negative and statistically significant.

On the other hand, wireless voice services were released on the market in the absence of the add-on. Under a rigid assumption that the adoption parametrization or coefficient values remained unchanged since wireless services were introduced in 1979, we would expect $\hat{a}$ to be strictly positive. Nevertheless, as discussed in Appendix A, until 1994, the Japanese wireless market was heavily regulated. Prior to 1994, consumers were not allowed to purchase their handsets and were required to rent them from the carriers. We do expect the wireless voice adoption model to have changed structurally across the years. For that reason, we do not form any expectation with regards to the sign of this coefficient as of 1999, given the existence at that time of a consistent mass of voice users that can spark data adoption. While our estimate for α is positive, it is not statistically significant.

Next, we discuss the sensitivity of adoption with respect to the price of the service and the evolution of the country-level macroeconomic condition. Our model captures a negative effect of prices on sales of wireless services through positive and statistically significant estimations for $\hat{\beta}_p$ and $\hat{\gamma}_p$. In terms of sensitivity to macroeconomic effects, we note that only the adoption of data services is affected by the percent change in GDP. The estimate $\hat{\gamma}_{GDP}$ is positive and statistically significant, indicating that economic growth may positively affect new subscriptions to wireless data services whereas economic shrinkage dampens sales. On the other hand, the estimate $\hat{\beta}_{GDP}$ is not statistically significant. In order to get a better understanding of the underlying phenomenon, we first note that price and macroeconomic effects are somewhat related to each other. Classic microeconomic theory states that price effects can be decomposed into income and substitution effects. We also expect a high correlation between income fluctuations and percentage change in GDP. The two income effects are similar in the implicit economic mechanism but one refers to the perceived purchasing power given a fluctuation in price but constant income, whereas the other refers to an actual fluctuation in income independent of price. Since wireless voice communication is becoming a necessity, we expect low income effects. There do still exist some minor substitution effects from fixed line telephony, public telephony, or local internet access. On the other hand, we expect substantial income and substitution effects for wireless data services. First of all, some of the dimensions of data services are mostly hedonic (e.g., downloading ringtones, listening to music, watching videos, or playing games on cell phones), many of them bearing features of luxury goods, and for that reason their consumption is going to be affected by income. On the other hand, for some utilitarian data services (e.g., mobile banking, mobile brokerage), there are alternative, more traditional channels that consumers can still use. For interpersonal communication, consumers can resort to substitutes such as mobile voice (the stand-alone service), fixed line telephony, and local Internet access. Furthermore, persistent trends in GDP percent change will likely have behavioral effects as well which are captured in our model by using a moving average measure. For example, a long economic downturn is likely to add uncertainty about future job and income security, leading to anxiety and increased reservation regarding the adoption of certain goods that are not perceived as a necessity.

Last, we explore the seasonality effects. The estimates for all the seasonality coefficients are positive and statistically significant. Our results are aligned with the real sales numbers, as seen in Figure 2, and seem to indicate that carriers offer better promotions in March compared to other months, in a last effort to improve fiscal year results, as described in §3.1 and §3.2.3. Interestingly, we see that for each month in the RM set, seasonality effects tend to be stronger for voice adoption compared to data adoption. One potential explanation could be that the adoption of voice services is also associated with the purchase of a cell phone, whereas the adoption of data services does not always involve a cell phone upgrade. We speculate that handset sales do exhibit seasonality. Furthermore, unsold handset stock usually depreciates very fast due to the frequent release of new models and, for that reason, hardware promotions are common when consumers sign up for voice contracts. Going back to the example of the end of the fiscal year, at that time, managers have simultaneous incentives to boost the number of subscriptions and also to get rid of unsold hardware inventory.

7. Conclusions

This paper presents one of the first studies of the parallel diffusion of wireless voice and data services, seeking to understand the differences and interactions between the two adoption processes. Our novel model captures various dimensions (e.g., dynamic evolution of the market size for each service, technological progress, consumer learning, consumption patterns, direct network/imitation effects) that cater to general contingent stand-alone/add-on products pairs. We empirically test our model on the Japanese wireless market and observe the existence of both direct network/immitation effects as well as two-way co-diffusion effects at the speed of adoption level. Interestingly, we also find that basic consumers have a stronger impact on the voice adoption speed compared to sophisticated consumers. This leads to a decreasing average marginal network effect of voice subscribers on the adoption of voice services. Furthermore, we show that the willingness of voice consumers to consider adopting data services is positively related to both time and penetration of 3G handsets among voice services adopters.

From a managerial perspective, wireless carriers, handset and accessories manufacturers, and independent wireless content providers are interested in understanding the joint adoption of voice and data services in order to efficiently coordinate their offerings and improve the profitability of their strategic decisions involving service enhancements, product pipeline, technology upgrades, advertising campaigns, and R&D investments. Poor diffusion forecasts will lead the firms to operate at suboptimal levels, which, in turn, may affect the adoption decisions of the consumers. For example, firms must assess the evolution of the market size for each product and internalize in their strategies the fact that these numbers can be different for voice and data services. In particular, they must understand the initially low but rapidly increasing willingness of voice subscribers to consider adopting data services. Moreover, firms also want to predict how fast wireless services diffuse in market. As illustrated in this paper, the adoption speed for wireless services does exhibit cross-product effects. Depending on the scenario, some mobile Internet content providers might choose to enter the market early but defer some of the revenue, while others might choose to delay the entry until there is a critical mass of subscribers. Furthermore, while add-ons are usually commercialized in order to extract additional consumer surplus, it is also important for the wireless carriers and handset manufacturers to understand the impact of the add-on on the demand for the stand-alone product. In addition, market players must consider the impact of price and macroeconomic conditions on the number of new subscriptions to these services and (not covered in our study) on the consumption of these services by existing subscribers.

