Cand. Merc. AEF

Master Thesis

The Pattern and Determinants of Diffusion of 3G Telephony in Europe

Huijuan Qi

Supervised by: Cédric Schneider

79 pages

113,784 characters

September 24,

Copenhagen Business School, 2012

Copenhagen Business School
HANDELSHØJSKOLEN

Declaration of Authorship

(To be placed at page 2 in the assignment])

Identification	
Title of assignment:	The Pattern and Determinants of Diffusion of 3G Telephony in Europe
Study programme:	Cand. Merc. AEF
Course:	Master Thesis
Type of Exam (e.g. Home assignment or Bachelor Project):	Master Thesis

Date of birth:	**Name of author(s):**	**Group no. (if relevant)**
August 24, 1987	Huijuan Qi	

Number of pages:

According to the exam regulations for this particular exam, the assignment must be of a maximum of 80 pages [Insert max. number of pages] exclusive front page, bibliography and appendices. Appendices are not included in the assessment.

Each individual page of the assignment may not comprise more than 2,275 characters (incl. spaces) on average. (E.g. similar to 35 lines of 65 characters). All pages must have a margin of min. 3 cm in top and bottom and min. 2 cm to each of the sides. The fount must be of a minimum of 11 pitch. Tables, diagrams, illustrations etc. are not included in the number of characters, but will not justify exceeding the maximum number of pages.

Code of conduct:

Undersigned author hereby declare:
- that I/we individually or together with the group members listed above have written and completed this assignment.
- that I/we have indicated all quotes with quotation-marks and provided references to their sources.
- that the assignment complies with all regulations stated above regarding size and form.

Date: Sep 20, 2012	Signature(s): Qi Huijuan

Abstract

This study aims at determining the external factors that influence the saturation level of diffusion of 3G telephony. The Gompertz model was selected as the best-fitting model for the diffusion of 3G telephony in Europe from 2003 to 2012. This model was also applied to estimate the diffusion of 3G telephony in each European country, and the coefficients of saturation level were used as input for further analysis. The saturation levels of 3G telephony in Europeans were modeled with various explanatory variables. Regression result of the model showed that the overall income and education level, the intensity of competition and the appropriate regulations in radio spectrum resources and licenses positively influence the saturation level of diffusion of 3G telephony in Europe. Some practical comments were made to the results.

Contents

1 Introduction

It is widely accepted that mobile telecommunication is playing an indispensible role in modern economic and social life. Mobile telecommunication is one of the major “enablers” of the global market. Mobile technologies eliminate the time and space limitations of business communication, and therefore greatly increase the transaction velocity of money and make remote transactions more convenient and reliable. Studies show that mobile telecommunication has a positive and significant impact on economic growth (Waverman, Meschi, & Fuss, 2005; Sridhar & Sridhar, 2007). Meanwhile, mobile telecommunication has changed people’s life style all around the world. Nowadays, mobile telecommunication means more than phone calls and text messages. It is convenient to obtain various types of information at very low cost using a mobile phone. What is more, more people are sharing their personal information and carrying out social activities via mobile technologies. Mobile devices have not only become an important way by which people interact with each other, but also a way how people show their taste and preference of consumption.

Various demands for mobile telecommunication contribute to rapid technological evolutions. The first generation of mobile technology (1G) was introduced to public in the late 1970s and prevailed in the most developed countries in the 1980s. The second generation of mobile technology (2G) was first deployed in the early 1990s. The core feature of 2G systems was the digitalization of voice signal. As a result, the call quality was improved, mobile devices became more portable and the cost of mobile communication reduced significantly as the 2G technology developed. The third generation of mobile technology (3G) was first deployed in Japan in 2001 and then widely deployed in many other developed countries. 3G technology allows high data transmission rate up to 21.6 MB/s, which brings about mobile broadband and enables massive mobile applications.

Each time when mobile technologies evolve, the latest generation of a technology coexists with the previous generation for several years, due to the heavy cost of network upgrades. But once the new technology is deployed, the substitution of the new technology for the older one is irresistible, because the new technology is superior to the old one not only in network capacities but also in call costs. Therefore, both mobile network operators and governments must figure out when the market of the new mobile technology starts and predict how the market develops. For mobile network operators, it is necessary to estimate both the revenues contributed by the new technology and the costs of deployment in order to ensure profitability. For governments, it is necessary to release adequate spectrum resources at proper time in order to ensure that new mobile telecommunication technology is available to most citizens at fair prices.

There are massive studies in the development of mobile telecommunication. Most of these studies shared a common view that the diffusion theory applies in the development of mobile telecommunication (Chu, Wu, Kao, & Yen, 2009; Gupta & Jain, 2012; Michalakelis, Varoutas, & Sphicopoulos, 2008). For most of these studies, the premise of analyzing mobile telecommunication diffusion is to select an appropriate model that best fits the actual diffusion. The Logistic, Gompertz and Bass model are the most frequently used model for this purpose (Meade & Islam, 1998). But to date, there has not been any strong argument or criteria of choosing the most suitable model (Wu & Chu, 2010). Therefore, it is necessary to choose a model that serves the study purpose and best fits the actual case in each specific study.

Numerous studies investigated the external factors that influence the diffusion patterns of mobile telecommunication. Most studies concluded that the intensity of competition, the government intervention and the substitution effect of previous generation of a technology influenced the speed of diffusion of mobile telephony (Gruber & Verboven, The Diffusion of Mobile Telecommunications Services in the European Union, 2001; Jang, Dai, & Sung, 2005; Rouvinen, 2006). On the other hand, few studies were devoted to investigate the external factors that influence the saturation level of diffusions. In this study, the determinants of the saturation level of diffusion of 3G telephony in Europe are detected and analyzed, which is the major innovation of this study.

Three major topics are elaborated in this study. First, determine the best fitting model for the 3G telephony diffusion in Europe. Second, estimate the diffusion pattern of 3G telephony in each European country. And last, study the external factors that influence the saturation level of diffusion of 3G telephony in European countries. Based on the results of the research topics above, several practical comments will be made to telecommunication regulations and marketing strategies of both network operators and handset manufacturers.

The rest of this study is organized as follows: Section 2 reviews previous literature on the diffusion of mobile telephony. Section 3 discusses the diffusion theories in details. Section 4 briefly describes the characteristics of 3G technologies and current market status of 3G telephony in Europe. Section 5 aims at determining the best-fitting model for diffusion of 3G telephony in Europe. Section 6 applies the selected model to estimate diffusion coefficients of each European country. Section 7 discusses possible determinants of the saturation level of diffusion of 3G telephony in European countries and estimates the influences of each determinant. Some policy implications of the results are discussed. Section 8 concludes the major finding of the study and brings about some suggestions for further study.

2 Literature Review

In the past century, a vast amount of literature has emphasized on the study of diffusion of innovations, either theoretically or empirically. The dominant literature of theories of diffusion of innovations was contributed by Everett Rogers (1962). Rogers summarized previous studies of diffusion of innovations in various fields, and described the characteristics of innovations, the decision process of adoption and the general pattern of diffusion systematically. Afterwards, numerous models have been developed and applied to study the diffusion of innovations empirically. Mead and Islam (2006) reviewed a large number of empirical studies from 1970 to 2005. They found that at least eight different basic models had been developed to estimate and forecast the diffusion of innovations. Studies in the period 1970 onwards emphasized on modifying the existing models to describe diffusions in more complicated context or to enhance the accuracy of estimation and forecasting. The authors further classified the modifications in three categories, namely the introduction of marketing variables in the parameterization of the models; generalizing the models to consider innovations at different stages of diffusions in different countries; and generalizing the models to consider the diffusion of successive generations of technology.

The studies in diffusions of mobile telecommunication services started in the 1990s. Since the history of mobile telecommunication is much shorter compared with the history of overall diffusion studies, the studies in this field did not appear to be very innovative. Most studies of diffusion of mobile telecommunication services concentrated in two areas, namely to select a best-fitting model to describe and forecast diffusion of mobile telephony in a certain geographical scope; and to detect possible determinants of diffusions. The two topics are discussed in Chapter 2.1 and 2.2 respectively.

2.1 Model Selection

Mead and Islam (2006) listed eight frequently used S-shaped diffusion models for cumulative adoption, and briefly described these models. The listed models included the Bass model, cumulative lognormal model, cumulative normal model, the Gompertz model, log reciprocal model, modified exponential model, the Weibull model and a group of Logistic models. Listed variations of the Logistic model include log-logistic variation, Flexible-Logistic (FLOG), Inverse Power Transform (IPT), Exponential (ELOG), the Box-Cox, non-symmetric responding logistic and local logistic. In most diffusion studies of mobile telephony, one or more of these models are selected to fit the actual diffusion process. In some studies, the authors estimated several models with the same samples and selected the one with the best fitting ability.

Michalakelis, Varoutas and Sphicopoulos (2008) evaluated eight aggregate technology diffusion models with company-level data of mobile subscriptions in Greece. The best-fitting model varied in each stage of diffusion. The Logistic family, including linear logistic, Box-Cox, FLOG and TONIC, showed best fitting ability in the whole sample period, as measured with mean absolute percentage error (MAPE). The Gompertz model did not fit the diffusion in the early stage, but it showed the best fitting ability in the take-off stage.

Chu et al. (2009) found that the Logistic model is the best-fitting model for mobile subscription in Taiwan from 1989 to 2007. In another study, Wu and Chu (2010) found that the model selection was stage-dependent. They found out that the Gompertz model outperformed the other models before diffusion take-off, and the Logistic model was superior after inflection and the over the aggregate range of the diffusion.

Gupta and Jain (2012) concentrated on three most widely used diffusion models, namely the Logistic model, the Gompertz model and the Bass model. The fitting ability of each model was measured with the estimated root mean square error (RMSE). The Gompertz model showed the best-fitting with observed penetration data in India from 1998 to 2008. However, the estimated saturation level of mobile telephony was 333% with the Gompertz model, which the author believed was unrealistic in India. When the saturation level was controlled at constant 120%, the Gompertz model still resulted in the lowest RMSE, which again showed that the Gompertz model was the best-fitting model for mobile telephony diffusion in India.

The inconsistency of the above evidence indicates that no strong arguments or principles have yet been developed for selecting diffusion models. Meanwhile, none of the models mentioned in this chapter, except the Bass model, were originally developed for the purpose of diffusion study. Therefore, it is hard to select the most appropriate model with explicit theories. In practice, it is necessary to select the best-fitting model with observed diffusion patterns before proceeding for further research.

2.2 Determinants of Diffusion

Another major research topic of telecommunication diffusion is to detect the determinants of diffusion patterns and to evaluate their influences. Possible determinants are usually modeled in linear forms to explain a specific coefficient of diffusion.

Some researchers tried to find out determinants of diffusion within one country by time series analysis. For example, Gupta and Jain (2012) developed a cause-effect loop with STEP – social, technological, economic and political – factors in India. However, the influences of the STEP factors were not tested empirically. The authors developed a model with three explanatory variables to determine their impact on the diffusion speed, namely a dummy for the Call Party Pays (CPP) system, the tariff and the number of fixed line subscribers. Although CPP could be treated as a proxy for government intervention, the rest two variables represented industrial-level factors instead of the STEP factors.

What is worse, Gupta and Jain's research is doubtful. In their study, the speed of diffusion was obtained by estimating the Gompertz model. One of the major characteristics of the Gompertz model is that the diffusion speed is a function of the intrinsic growth rate and the number of cumulative adopters at a specific time point (The Gompertz model is discussed in details in Section 5). Therefore, it is unreasonable to link the diffusion speed with external factors. The statistical significance of the linear regression may be a result of spurious regression.

Some other studies evaluated influence of external factors with cross-sectional data.