Our model is generalizable to many other pairs of stand-alone/add-on products or services that satisfy one condition: every adoption instance for the stand-alone product can be associated with at most one adoption instance for the add-on. Examples include basic TV cable plans and the optional premium channel additional plan, or baseline software products and premium add-on modules or function libraries.

We conclude by suggesting several potential directions for further research. First, our model is applicable only at the aggregate level, disregarding inter-firm competition. It would be a valuable exercise to capture competition using similar co-diffusion models. Second, empirical results in this paper may reflect the fact that Japan is a technologically advanced country that experienced every stage of voice telecommunication progress, and whose population is accustomed to and embracing frequent technological innovation. By contrast, various developing countries had a significantly lower penetration of fixed-line voice communication, and they experienced significant technology leapfrogging when wireless telecommunications were introduced, due to lower necessary investments in infrastructure (James 2009). Our model can still apply to such markets, but the market potential m_t for wireless voice services must be estimated in a different manner, since we do need to account for a learning curve also for voice communication. Third, as discussed in §3.2.2, in the particular case of Japan, the multiple connection phenomenon is not significant. However, according to GSM Asia Pacific (2008), there are several countries with over 100% market penetration for wireless voice services. Again, such cases can still be described by our model but they warrant a different estimation approach for m_t.

Appendix

A. A Brief History of the Wireless Voice Services in Japan prior to 1999.

The first Japanese cellular telephony system was introduced in Tokyo in 1979 by government-owned NTT (Nippon Telegraph and Telephone Corporation) using analog technology (Padgett et al. 1995). Due to very high prices, the plans did not fare very well on the market, attracting a relatively small installed base. For the first nine years NTT had monopoly over the Japanese wireless market. In 1985 the wireless telecommunications market was liberalized and the company was privatized (Hayasi and Fuke 1998). In 1988 competition stepped in, causing prices to drop and subscriptions to increase. It is worthwhile to mention two deregulatory measures implemented prior to the end of 1996. In 1994, MPT (Japanese Ministry of Posts and Communications) allowed customers to purchase their own handsets instead of renting them from carriers - a move which significantly lowered costs for consumers and caused an explosion in cell phones and voice plan sales. Neil (1996) reports that subscriber installed base grew from 2.2 million in 1994 to 15 million in 1996, and it continues to grow at a sustained pace even at present. Also, in 1996, phone rates were deregulated (Hayasi and Fuke 1998).

B. Estimation of the First Four Months of J-Sky Subscribers.

At a firm level, we observed that the data penetration rate among voice subscribers (D_t/V_t) was increasing each month for the first years for each of i-mode, EZweb, and J-sky (in the case of the latter, only after April 2000). Following this pattern, we approximated the missing J-sky penetration rates as linearly increasing between December 1999 and April 2000. Since we have the actual J-phone voice installed base corresponding to each J-sky missing month, we computed estimates for the missing data installed bases from the penetration rate estimates. Note that, since the monthly voice installed bases are actual, the data services installed base estimates incorporate some of the true seasonality in the wireless market. This method makes more sense than simply assuming a linearly increasing J-sky installed base, which would have implied constant monthly sales (ignoring the seasonality implications). Note that we add the J-sky estimates to the real EZweb and i-mode numbers to obtain the aggregated market installed base for data services, and that we approximate only four months of missing data. Thus, we do not expect our results to be significantly different from the results if all J-sky numbers were available.

C. Estimation of Descriptive Data for Mobile Internet Consumption

NTT DoCoMo (2009) reports quarterly ARPU for both voice and data services starting with the first quarter in fiscal year 2001, as the ratio between the quarter revenue from monthly related usage charges associated solely with the consumption of the particular service (net of any activation fees or other unrelated charges) and the sum of active subscriptions to that service during each month of the current quarter. For any given month, the active subscriptions are computed as the average between the subscriptions at the end of the previous month and the subscriptions at the end of the current month. In essence, we note that quarterly ARPU is still a monthly measure, in spite of the confusing name. Prior to 2001, voice and data ARPU are reported for each fiscal year.

We consider the quarterly ARPU to correspond to the middle month of the respective quarter and yearly ARPU to correspond to September, and we linearly interpolate the values for the missing months.

We point out that, for data, NTT DoCoMo reports two ARPU numbers: aggregate i-mode ARPU and ARPU generated purely from i-mode. The first divides total data revenues by the number of voice subscribers (in order to have meaning when added to voice ARPU), while the second divides the total data revenue solely by the number of data subscribers. In that sense, the second measure is more relevant to isolate price and consumption patterns for wireless data services. This is the value that we use in our analysis.

Next, we discuss the estimation of missing data for $k_{e,t}$ (average number of emails sent and received per month per user) and $r_{web/mail,t}$ (ratio of packets transferred via web access over packets transferred via email communication) for the i-mode mobile Internet service provided by NTT DoCoMo. Monthly values for $k_{e,t}$ are available online at NTT DoCoMo (2009) from April 2001 till present. These quantities are reported per user per day and we transformed them in monthly averages by multiplying each with the number of days in the respective month. A couple of other data points have been collected from various press releases. Based on the available data, we observe that the average sum of sent and received email messages does not fluctuate dramatically after April 2001. For that reason, we estimate the missing months of data via a moving average method, whereby we average over the same month of the following four years, using weights of 1/2, 1/4, 1/8 and 1/8 (highest weight goes to closest data point). For $r_{web/mail,t}$, we have average quarterly values from Q1 of fiscal year 2002 until Q4 of fiscal year 2007. We associate these values with the middle month in the quarter. Before that we have sparse data points from market reports. We do observe an increasing pattern in the available values. In order to get the missing monthly values, we linearly interpolate between observed data points.

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