Studies by Gruber and Verboven (2001a; 2001b), Rouvinen (2006), and Jang, Dai and Sung (2005) are widely cited.

Gruber and Verboven studied the diffusion of mobile telecommunication services in 15 countries of European Union (2001a). The authors found that the transition from the analogue to the digital technology, the increase in spectrum capacity, the timing of the awarding of licenses, and the level of competition had a significant effect on diffusion. In a parallel global study of 205 countries by Gruber and Verboven, the authors further determined that the uniform and standardized regulations had an important impact on the diffusion of telecommunication (2001b).

Rouvinen's study aimed at finding out whether factors determining the diffusion of digital mobile telephony are different across developed and developing countries (2006). Rouvinen modeled the speed of diffusion with 17 explanatory variables based on the Gompertz model. These variables were selected as proxies of the potential user base, the overall wealth, the social development, the availability of finance, the openness, the technology development, and the development of telecommunication in a country. Model estimation result showed that the variables for total population, political openness, technology development and the joint variables of telecommunication development influenced the speed of digital mobile diffusion, especially in a developing country context. These factors had stronger influences on developing countries than on developed countries, which led to convergence between countries. Meanwhile, the speed of diffusion *per se* was found not significantly different between the two groups of countries, after controlling for other factors.

Jang, Dai and Sung found that the diffusion patterns of all OECD countries and Taiwan exhibited an S-shaped curve from 1980 to 2001. However, the diffusion patterns of each group of countries were discernibly different. The S-curves for Northern Europe, the US, Canada and Japan were relatively flat, while contrasting sharper S-shaped curves were found in Western Europe, Southern Europe and Taiwan. The differences in the diffusion coefficients of each group of countries were explained with the differences of a series of external factors, including the evolution of mobile technology, the level of market competition, the emerging of Calling Party Pays (CPP) system and the substitution effect of the fixed line telephony.

After determining the factors that influence the diffusion of mobile telephony, relevant policy implications are usually discussed. For example, Jang, Dai and Sung (2005) suggested that a telecommunication company should continually invest in advanced technologies, seek and seize the opportunities created by economies of scale and select an appropriate payment plan, in order to succeed in the market. Gruber and Verboven (2001a, 2001b), on the other hand, suggested that governments should actively release spectrum resources, encourage competition and standardize regulations in order to promote diffusion of mobile telecommunication services.

It is noteworthy that almost all of existing literature emphasized on the determinants of the speed of diffusion, and as far as the author perceives, yet no studies were devoted to find out possible determinants of the saturation level of diffusions. However, the saturation level of diffusion of mobile telephony is of the same importance as the speed of diffusion for mobile network operators, governments and mobile subscribers. In this study, the saturation level of diffusion of 3G mobile telephony of each European country is estimated with a selected model, and the determinants of the saturation level are detected for further discussion.

3 Technology Diffusion

Researches of diffusion can be traced back to the beginning of the 20th century. Gabriel Tarde, a French sociologist and social psychologist, was one of the first researchers who observed the diffusion of innovations. Tarde identified the adoption or rejection of innovations as a crucial research question in his influential book "The Laws of Imitation" (Rogers, 1983, pp. 40-42), most of which are widely accepted by today's researchers of diffusion.

After Tarde, a group of early anthropologists started to use diffusionism viewpoint to explain changes in a given society. Most of these anthropologists claimed that all social changes could be explained by diffusion of innovations spread from another society. However, there are few subsequent studies of these claims, because the influences of invention are neglected to different extends.

Early studies of diffusion focused on specific fields. Everett M. Rogers (1983, pp. 42-79) summarized nine research traditions of diffusion, including anthropology, early sociology, rural sociology, education, public health and medical sociology, communication, marketing, geography and general sociology. What is more, Rogers synthesized the previous studies of diffusion and produced a generalized theory for the adoption of innovations among individuals and organizations. In his distinguished book "*Diffusion of Innovations*", Rogers systematically reviewed the history of diffusion researches, outlined the characteristics of innovations, defined the process of diffusion and categorized the adopters of innovation. Rogers' theory has nowadays become the foundation of most subsequent studies of diffusion, and its validation has been well proved with empirical evidence.

According to Rogers, diffusion is the process during which an innovation is communicated through certain channels over time among members of a social system (1983, p. 5). For a single member of the social system, his/her individual decision of adoption follows a 5-step process, including:

1. Knowledge: A person becomes aware of an innovation and gains some understanding of how it functions.

2. Persuasion: A person forms a favorable or unfavorable attitude toward the innovation.
3. Decision: A person engages in activities that lead to a choice to adopt or reject the innovation.
4. Implementation: A person puts an innovation into use.
5. Confirmation: A person evaluates the results of an innovation-decision already made.

It is clear that "knowledge" and "persuasion" are premises of any activity of adoption. The information one perceives in these two steps determines whether he/she adopts or rejects the innovation, and how he/she spreads his/her attitude to the innovation. In other words, an individual's decision of adoption is heavily influenced by innovation decisions of other members of the system.

Not all members in a social system adopt an innovation at the same time. The early adopters of an innovation require a shorter adoption process than the late adopters. According to Rogers, the time an individual requires to adopt an innovation is determined by three factors: personalities, communication behaviors and socioeconomic characteristics. Personalities determine an individual's inherent attitude to changes. Communication behaviors determine to what extend an individual can gain information about an innovation. Socioeconomic characteristics determine how an individual evaluate the costs and benefits of an innovation. For example, adoption process is much shorter for those who have a more favorable attitude toward change, higher exposure to mass media and a higher social status. Rogers classified all adopters of an innovation into 5 categories: innovators, early adopters, early majority, later majority and laggards. The classification is based on the time length of an individual's adoption process. Based on the classification, the attributes of adopters in each category can be standardized and empirically determined.

If the cumulative number of adopters is plotted against time variable, the result is usually an S-shaped curve. The S-shaped diffusion curve rises slowly in the early stage when there are only innovators and early adopters. When early majority join the diffusion process, the rate of adoption accelerates until half of potential adopters are involved. The number of adopters then increases with a gradually slower rate until all remaining individuals adopt. Rogers further defined the first 2.5% of adopters as innovators, the next 13.5% of adopters as early adopters, the next 34% of adopter as early majority. After the peak growth rate, the next 34% of adopters are defined as late majority, and the final 16% are called laggards. According to Rogers, the frequency curve of diffusion is a bell-shaped curve which is symmetrically distributed around the time spot when the highest diffusion rate is reached. Figure 3-1 shows the S-shaped curve described by Rogers. The S-shaped curve has been applied in a vast amount of literature. Most studies prove that the adoption of new technologies over time follows an S-shaped curve.

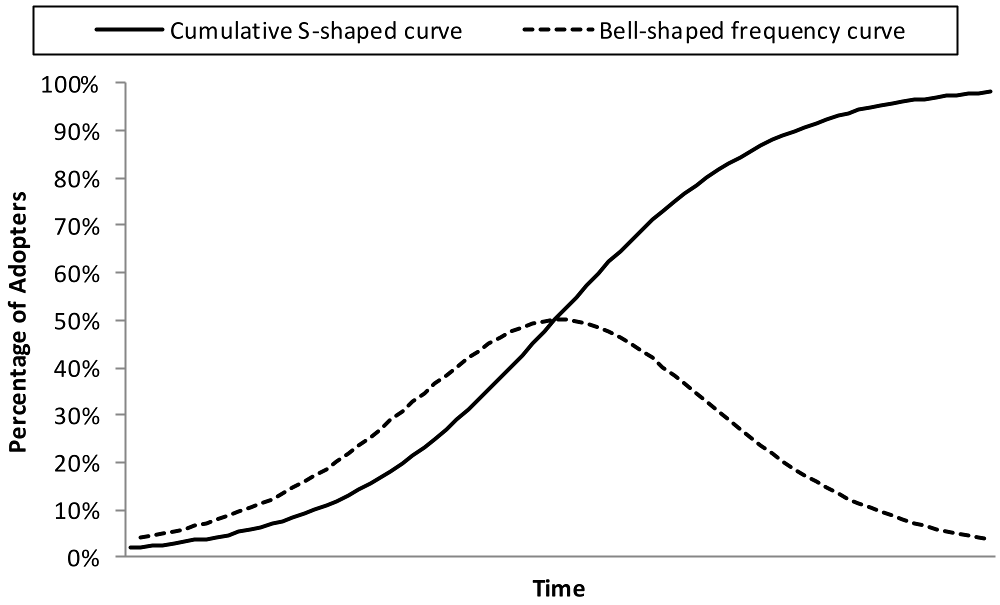


Figure 3-1 **The Bell-shaped frequency curve and the S-shaped cumulative curve for and adopter distribution. Adopted from *Diffusion of Innovation* (p. 243) by Everett M. Rogers, 1983, New York. Copyright 1983 by The Free Press.**

Although there is a large amount of literature studying the diffusion of innovations and the adoption decisions, few studies emphasized on the saturation level of diffusion. The theories of diffusion emphasize on the demands for an innovation, while the market potential of an innovation is determined by both demands and supplies. Although the supply of innovations has rarely been discussed in previous researches, there are some hints in existing diffusion theories. Rogers defined five intrinsic characteristics of innovations influencing an individual's decision of adoption. These characteristics include: relative advantage over the previous generation, the compatibility how an innovation can be assimilated into an individual's life, the simplicity of adoption, the trialability which enables an individual to experiment an innovation, and the observability of an innovation. These characteristics of innovation are determined by the suppliers of an innovation to a large extend. For example, in order to make an innovation more advantageous to the previous generation, the developer may have to invest more in research and development of the innovation. Similarly, in order to enhance the observability of an innovation, the suppliers to the innovation may have to deply more resources in marketing campaigns.

Previous researchers have developed numerous models to describe the S-shaped curves. Generally speaking, these models can be classified into two types. The first type is epidemic models. These models are built on the premise that the speed of usage is affected by the lack of information available about the new technology and its usage and function (Geroski, 2000). In other words, the epidemic models assume that the diffusion process is purely a result of spread of information. Personality and socioeconomic characteristics of potential adopters are not measured in these models. The most frequently used models, namely the Logistic model, the Gompertz model and the Bass model are all epidemic models. The second type of models is the probit model. The probit model is used to analyze individual adoption decisions, and follows the premise that different individuals are likely to adopt a new technology at different time, based on their individual needs and abilities. More specifically, the probit model emphasizes on individual characteristics that affect the probability of adopting a new technology. To sum it up, the epidemic model is more applicable in the study of diffusion of innovations in a social system, while the probit model is more suitable in the study of individual decisions of adoption.

Clearly, neither the epidemic model nor the probit model emphasizes on the saturation level of a diffusion process. The saturation level of diffusion is usually set as a constant variable in existing epidemic models, and in most empirical studies the constant is simply estimated without further analysis. The saturation level of diffusion is not involved in the probit model. Although market potential of an innovation can be obtained by cumulating probability of adoption of all members in a social system at expected time of equilibrium, such results highly rely on accurate judgment to the distribution of each determinant factors of adoption and accurate estimation of how an individual reacts on these determinants.

The goal of this study is to analyze the 3G telephony diffusion in Europe as a whole and each European country, and to determine factors that influence the saturation level of 3G market. For this purpose, the epidemic model is selected in this study.

4 Overview of 3G Telephony in Europe

4.1 Overview of Mobile Technologies

Ever since the first radiotelephone service was introduced in the US at the end of the 1940s, the world has witnessed rapid development of mobile telecommunication. The first generation (1G) and the second generation (2G) were introduced to public in the 1970s and 1980s respectively. As new technologies were deployed, mobile communication service providers were able to provide better call quality and higher capacity with lower cost to consumers.

However, neither 1G nor 2G mobile telecommunication has changed the world as much as 3G mobile telecommunication does. The third generation (3G) refers to a set of standards of mobile telecommunication that comply with the International Mobile Telecommunications-2000 (IMT-2000) specifications by the International Telecommunication Union (ITU). According to the IMT-2000 standards, a 3G network is required to provide a peak rate of at least 200 KB/s. In reality, most network operators provide much higher peak rates than the minimum requirements. The latest released 3G technology standard can provide peak rates up to 56 MB/s in downlink. The data rates provided by 3G technologies are highly advantageous compared with 2G technologies, which only provide speed ranging from 2.8 KB/s to 28.8 KB/s (ITU, 2012). The high data rate provided by 3G technologies enables various functions of mobile applications, including multimedia entertainment, mobile surfing and location based services. As a result, the 3G technology rapidly substituted the previous generation since it was first deployed.

At least four standards meet the requirements of IMT-2000 and therefore are branded as 3G. These standards include CDMA2000, W-CDMA, TD-SCDMA and WiMax. In most European countries, only W-CDMA standard was deployed and commercialized. For the rest countries, both W-CDMA standard and CDMA2000 standard are deployed. CDMA2000 standard is not compatible with GSM, the dominant 2G standard. As a result, the diffusion of 3G with CDMA2000 standard may be hindered by the switching cost from 2G to 3G.

4.2 Overview of 3G Diffusion in Europe

The first commercial 3G network in Europe was launched by a Romanian operator Cosmote in December 2001, based on CDMA2000 1x technology. (CDG, 2012). The last country that launched 3G network in Europe is Albania, where the 3G network was not available until the first quarter of 2011.

Table 4-1 shows how the aggregate penetration rate of 3G telephony increases with time in Europe. By the end of the 1st quarter in 2012, the average 3G penetration rate in Europe is 44.22%. Among all the European countries, the 3G technology is most accepted in Austria, where the penetration rate reaches 114.79%. Meanwhile, the 3G penetration rate in Bosnia and Herzegovina is merely 4.46%.

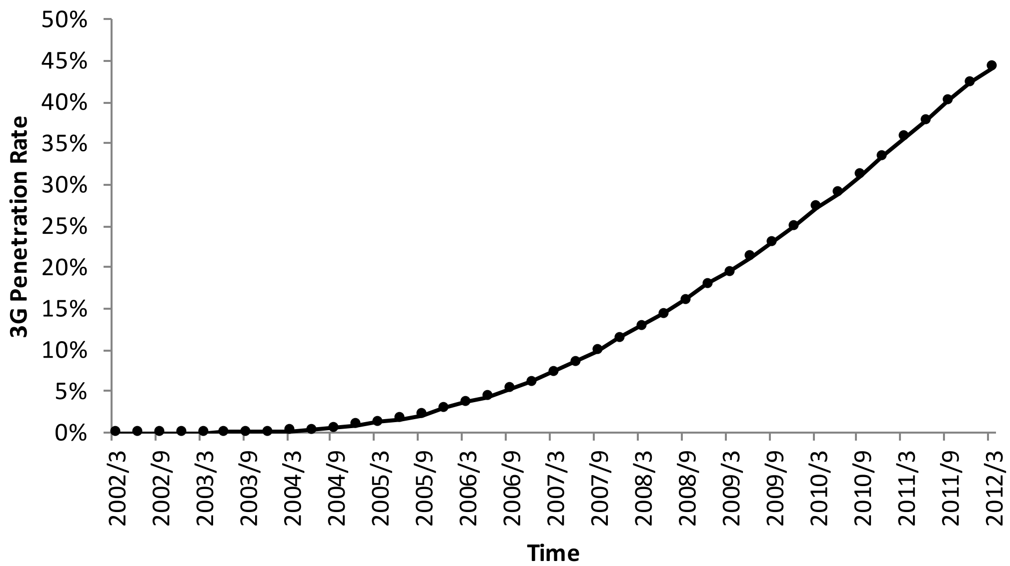


Figure 4-1 **Penetration rate of 3G telephony in Europe**

The start time and the current penetration rate of 3G telephony in each European country are summarized in Table A1-1 in the Appendix. It is apparent in Table A1-1 that the 3G diffusion status in each European country highly varies. Even for these countries where 3G started at the same time, the difference in growth rate leads to difference in current penetration rate. In the next sections, a best-fitting model for diffusion of 3G telephony is selected and applied in the study of 3G diffusion in European countries.

5 Best-Fitting Model

As discussed above, the most frequently used epidemic models in diffusion studies are the Logistic model, the Gompertz model and the Bass model. Various authors may choose one or more of these models. In some cases such selection is based on the theoretical meanings of the models, and in some other cases, the authors compare the fitting capability of the three models and choose the one that fit the data sample the best.

The reason why these models are frequently discussed together is that these models share some features. These three models describe the cumulative market potential and the diffusion rate of an innovation with three coefficients. These models fit the S-shaped diffusion process. Wu and Chu (2010) made comparisons among the Logistic model, the Gompertz model and the Bass model and summarized the similarity of these models. These models are expressed as following:

$$\frac{dN}{dt} = rN\left(1 - \frac{N}{K}\right) \qquad \text{(the Logistic model)}$$

$$\frac{dN}{dt} = rN\ln\frac{K}{N} \qquad \text{(the Gompertz model)}$$

$$\frac{dN}{dt} = \left(p + q\frac{N}{K}\right)(K - N) \qquad \text{(the Bass model)}$$

In Wu and Chu's study, the coefficient N denotes the number of adopters at specific time t, r is the intrinsic growth rate, and K is the maximum or equilibrium number of adopters. For the Bass model, p is the innovation coefficient and q is the imitation coefficient. Clearly, for these three models, the saturation level of the diffusion of a new technology is fixed during the entire diffusion process, while the growth rate of the number of adopters is described with a function of the cumulative number of adopters at the observed time and the intrinsic growth rate. Therefore, the core issue of diffusion studies is to determine the maximum market potential and the intrinsic growth rate of a new technology.

The rationale and features of the three diffusion models are discussed in more details respectively in the following chapters.

5.1 Logistic Model

A frequently used form of the logistic model is called the Fisher-Pry model. It is a variant of the logistic model which is first developed by Fisher and Pry to measure and forecast the substitution of technologies (Fisher & Pry, 1971).

The Fisher-Pry model is based on the following assumptions. First of all, technological evolution can be considered as a process of substitutions of one method of satisfying a need for another. The rationale of the substitution is that the new technology brings more benefits to its users than the older one does, either with lower cost or with higher utility. Therefore, once a substitution process starts, it will proceed to completion. Another major assumption of the Fish-Pry model is that the fractional rate of fractional substitution of new for old is proportional to the remaining amount of the old left to be substituted. That is, the Fisher-Pry model applies where a technological change is not radical but continuous, and is driven by a technology that is superior to the former generation.

The first assumption of Fisher-Pry model fits the diffusion of 3G mobile telephony well. 3G technology brings about not only higher call quality than 2G does for phone callers, but also better experience for mobile internet surfers. Meanwhile, the price of 3G telephony gradually becomes advantageous as the initial network deployment costs are spread among more and more 3G subscribers, while the price of 2G telephony changes in the opposite way. The second assumption is also consistent with the 3G diffusion case. When 3G technology is first introduced, its advantages are gradually perceived by the public. Therefore the rate of substitution grows exponentially in the beginning. During this process, the remaining users of 2G network may be more conservative and less likely to adopt the new technology. As a result, the rate of substitution may decline exponentially in the later stage of the substitution. Since the fractional substitution also tends to proceed exponentially, it is likely that the fractional rate of fractional substitution is linear correlated with the amount of remaining 2G users who will switch to 3G in the future.

Fish and Pry composed the following model:

$$f(t)=\frac{1}{2}\left[1+\tanh\frac{1}{2}r(t-m)\right]=\frac{1}{1+e^{-r(t-m)}} \tag{5.1}$$

where *f(t)* is the fraction of the market substituted by the new technology at time t, r is the coefficient of growth rate, and m is the time at which f=1/2, or the "infection point".

Clearly the Fisher-Pry model is symmetric around the point where t=m, or the "infection point". It is yet to be determined if this feature fits the actual diffusion pattern of 3G telephony.

Assume that all of the 2G subscribers are potential 3G users, the cumulative amount of 3G subscribers at time t is denoted as:

$$\mathrm{N}(t)=Kf(t)=\frac{K}{1+e^{-r(t-m)}} \tag{5.2}$$

where K is the aggregate market potential of 3G technology, measured by the amount of subscribers.

However, the assumption for equation (5.2) may not stand in reality. The 2G technology is not likely to be completely substituted by 3G technology. In fact, the 2G technology always coexists with 3G from the start year of 3G till now. And so far, no European network operator has announced 2G shutting down plans[1]. What is more, the 4G technology has been deployed in many European countries. It means that part of the remaining 2G subscribers may switch from 2G to 4G, skipping the 3G phase. Therefore, the coefficient S in equation (5.2) actually denotes the sum of the aggregate market potential of 3G technology and the remaining amount of 2G subscribers when 3G telephony market reaches saturation. The estimated result of S may be much higher than the actually "ceiling" of 3G market.

Another concern of the Fisher-Pry model is specific in this study. After the best fit model is determined in this section, the model will be applied to each European country in the next section of this study. The data used in this study is collected from 47 European countries. Due

[1] Korean network operator KT has started to switch off its 2G network from January 3rd, 2012. American network operator AT&T has announced its plan to decommission its GSM voice and EDGE data networks by January 1st, 2017.

to the fact that both the population size and the number of 3G users vary among European countries, the estimation result, especially the maximum number of 3G adopters K, is not comparable among countries. Therefore, it is necessary to convert model into the following:

$$\mathrm{n}(t) = \frac{k}{1 + e^{-r(t-m)}} \tag{5.3}$$

where *n(t)* is the penetration rate of 3G at time t, and k is the penetration rate of 3G at its saturation level. The penetration rate is defined as the percentage of 3G subscribers of a certain country out of its total population size at specific time t.

Clearly, equation (5.3) is an approximation of equation (5.2). The penetration rate at time t is calculated with the population size at time t, while the maximum penetration rate is calculated with the population size at the time when 3G market reaches saturation. This approximation stands based on the following reasons. Firstly, for most European countries, the population size changed at such low rates during the sample period that the influence of the approximation is negligible. Secondly, although the coefficient k is likely to be slightly overestimated because of the approximation, it is still more comparable among European countries than the absolute term. The same approximation also applies in the Gompertz model and the Bass model, which will be discussed in the rest of the study.

5.2 Gompertz Model

The Gompertz model was first developed by British mathematician Benjamin Gompertz to describe his law of human mortality (Gompertz, 1825). The initial form of the Gompertz model is $L_x = kg^{q^x}$. It indicates that the number of persons living at the age x is a function of x, based the assumption that a human's power to avoid death decreases as his or her age increases.

Since the beginning of the 20th century, the Gompertz model has been used as a growth curve for biological and economic phenomena (Winsor, 1932). For these purposes, the model is also written as:

$$\mathrm{N}(t) = Ke^{-e^{-r(t-m)}} \tag{5.4}$$

where $\mathrm{N}(t)$ represents the cumulative number of individuals at time t, K is the saturation level of the diffusion, and r and m are positive constants (Winsor, 1932). Therefore, for any non-negative value of t, $\mathrm{N}(t)$ is always positive.

The first order differential form of equation (5.4) is:

$$\frac{dN(t)}{dt} = Kre^{-r(t-m)}e^{-e^{-r(t-m)}} = rN(t)e^{-r(t-m)} \tag{5.5}$$

It is apparent that the slope of the Gompertz model is always positive for any t>0, and it approaches zero when the value of t grows to infinity.

The second order differential form of equation (5.4) is:

$$\frac{d^2N(t)}{d^2t} = r^2N^2(t)e^{-r(t-m)}\left(e^{-r(t-m)} - 1\right) \tag{5.6}$$

Equation (5.6) shows that when $\mathrm{t} = \mathrm{m}$, the second order differential equation of the Gompertz model $\frac{d^2N(t)}{d^2t} = 0$; when $\mathrm{t} \in [\mathrm{o}, \mathrm{m})$, $\frac{d^2N(t)}{d^2t} > 0$; when $\mathrm{t} \in (\mathrm{m}, +\infty)$, $\frac{d^2N(t)}{d^2t} < 0$. That is, $\mathrm{t} = \mathrm{m}$ is the point of inflection of the function of the Gompertz model. And when $\mathrm{t} = \mathrm{m}$, $\mathrm{N}(t) = \frac{K}{e} \approx 0.3679S$. It indicates that the maximum growth rate is met when the cumulative number of adopters of the innovation reaches about 37% of the market potential. This feature of the Gompertz model makes it more suitable for estimating a growth cycle of which the inflection point appears in its early stage.

For the purpose of comparing diffusion patterns among European countries, an approximate form of Gompertz model is derived with the same rationale as that of the Logistic model. The approximation of the Gompertz model is written as:

$$n(t) = ke^{-e^{-r(t-m)}} \tag{5.7}$$

where n(t) is the penetration rate of 3G at time t, and k is the penetration rate of 3G at its saturation level. Again, coefficient k is likely to be slightly overestimated. But it is tolerable for the purpose of comparing 3G diffusion patterns of various European countries.

5.3 Bass Model

The Bass model was developed by Frank M. Bass in his study of the timing of initial purchase of consumer durables (Bass, A New Product Growth for Model Consumer Durables, 1969). The Bass model has been proved applicable to not only the growth of initial purchases consumer durables, but also to that of “a broad range of distinctive ‘new’ generic classes of products”, including the diffusion of mobile telephony (Bass, A New Product Growth for Model Consumer Durables, 1969; Michalakelis, Varoutas, & Sphicopoulos, 2008; Gupta & Jain, 2012).

The Bass model is based on a series of assumptions of the distinctive behavioral pattern of the “innovators” and the “imitators”. According to Bass, “innovators” are those who decide to adopt an innovation independently of decisions of other individuals in a social system, whereas “imitators” are influenced in the timing of adoption by the pressure of previous adopters the social system. More specifically, the pressure increases for later adopters as the number of previous adopters increases. (Bass, 1969). The above assumptions fit the case of mobile telecommunication evolution. The initial subscribers of 3G networks did not make their purchase decision under the pressure of the social system, because the 3G technology is downward compatible to the 2G technology. It is more likely that the initial subscribers of 3G technology are attracted by the advanced technology itself, instead of by their social connections. In fact, the innovators may even be hindered by the social system because the penetration of the new technology is so limited that its “ecosystem” is far from maturity. The “imitators”, however, are highly influenced by the social system. As the number of 3G subscriptions increases, the advantages of 3G technologies are spread via word-of-mouth, which attracts new subscribers. Meanwhile, the 3G “ecosystem” gradually substitutes for the 2G “ecosystem”, that is, the price of 3G telephony decreases to the level of 2G telephony or even lower, the majority of newly shipped mobile handsets are designed for 3G networks, and plentiful of 3G value-add services and applications are available in the market. Based on the discussion above, the Bass model is well qualified to be one alternative model in this study.

The Bass model is formulated as following:

$$S(t) = K\frac{(p+q)^2}{p}\frac{e^{-(p+q)t}}{\left[1+\frac{q}{p}e^{-(p+q)t}\right]^2} \tag{5.8}$$

where *S(t)* is the sales at time t, *K* is the ultimate market potential, *p* is the coefficient of innovation and *p* is the coefficient of imitation.

In order to keep consistent with the Logistic model and the Gompertz model, the cumulative distribution function of the Bass model is:

$$N(t) = K\frac{1-e^{-(p+q)t}}{1+\frac{q}{p}e^{-(p+q)t}} \tag{5.9}$$

where *N(t)* is the total number purchasing in the (0,t) interval (Bass, Krishnan, & Jain, 1994).

The Bass model can also describe the growth pattern of 3G penetration rate, as discussed above. Equation (5.9) is then written as:

$$n(t) = k\frac{1-e^{-(p+q)t}}{1+\frac{q}{p}e^{-(p+q)t}} \tag{5.10}$$

where n(t) is the penetration rate of 3G at time t, and *k* is the penetration rate of 3G at its saturation level.

The growth rate of the number of new technology adopters can be derived from equation (5.10):

$$\frac{dn(t)}{dt} = \frac{m(p+q)^2}{p}\frac{e^{-(p+q)t}}{\left[\frac{q}{p}e^{-(p+q)t}+1\right]^2} \tag{5.11}$$

The infection point of a diffusion process is defined as the point when the growth rate of the number of new adopters reaches maximum level. Take the second order differential of equation (5.11), we get:

$$\frac{d^2n(t)}{dt^2} = \frac{m(p+q)^3}{p}\frac{e^{-(p+q)t}\left[\frac{q}{p}e^{-(p+q)t}-1\right]}{\left[\frac{q}{p}e^{-(p+q)t}+1\right]^3} \tag{5.12}$$

Clearly, when $t = -\frac{\ln\left(\frac{p}{q}\right)}{p+q}$, the second order differential of the Bass model equals to zero, which means the growth rate is highest at this time spot. Therefore, the infection point of the Bass model is defined as:

$$m = -\frac{\ln\left(\frac{p}{q}\right)}{p+q} \tag{5.13}$$

Equation (5.3), (5.7) and (5.10) will be used for estimation to determine the model with the best fit performance.

5.4 Model Estimation Methods

The first issue of this study is to examine the fitting performance of each diffusion model and to determine the one with the best fitting capability for further study. For this purpose, the Logistic model, the Gompertz model and the Bass model are estimated respectively with seasonal European 3G subscription statistics. The data are collected from Worldwide Cumulative Subscription database tracked by World Cellar Information Service (WCIS), a leading mobile telecommunication benchmarking program. The sample period lasts from the first quarter in 2003 to the first quarter in 2012 and includes 37 samples.

It is apparent that all of the three diffusion models are non-linear models. Therefore, the estimation technique requires attention. There are numerous studies dedicated to determine the most superior estimation technique of diffusion models. Take the Bass model for example, when Frank M. Bass first proposed the Bass diffusion model, he developed a discrete analogue of the non-linear model and used ordinary least square (OLS) method to estimate the coefficients of diffusion with the linear analogue as an approximation (Bass, 1969). After that, a maximum likelihood (MLE) approach was used to estimate the Bass model, and this method is reported to be superior to the OLS method, in terms of both goodness of fit measures and one-step ahead forecasts (Schmittlein & Mahajan, 1982). Later on, further improvement in the estimation of the Bass model was made using the nonlinear least square (NLS) approach. The fit and the predictive validity are both enhanced with the NLS method (Srinivasan & Mason, 1986). In Srinivasan and Mason's study, they argue that the NLS approach is also applicable to other diffusion models for which cumulative adoption can be expressed as an explicit function of time. Based on previous researches, the NLS approach is used in this study.

The NLS approach requires initial values of coefficients for the iteration process. In practice, the corresponding OLS estimates are usually set as the initial values of NLS estimation (Gupta & Jain, 2012). The linear approximation of each diffusion model is discussed below.

The linear form of the Logistic model is derived by rearranging equation (5.3):

$$\frac{n(t)}{n(t-1)} = e^r + \frac{1-e^r}{k} n(t) \tag{5.14}$$

Let $\Delta n(t) = n(t) - n(t-1)$, $\alpha = e^r$, $\beta = \frac{1-e^r}{k}$, and add error term to equation (5.14), the model becomes the following:

$$\Delta n(t) = \alpha + \beta n(t-1) + \varepsilon_t \tag{5.15}$$

It is apparent that equation (5.15) is a linear regression model and it can be estimated with ordinary least square (OLS) method. Equation (5.15) also applies in the panel data estimation of all European countries.

The estimated results of the original coefficients of the Logistic model can be obtained with the following formula:

$$\hat{r} = \ln \widehat{\alpha} \tag{5.16}$$

$$\hat{k} = \frac{1-\widehat{\alpha}}{\widehat{\beta}} \tag{5.17}$$

It is noteworthy that the coefficient of the infection point of the original Logistic model cannot be estimated with equation (5.15). It partially explains why the OLS method is not suitable for estimating the Logistic model.

Similarly, the linear form of the Gompertz model is derived by rewriting equation (5.7) as:

$$\ln n(t) = \left(1 - \frac{1}{e^r}\right)\ln k + \frac{1}{e^r}\ln n(t-1) \tag{5.18}$$

Let $\alpha = \left(1 - \frac{1}{e^r}\right)\ln k$, $\beta = \frac{1}{e^r}$ and add error term ε to equation (5.18), the model is then written as:

$$\ln n(t) = \alpha + \beta \ln n(t-1) + \varepsilon_t \tag{5.19}$$

The estimated results of the original coefficients of the Gompertz model can be calculated with the following formula:

$$\hat{k} = e^{\frac{\hat{\alpha}}{1-\hat{\beta}}} \tag{5.20}$$

$$\hat{r} = \ln\left(\frac{1}{\hat{\beta}}\right) \tag{5.21}$$

Again, the coefficient of the infection point of the original Gompertz model cannot be obtained with equation (5.19).

The discrete analogue of the Bass model is the most frequently used linear form of the Bass model. The discrete Bass model writes as:

$$s(t) = pk + (q-p)n(t) - \frac{q}{k}N^2(t) \tag{5.22}$$

In order to keep consistent with the Logistic model and the Gompertz model in this study, the discrete Bass model is rewritten as:

$$\Delta n(t) = \alpha + \beta_1 n(t) + \beta_2 n^2(t) + \varepsilon \tag{5.23}$$

Equation (5.23) is identical to equation (5.22) where $\Delta n(t) = n(t) - n(t-1)$, $\alpha = pk$, $\beta_1 = q - p$, $\beta_2 = -\frac{q}{k}$ and ε is the error term.

The estimated results of the original coefficients are identified with the following equations:

$$\hat{k} = \frac{-\widehat{\beta_1} \pm \sqrt{\widehat{\beta_1}^2 - 4\hat{\alpha}\widehat{\beta_2}}}{\sqrt{2\widehat{\beta_2}}} \tag{5.24}$$

$$\hat{p} = \frac{\widehat{\beta_1} \mp \sqrt{\widehat{\beta_1} - 4\hat{\alpha}\widehat{\beta_2}}}{\sqrt{2}} - \widehat{\beta_1} \tag{5.25}$$

$$\hat{q} = \frac{\widehat{\beta_1} \mp \sqrt{\widehat{\beta_1} - 4\hat{\alpha}\widehat{\beta_2}}}{\sqrt{2}} \tag{5.26}$$

The coefficient of the infection point of the Bass model is then calculated as:

$$\hat{m} = -\frac{\ln\left(\frac{\hat{p}}{\hat{q}}\right)}{\hat{p} + \hat{q}} \tag{5.27}$$

5.5 NLS Regression Results

The regression results of the linear form of the Logistic model are listed in Table 5-1. Both the estimated α and β are statistically significant. The estimated values of α and β are used to calculate the original Logistic coefficients with equation (5.16) and (5.17). Therefore the OLS estimated $\hat{r} = 0.3904$ and $\hat{k} = 34.9549$. These values are set as initial values in the NLS regression of the Logistic model.

In order to keep consistency, all NLS regressions processed in this study are based on Gauss-Newton method. The convergence criteria are set as 1.0E-0.5, and the singularity criteria are set as 1.0E-0.8. Since the OLS estimation results are used as initial values of NLS estimation, it is assumed that number of iterations executed in each NLS regression process is relative low. The maximum number of iterations is therefore set as 500. If the estimates fail to meet the convergence criteria after 500 iterations, it is likely that the target diffusion process is not in accordance with the selected model.

Table 5-1 **Regression result for linear form of the Logistic model**

Coefficient	Estimated value	Standard error
α	1.4775**	0.0708
β	-0.0137**	0.0034
R-squared	0.3158	
RSS	2.8785	

*Indicates the coefficient is significant at 95% confidence level.

**Indicates the coefficient is significant at 99% confidence level.

The NLS regression results of the Logistic model are listed in Table 5-2.

Table 5-2 **NLS Regression Results of the Logistic Model**

Coefficient	Estimated value	Standard error
k	55.5039**	1.7734
r	0.1596**	0.0048
m	29.0501**	0.4732
R-squared	0.9977	
RSS	16.6210	
RMSE	0.6702	

*Indicates the coefficient is significant at 95% confidence level.

**Indicates the coefficient is significant at 99% confidence level.

The regression results of the linear form of the Gompertz model are listed in Table 5-3. Both the estimated α and β are statistically significant. The estimated values of α and β are used to calculate the original Gompertz coefficients with equation (5.20) and (5.21). The OLS estimated coefficient $\hat{r} = 0.0924$ and $\hat{k} = 51.5907$. These values are set as initial values in the NLS regression of the Gompertz model.

Table 5-3 **Regression result for linear form of the Gompertz model**

Coefficient	Estimated value	Standard error
α	0.3481**	0.0225
β	0.9117**	0.0087
R-squared	0.9969	
RSS	0.4076	

*Indicates the coefficient is significant at 95% confidence level.

**Indicates the coefficient is significant at 99% confidence level.

The NLS regression results of the Gompertz model are listed in Table 5-4.

Table 5-4 **NLS Regression Results of the Gompertz Model**

Coefficient	Estimated value	Standard error
k	97.3173**	2.62246685
r	0.0595**	0.00113814
m	33.0229**	0.45431798
R-squared	0.99977395	
RSS	1.65840829	
RMSE	0.21171170	

*Indicates the coefficient is significant at 95% confidence level.

**Indicates the coefficient is significant at 99% confidence level.

The regression results of the discrete analogue of the Bass model are listed in Table 5-5. The estimated coefficients α, β_1 and β_2 are all statistically significant. The estimated values of α, β_1 and β_2 are used to calculate the original Bass coefficients with equation (5.24), (5.25) and (5.26). According to equation (5.24), the estimated value of k equals to -1.6348 when the plus sign is used, or 68.8124 when the minus sign is used. Since the coefficient k denotes the maximum penetration rate of 3G in Europe, it is more reasonable to use the minus sign and $\hat{k} = 68.8124$. Then we get the OLS estimated $\hat{p} = 0.0029$ and $\hat{q} = 0.1214$. These values are set as initial values in the NLS regression of the Bass model.

Table 5-5 **Regression result for linear form of the Bass model**

Coefficient	Estimated value	Standard error
α	0.1985**	0.0514
β_1	0.1186**	0.0073
β_2	-0.0018**	0.0002
R-squared	0.9536	
RSS	1.0004	

*Indicates the coefficient is significant at 95% confidence level.

**Indicates the coefficient is significant at 99% confidence level.

The NLS regression results of the Bass model are listed in Table 5-6.

Table 5-6 **NLS Regression Results of the Bass Model**

Coefficient	Estimated value	Standard error
k	59.6487**	1.870
p	0.0019**	8.0478e-05
q	0.1448**	0.0041
R-squared	0.9988	
RSS	8.6193	
RMSE	0.4827	

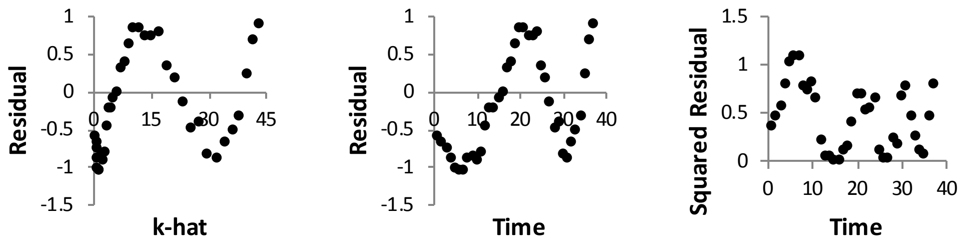
*Indicates the coefficient is significant at 95% confidence level.

**Indicates the coefficient is significant at 99% confidence level.

5.6 Residual Tests

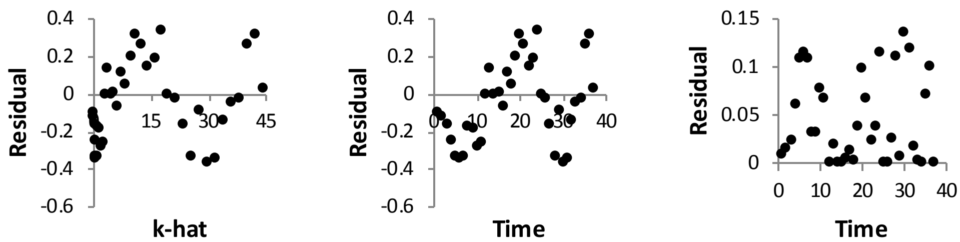
In the last chapter, the Logistic model, the Gompertz model and the Bass model are estimated with NLS method respectively. Although the estimated coefficients of all three models are statistically significant, it is necessary to test several principal assumptions of residuals in order to ensure the estimators are best and unbiased.

The residuals of regressions of the above mentioned diffusion models are plotted against predicted values and independent values respectively in Figure 5-1, 5-2 and 5-3.



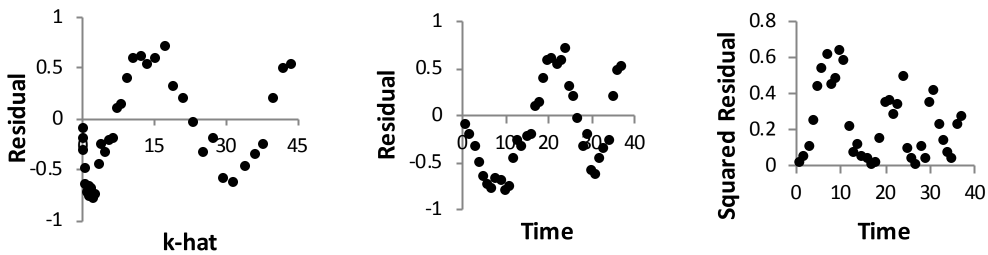
(a) (b) (c)

Figure 5-1 **Regression Residuals of the Logistic Model**



(a) (b) (c)

Figure 5-2 **Regression Residuals of the Gompertz Model**



(a) (b) (c)

Figure 5-3 **Regression Residuals of the Bass Model**

5.6.1 Heteroscedasticity

In Figure 5-1(c), 5-2(c) and 5-3(c), the squared residuals generated from regressions of the Logistic model, the Gompertz model and the Bass model are plotted against time variable respectively. Judging from the graphs, there is no systematical pattern between the independent variable and the squared residuals for all the three regression results. It indicates that none these models suffers from heteroscedasticity problem. The White test is applied to the three models and the results are listed in Table 5-7.

Table 5-7 **White Test Results**

	Logistic Model	Gompertz Model	Bass Model
n*R-squared	15.34095449	3.33079242	4.16416223
Prob.	0.01776433	0.64913078	0.65447169

$\chi^2_{0.05}(6)$ =12.59516

As shown in Table 5-7, the chi-squared values obtained from the Gompertz model and the Bass model does not exceed the critical chi-squared value at 5% level of significance, which indicates that there is no heteroscedasticity in the regression of the Gompertz model and the Bass model. However, the chi-squared value obtained from the White test of the Logistic model shows that there is heteroscedasticity in the regression of the Logistic model.

Since the data used in the three regressions are identical, it is likely that the heteroscedasticity of the Logistic model is resulted from specification error, or more specifically, the Logistic model may not properly describe the 3G diffusion pattern in Europe. As a result, the standard errors of the coefficient estimates are biased, and therefore the t-test results are suspected.

5.6.2 Autocorrelation

It is clear from Figure 5-1(a)(b), Figure 5-2(a)(b) and Figure 5-3(a)(b) that the regression residuals of the Logistic model, the Gompertz model and the Bass model all show apparent cyclical pattern. Durbin-Watson d test and Breusch-Godfrey test from the NLS regressions also show strong evidence of first-order autocorrelation in the three models, as summarized in Table 5-8 and Table 5-9.

Table 5-8 **Results of Durbin-Watson d Test**

	Logistic Model	Gompertz Model	Bass Model
Durbin-Watson stat	0.11003375	0.48217671	0.14921566

For 37 observations, $d_L = 1.419$ at 0.05 level of significance

Table 5-9 **Results of Breusch-Godfrey Test with AR(6)**

	Logistic Model	Gompertz Model	Bass Model
n*R-squared	34.52332578	23.08728631	33.72107825
Prob.	5.32974013e-06	0.00076776	7.61516518e-06
lag 1 residual	0.95396516**	0.73460210**	0.93142945**
	(0.18701094)	(0.19294507)	(0.18780120)
lag 2 residual	0.03785360	-0.03971800	0.01404679
	(0.26063850)	(0.23739453)	(0.25736258)
lag 3 residual	0.28802354	0.32384413	0.35552824
	(0.26540838)	(0.24546658)	(0.26292625)
lag 4 residual	-0.17886555	-0.23319606	-0.25240116
	(0.26651888)	(0.24907198)	(0.26503938)
lag 5 residual	-0.10226641	-0.09064655	-0.08093467
	(0.26912732)	(0.25544352)	(0.27017132)
lag 6 residual	-0.33133352	-0.37002117	-0.39329493
	(0.22949303)	(0.25298652)	(0.24230867)

$\chi^2_{0.05}(6)$ =12.59516

**Indicates the coefficient is significant at 99% confidence level.

Standard errors are presented in parentheses.

The Durbin-Watson test and the Breusch-Godfrey test of the three models suggest that there is significant first-order autocorrelation in these models. Therefore, it is necessary to transform the dependent and independent variables accordingly to solve the problem.

The coefficients of first-order autocorrelation of the three models are estimated with regressions of residuals on the lagged value of residuals. The results are summarized in Table 5-10.

Table 5-10 **Estimation of Coefficients of Autocorrelation**

	Logistic Model	Gompertz Model	Bass Model
Coefficient of autocorrelation	0.9561** (0.0570)	0.7561** (0.1099)	0.9386** (0.0655)

**Indicates the coefficient is significant at 99% confidence level.

Standard errors are presented in parentheses.

Coefficients of first-order autocorrelation of the three models are all statistically significant. The three models are estimated again after transformation using corresponding coefficient of autocorrelation.

The regression result of the Logistic model after transformation is listed in Table 5-11.

Table 5-11 **Regression Results of the Logistic Model after Transformation**

Coefficient	Estimated value	Standard error
k	65.2873**	3.0214
r	0.1338**	0.0067
m	31.2923**	0.7347
R-squared	0.9829	
RSS	1.1348	

*Indicates the coefficient is significant at 95% confidence level.

**Indicates the coefficient is significant at 99% confidence level.

The regression result of the Gompertz model after transformation is listed in Table 5-12.

Table 5-12 **Regression Results of the Gompertz Model after Transformation**

Coefficient	Estimated value	Standard error
k	98.3808**	4.7885
r	0.0590**	0.0022
m	33.2089**	0.8467
R-squared	0.9988	
RSS	0.7019	

*Indicates the coefficient is significant at 95% confidence level.

**Indicates the coefficient is significant at 99% confidence level.

The regression result of the Bass model after transformation is listed in Table 5-13.

Table 5-13 **Regression Results of the Bass Model after Transformation**

Coefficient	Estimated value	Standard error
k	66.0840**	3.1127
p	0.0022**	0.0002
q	0.1304**	0.0067
R-squared	0.9883	
RSS	1.0606	

*Indicates the coefficient is significant at 95% confidence level.

**Indicates the coefficient is significant at 99% confidence level.

5.7 Model Comparison

The S-shaped diffusion curves over the sample period generated by the Logistic model, the Gompertz model and the Bass model are presented in Figure 5-4, and the actual annual growth in the penetration rate together with that estimated by the three models are presented in Figure 5-5. The corresponding estimation results of each model are listed in Table 5-14.

Two intuitive findings can be drawn from the Figure 5-4 and Figure 5-5. Firstly, it is visible that the Gompertz model fits the 3G diffusion in Europe the best, especially in the early stage of diffusion. Secondly, the infection point of the Logistic model and the Bass model appears in the 3rd quarter and the 4th quarter in 2010 respectively, while the infection point of the Gompertz model appears later, around the 2nd quarter in 2011. The two preliminary findings are discussed respectively to determine the best-fitting model of European 3G diffusion.

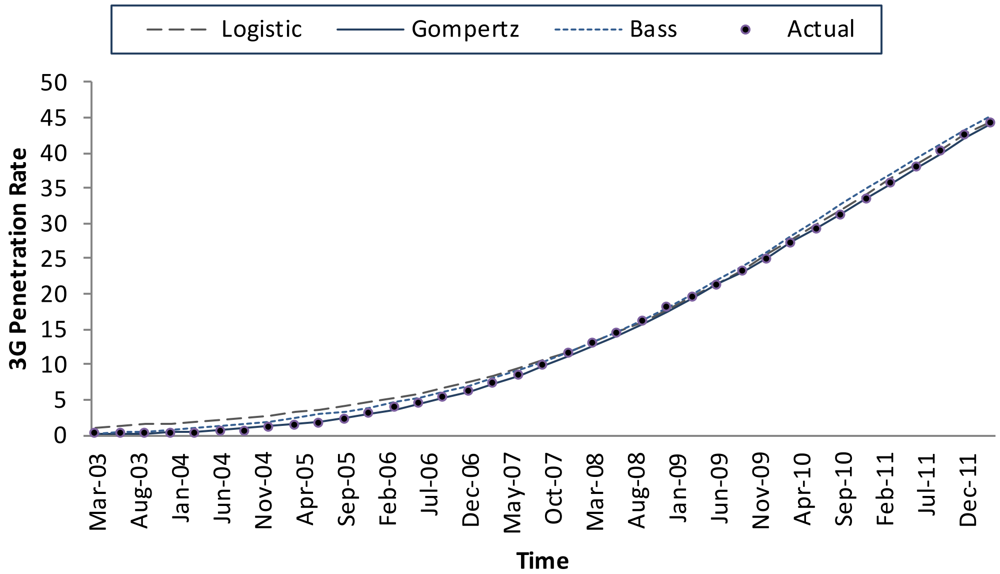


Figure 5-4 **Diffusion curves of 3G telephony**

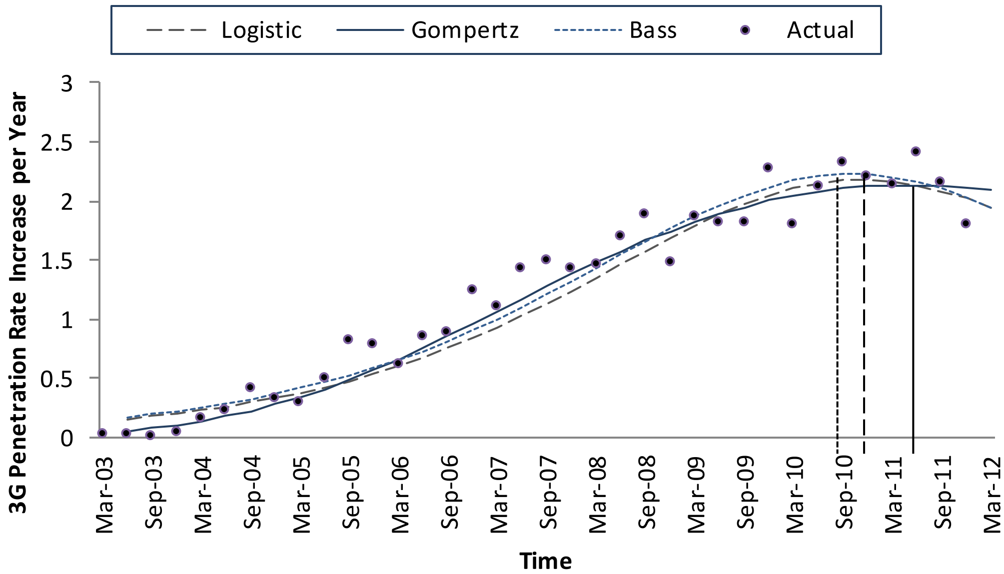


Figure 5-5 **Growth rate of 3G telephony**

As shown in Table 5-14, the estimated coefficients of all the three diffusion models are statistically significant (p<0.01).

The R-squared is a statistic that measures the goodness of fit of a model. The R-squared values for all the three diffusion models are very close to 1. Among them, the R-squared value yielded by the Gompertz model is the highest ($R^2 = 0.99980401$), which indicates that about 99.98% of the 3G diffusion pattern is explained by the Gompertz diffusion models.

The residual sum of square (RSS), on the contrary, is a measure of the discrepancy between the data and an estimation model. A small RSS indicates that the regression model fits the data well. As shown in Table 5-8, the RSS value of the Gompertz model is the lowest among the three diffusion models, indicating that the Gompertz model fits the 3G diffusion process the best among the three models. This conclusion is consistent with what the R-squared values show.

Besides the R-squared and RSS, the most frequently used criteria for fitting capability of regression models are Root Mean Square Error (RMSE) (Gupta & Jain, 2012; Chu, Wu, Kao, & Yen, 2009).

RMSE measures the difference between the predicted values of a model and the actual observed value. The smaller RMSE is, the better the model fits the reality. In this study, the RMSE are used to measure how close the predicted penetration rates to the actual ones with 37 samples. The formula of RMSE writes as the following in this study:

$$RMSE(\hat{n}, n) = \sqrt{\frac{\sum_{t=1}^{37}\left[\widehat{n(t)} - n(t)\right]^2}{37}} \tag{5.28}$$

As shown in Table 5-14, the RMSE value of the Gompertz model is the lowest among the three models, which indicates the fitness of the Gompertz model is superior to that of the Logistic model and the Bass model. Clearly, the RMSE value, together with the R-squared value and the RSS value, all support the conclusion that the Gompertz model is the best fitting model for 3G diffusion in Europe in this study.

Table 5-14 **Summary of regression results**

	Logistic model	Gompertz model	Bass model
Saturation level	k=65.2873**	k=98.3808**	66.0840**
	(3.0214)	(4.7885)	(3.1127)
Intrinsic growth rate	r=0.1338**	r=0.0590**	p=0.0022**
	(0.0068)	(0.0022)	(0.0002)
			q=0.1304**
			(0.0067)
Infection point	m=31.2923**	m=33.2089**	m=30.8985
	(0.7347)	(0.8467)	
Infection point (time)	2010Q4	2011Q2	2010Q3
R-squared	0.9829	0.9988	0.9883
RSS	1.1348	0.7018	1.0606
RMSE	1.6703	0.0020	0.8081

*Indicates the coefficient is significant at 95% confidence level.

**Indicates the coefficient is significant at 99% confidence level.

Standard errors are presented in parentheses.

The maximum market potential of 3G telecommunication in Europe estimated with the Gompertz model is much larger than that estimated with the Logistic model and the Bass model. Saturation level of diffusion of 3G telephony is about 98.38% according to the regression results of the Gompertz model. The corresponding penetration rate estimated with the Logistic mode and the Bass model is 65.29% and 66.03% respectively. Assume that the 4G technology had not been deployed and the 3G technology would not evolve in the future, the 3G diffusion will progress until a large partial of the 2G market is captured by the 3G technology. Given the fact that the mobile penetration rate in Europe has reached 136.26%, it is reasonable that saturation level of 3G telephony is close to this value, which is the case of the Gompertz model. Actually, by the end of the sample period, there are already 20 European countries where the 3G penetration rate is above 50% and 4 countries where the penetration rate is above 100%. However, it is noteworthy that the penetration rate of 3G may never reach its equilibrium level, as the 4G technology has been deployed by many European countries and more countries will adopt this technology in the near future.

Meanwhile, the infection point estimated with the Gompert model appears in the 2nd quarter in 2011, while the infection point estimated with both the Logistic model and the Bass model is in the 3rd and 4th quarter in 2010 respectively. The infection point of diffusion is of significant practical interest. The growth rate of 3G penetration rate, or the number of new subscribers, peaks at the infection point, and declines gradually afterwards. Prior to the infection point, a mobile operator may enjoy stable growth in revenue which is benefitted from the natural growth of 3G subscription. Once the infection point is reaches, the growth rate of new 3G subscription declines, therefore the competition for new subscribers becomes more intense. A mobile operator is then forced to reduce prices, expend more resources in customer retention programs, or invest in new technologies, namely 4G technologies. The observed 3G diffusion process suggests that average growth rate of 3G penetration rate is higher in 2011 than that in 2010 (Figure 5-5). It supports the regression results of the Gompertz model, which, again, proves the Gompertz model the best-fitting model for European 3G diffusion.

In the rest of the study, the Gompertz model will be used to estimate the 3G diffusion pattern in each European country for further discussion.

6 3G Diffusion in European Countries

In Section 5, the Logistic model, the Gompertz model and the Bass model are estimated respectively with 3G penetration rate in data in Europe. The Gompertz model is identified as the best-fitting model for 3G diffusion in Europe. In this section, the 3G diffusion pattern in each European country will be analyzed.

6.1 Data

"European countries" in this study refers to member states of the Council of Europe. However, San Mario is not included because the mobile subscription data of this country is missing in the database used in this study. Therefore, 3G diffusion processes of 46 countries are analyzed in this section.

The actual 3G penetration rates in each country are plotted against time. The start time of 3G telephony in each country is numbered as t=1, and the rest quarterly data samples are numbered as t=2, 3, 4… respectively within the sample period of each country.

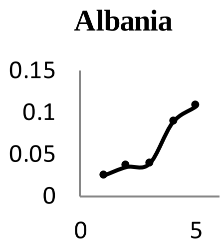
It is apparent from Figure 6-1(1)-(46) that the 3G diffusion patterns in some European countries cannot be explained with the diffusion theory. For example, the 3G subscription increased from 21,500 in the 1st quarter to 266,090 in the 2nd quarter in 2009. 3G penetration rate therefore increased from 1.05% to 12.95% with the growth rate of 1137.31%. Such growth rate is much higher than the average growth rate during the entire diffusion process (38.64%). This dramatic increase in 3G penetration rate was resulted by a major activity of the market leader, in this case T-Mobile Macedonia. T-Mobile Macedonia switched over 240,000 of its 2G subscribers to its 3G networks as soon as it launched its 3G networks. The similar situation occurs in Azerbaijan. In Azerbaijan, after two major network operators in Azerbaijan, Azercell and Bakcell launched 3G services in the 4th quarter in 2011, the 3G penetration rate increased by 86.77%, in contrast with a growth rate of 14.60% in the 3rd quarter in 2011. Apparently, the 3G diffusion processes in Macedonia and in Azerbaijan were seriously influenced by activities of market leaders. Such impact factor is not in accordance with the underlying theory of any diffusion model discussed above. Therefore, the data samples from Macedonia and Azerbaijan are excluded in the following study.

The 3G diffusion pattern in Russia is also seriously influenced by major market players. The charts show that the 3G penetration rate grows very slowly in the early stage, and starts to grow with a much higher rate from a specific time spot. Since 3G network was first deployed in Russia in the 1st quarter in 2003, 3G penetration rate remained very low (less than 1%) for over 5 years. However, from the 2nd quarter in 2008 to the 1st quarter in 2012, the 3G penetration rate grew from 1.29% to 13.01%. This high-rate growth was mainly driven by the development of W-CDMA networks, which were rolled out in Russia in the 2nd quarter in 2008. Prior to that, all 3G networks in Russia were based on CDMA2000 1x technology. As discussed in Section 4, the CDMA2000 1x is not compatible with GSM, the dominant 2G standard, which severely hindered its diffusion. Therefore, 3G subscriptions increased rapidly only after the W-CDMA networks were launched. Meanwhile, three largest network operators, MegaFon, MTS and VimpelCom did not join the competition of CDMA networks at all. These operators initiated W-CDMA networks in the 2nd quarter in 2008, a year after they were awarded W-CDMA licenses from the regulatory authority. The high-rate increase of 3G subscription was therefore driven not only by the W-CDMA technology itself, but also by the power of major market players. Clearly, under the circumstance of imperfect competition, the diffusion pattern in Russia is not in accordance with the diffusion theory. In order to make a more accurate estimation of the 3G diffusion curve in Russia, the samples from 2003Q1 to 2008Q1 are not included in the following study.

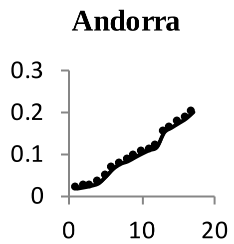
The 3G diffusion pattern in Montenegro does not follow the S-shaped diffusion model either. 3G penetration rate in Montenegro peaked at 25.61% in the 1st quarter in 2010, and then declined to 15.33% by the end of 2011. This is because a major network operator in Montenegro, MTEL, has started to drag its 3G subscribers back to 2G network since the beginning of 2010 due to high operational cost of 3G network. Therefore, Montenegro is excluded in the following study.

Another country excluded is Albania. There are merely 5 observed sample of its 3G diffusion in Albania, which may lead to inaccurate regression.

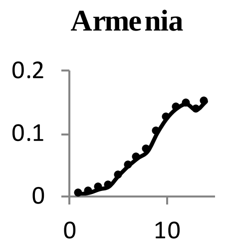
Based on the discussion above, 3G diffusion patterns of 42 European countries are analyzed in the next part of this section.



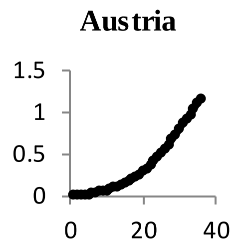
(1)



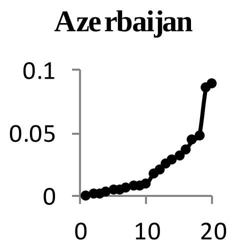
(2)



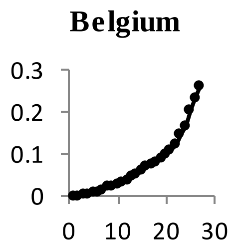
(3)



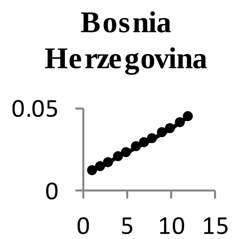
(4)



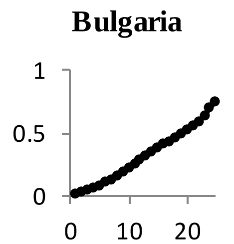
(5)



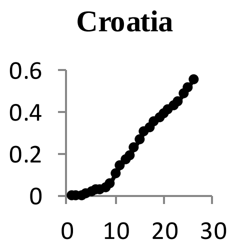
(6)



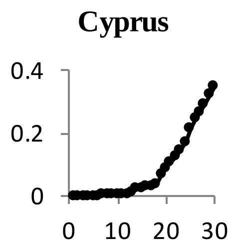
(7)



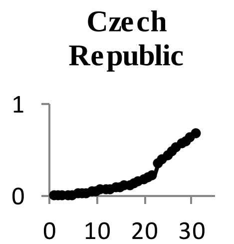
(8)



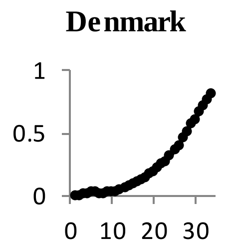
(9)



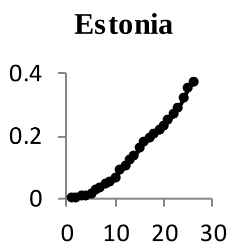
(10)



(11)

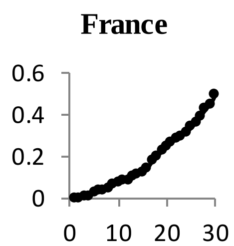


(12)

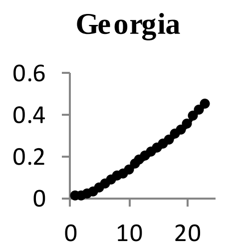


(13)

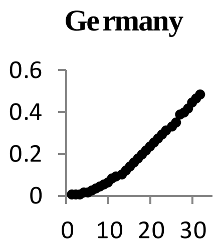
(14)



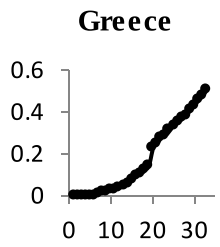
(15)



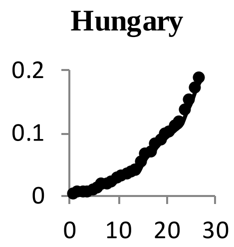
(16)



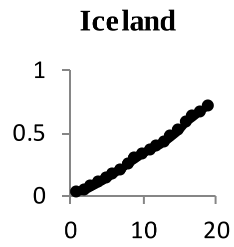
(17)



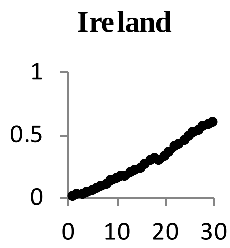
(18)



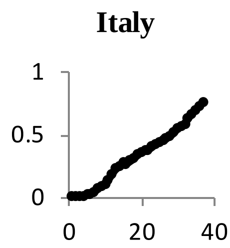
(19)



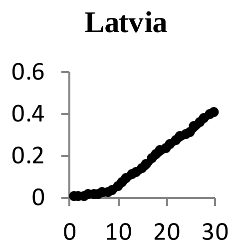
(20)



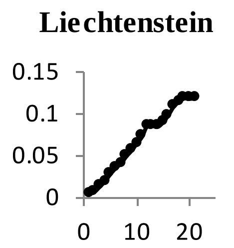
(21)



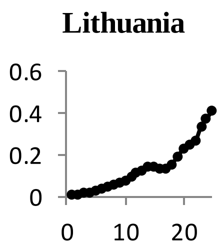
(22)



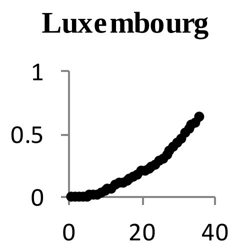
(23)



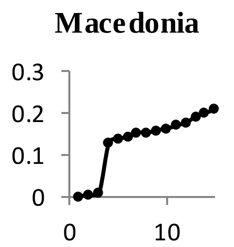
(24)



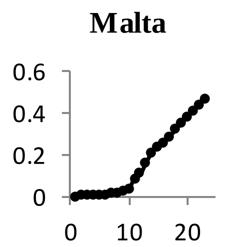
(25)



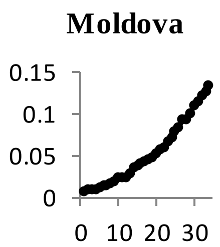
(26)



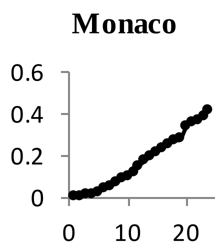
(27)



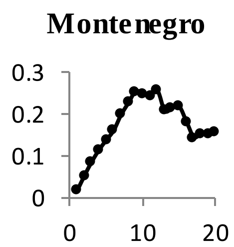
(28)



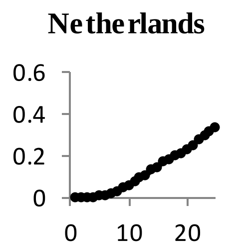
(29)



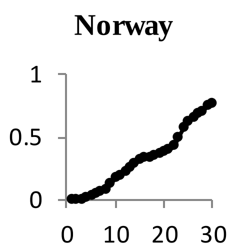
(30)



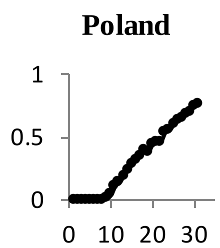
(31)



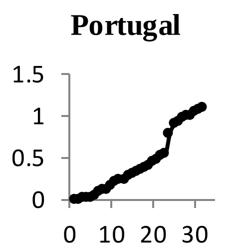
(32)



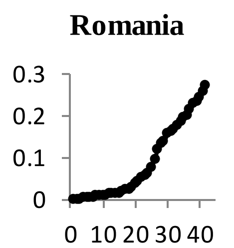
(33)



(34)



(35)



(36)

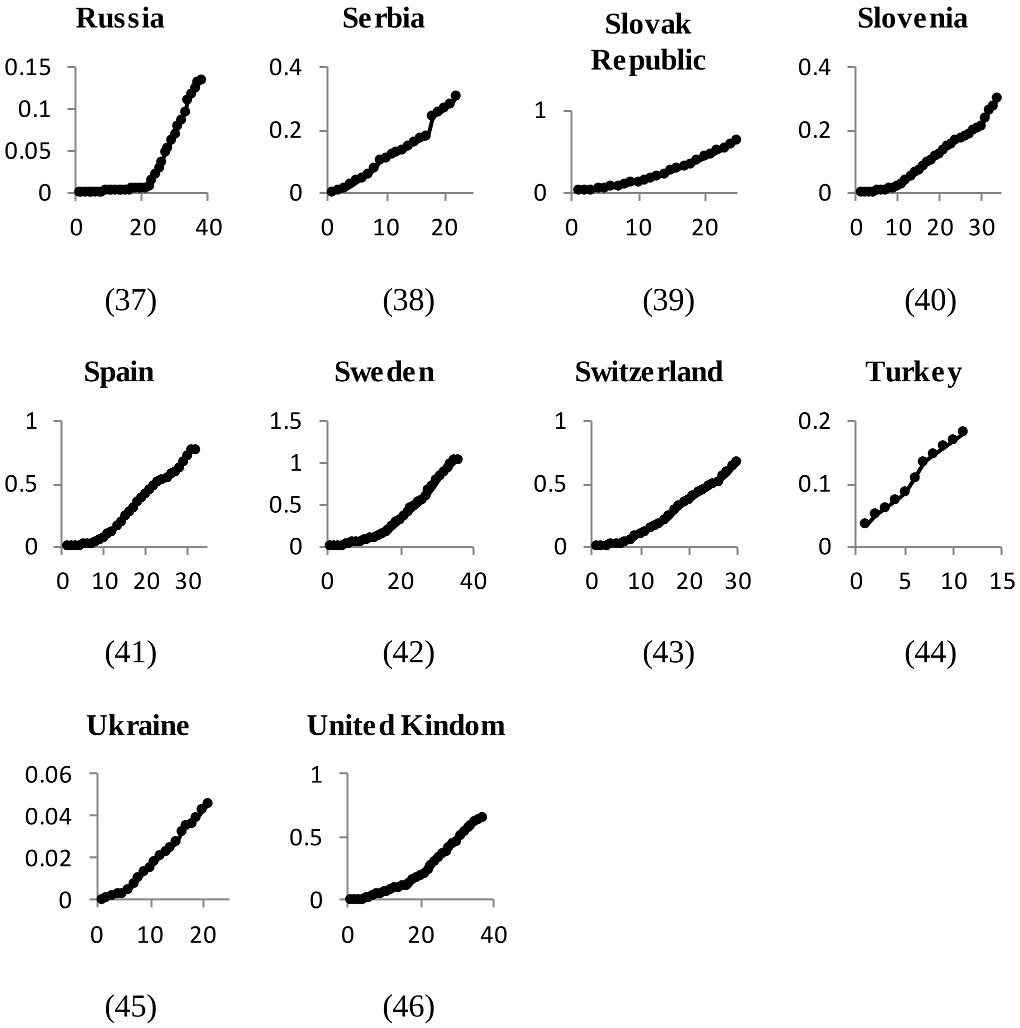


Figure 6-1 **Diffusion of 3G telephony in European countries**

6.2 Regression Results

In this part of study, the 3G diffusion pattern in each European country is analyzed under the framework of diffusion theories. The first step is to estimate the major coefficients of diffusion, namely the saturation level, the intrinsic growth rate and the infection point of 3G diffusion in each country. In order to compare the 3G diffusion pattern among each European country and with the average Europe level, it is necessary to adopt one specific model to estimate the diffusion coefficients. The Gompertz model is selected for the sake of consistency.

In order to enhance the accuracy of estimation, the diffusion coefficients are first estimated with OLS method, and the results are used as initial values of NLS estimation. The NLS regressions to 3G diffusion patterns of European countries are all based on Gausss-Newton method.

The estimation results of 3G diffusion in 42 European countries are listed in Table 6-1.

***Table 6-1* Regression results of diffusion of 3G telephony in European countries**

Country	Obs.	Saturation level	Intrinsic growth rate	Infection point	Infection time	R-squared	RSS	RMSE
Andorra	17	40.9931**	0.0922**	13.3690**	2011Q2	0.9897	6.0158	0.5949
		(9.051)	(0.0161)	(2.4597)				
Armenia	14	17.4468**	0.2985**	6.9386**	2010Q2	0.9866	5.6897	0.6375
		(1.2767)	(0.0435)	(0.3467)				
Austria	36	355.5924**	0.0511**	38.2501**	2012Q4	0.9997	11.5671	0.5668
		(15.0812)	(0.0012)	(0.7559)				
Bosnia Herzegovina	12	9.9125**	0.0859**	9.4956**	2011Q3	0.9984	0.0192	0.0400
		(1.3180)	(0.0094)	(1.5693)				
Bulgaria	25	123.3129**	0.0784**	17.4143**	2010Q2	0.9945	65.7005	1.6211
		(12.2962)	(0.0071)	(1.3806)				
Croatia	26	62.1466**	0.1445**	14.1363**	2009Q2	0.9957	37.9586	1.2083
		(2.4433)	(0.0093)	(0.3551)				
Cyprus	30	79.8200**	0.1007**	27.9388**	2011Q3	0.9982	6.6167	0.4696
		(7.8234)	(0.0070)	(0.9739)				

Table 6-2 **(Continued)**

Country	Obs.	Saturation level	Intrinsic growth rate	Infection point	Infection time	R-squared	RSS	RMSE
Czech Republic	31	211.3733**	0.0687**	32.3736**	2012Q3	0.9869	190.4771	2.4788
		(71.4457)	(0.0132)	(4.5178)				
Denmark	34	342.2992**	0.0501**	41.0230**	2014Q1	0.9989	22.6234	0.8157
		(41.7806)	(0.0029)	(2.0518)				
Estonia	26	61.1481**	0.0868**	19.0883**	2010Q3	0.9943	19.5038	0. 8661
		(6.4344)	(0.0082)	(1.3196)				
Finland	30	314.6938**	0.0556**	30.5945**	2012Q2	0.9960	146.2347	2.2078
		(50.9617)	(0.0054)	(2.7178)				
France	30	118.5212**	0.0578**	28.3235**	2011Q4	0.9966	22.3705	0.8635
		(14.9341)	(0.0047)	(2.1115)				
Georgia	23	85.6270**	0.0789**	18.1134**	2011Q1	0.9950	20.5415	0.94504
		(10.6583)	(0.0078)	(1.6434)				
Germany	32	76.8452**	0.0757**	22.5674**	2009Q4	0.9990	7.8695	0.4959
		(2.8066)	(0.0027)	(0.5362)				

Table 6-3 **(Continued)**

Country	Obs.	Saturation level	Intrinsic growth rate	Infection point	Infection time	R-squared	RSS	RMSE
Greece	33	63.6463**	0.1160**	21.3231**	2009Q2	0.9943	54.9384	1.2903
		(3.5022)	(0.0087)	(0.5860)				
Hungary	27	148.8292	0.0398**	45.7730**	2016Q4	0.9937	4.9603	0.4286
		(80.4765)	(0.0076)	(9.8572)				
Iceland	19	120.3947**	0.1023**	13.2147**	2010Q4	0.9951	42.9616	1.5037
		(13.2456)	(0.0103)	(1.1697)				
Ireland	30	103.1049**	0.0671**	21.3584**	2010Q1	0.9953	48.1427	1.2668
		(8.9399)	(0.0052)	(1.3982)				
Italy	37	100.7606**	0.0661**	21.7464**	2008Q2	0.9825	334.3690	3.0062
		(10.2885)	(0.0077)	(1.7999)				
Latvia	30	52.7455**	0.1039**	18.1896**	2009Q2	0.9978	12.1930	0.6375
		(1.9467)	(0.0049)	(0.4303)				
Liechtenstein	21	13.8643**	0.1542**	8.2818**	2009Q1	0.9927	2.2353	0.3263
		(0.5612)	(0.0116)	(0.3504)				

Table 6-4 **(Continued)**

Country	Obs.	Saturation level	Intrinsic growth rate	Infection point	Infection time	R-squared	RSS	RMSE
Luxembourg	36	220.6585**	0.0429**	41.2797**	2013Q3	0.9964	48.0655	1.1555
		(39.0444)	(0.0039)	(3.6209)				
Malta	23	56.9733**	0.1792**	14.5863**	2010Q1	0.9954	27.5453	1.0944
		(3.0503)	(0.0143)	(0.3790)				
Moldova	34	88.2709**	0.0282**	56.4208**	2017Q1	0.9986	0.7254	0.1461
		(16.9609)	(0.0021)	(5.1949)				
Monaco	24	67.3746**	0.0948**	16.3905**	2010Q2	0.9967	14.1787	0.7686
		(4.8913)	(0.0067)	(0.8533)				
Netherlands	32	125.4627**	0.0583**	29.0229**	2011Q3	0.9946	50.3399	1.2542
		(18.0494)	(0.0057)	(2.4371)				
Norway	30	152.9518**	0.0619**	24.0674**	2010Q4	0.9828	300.4292	3.1645
		(32.1499)	(0.0101)	(3.5170)				
Poland	31	86.8202**	0.1273**	16.8497**	2008Q3	0.9922	172.5852	2.3595
		(4.0908)	(0.0102)	(0.4891)				

Table 6-5 **(Continued)**

Country	Obs.	Saturation level	Intrinsic growth rate	Infection point	Infection time	R-squared	RSS	RMSE
Portugal	32	242.8598**	0.0620**	27.1115**	2011Q1	0.9782	949.0455	5.4459
		(60.9362)	(0.0116)	(4.1238)				
Romania	41	36.1589**	0.0877**	28.0418**	2009Q1	0.9949	16.5908	0.6361
		(2.0008)	(0.0059)	(0.7531)				
Russia	16	19.5090**	0.1303**	8.0920**	2010Q2	0.9979	0.5130	0.179059
		(0.9640)	(0.0079)	(0.4372)				
Serbia	22	69.6121**	0.0727**	19.6488**	2011Q3	0.9816	34.5470	1.2531
		(21.8827)	(0.0159)	(4.2829)				
Slovak Republic	25	205.9596**	0.0565**	28.1205**	2013Q1	0.9994	5.7323	0.4788
		(16.9536)	(0.0025)	(1.3050)				
Slovenia	34	45.7362**	0.0711**	24.5157**	2009Q4	0.9892	30.2698	0.9436
		(5.5275)	(0.0080)	(1.8747)				
Spain	32	94.0788**	0.1072**	18.5306**	2008Q4	0.9957	92.0559	1.6961
		(4.0049)	(0.0065)	(0.4967)				

Table 6-6 **(Continued)**

Country	Obs.	Saturation level	Intrinsic growth rate	Infection point	Infection time	R-squared	RSS	RMSE
Sweden	36	214.0630**	0.0642**	30.3381**	2011Q4	0.9989	45.9186	1.1294
		(11.1466)	(0.0026)	(0.8389)				
Switzerland	30	94.9472**	0.0891**	19.6334**	2009Q3	0.9973	35.7682	1.0919
		(4.7721)	(0.0049)	(0.6512)				
Turkey	11	25.6938**	0.1794**	5.0306**	2010Q4	0.9936	1.6808	0.3909
		(2.6265)	(0.0242)	(0.6491)				
Ukraine	21	6.6925**	0.1205**	13.5133**	2010Q2	0.9971	0.1336	0.0798
		(0.4228)	(0.0082)	(0.6040)				
UK	37	140.8515**	0.0564**	31.7801**	2010Q4	0.9982	30.4185	0.9067
		(9.7562)	(0.0029)	(1.2489)				

*Indicates the coefficient is significant at 95% confidence level.

**Indicates the coefficient is significant at 99% confidence level.

Standard errors are presented in parentheses.

Table 6-1 shows that 3G diffusion patterns of most European countries are well described with the Gompertz model. For most countries, the estimated coefficients are statistically significant at the 99% level. Meanwhile, the R-squared values of 40 countries are larger than 0.97, and for 32 countries the R-squared value is larger than 0.99, indicating that estimated diffusion curves fit the observed data well. The F statistics of 40 countries are higher than corresponding critical values of F at 99% confidence level, which indicates that it is justified to use the Gompertz model to fit the 3G diffusion processes in these European countries.

Three exceptions are Belgium, Hungary and Lithuania. The estimates for Belgium and Lithuania fail to meet the convergence criteria after 500 iterations, and therefore it is likely that the 3G diffusion in these countries do not follow an S-shaped curve. The estimated 3G diffusion curve for Belgium generated by the previously defined regression processes is plotted together with the observed penetration rates in Figure 6-2. It is hard to determine from the chart whether the 3G diffusion pattern in Belgium follows an S-shaped curve. However, when the second order differential of the observed diffusion data is plotted against time, it is clear that the 3G diffusion in Belgium is not in accordance with the nature of an S-shaped model. The slope of an S-shaped curve is relatively small at the early stage, and it keeps increasing until the infection point is reached. The slope of the curve starts to decline thereafter, and it approaches zero at equilibrium level. Meanwhile, the second derivative of the function of an S-shaped curve is positive prior to the infection point and is negative afterward. Figure 6-3 shows that the second derivative of the observed samples in Belgium fluctuates around zero, which apparently violate the nature of the S-shaped model. Similar situation occurs in Lithuania. It is apparent from Figure 6-4 that the 3G diffusion in Lithuanian does not follow the S-shaped pattern. An in depth analysis of the observed data shows that 3G diffusion in Lithuania is not in accordance with the nature of an S-shaped model, as shown in Figure 6-5.

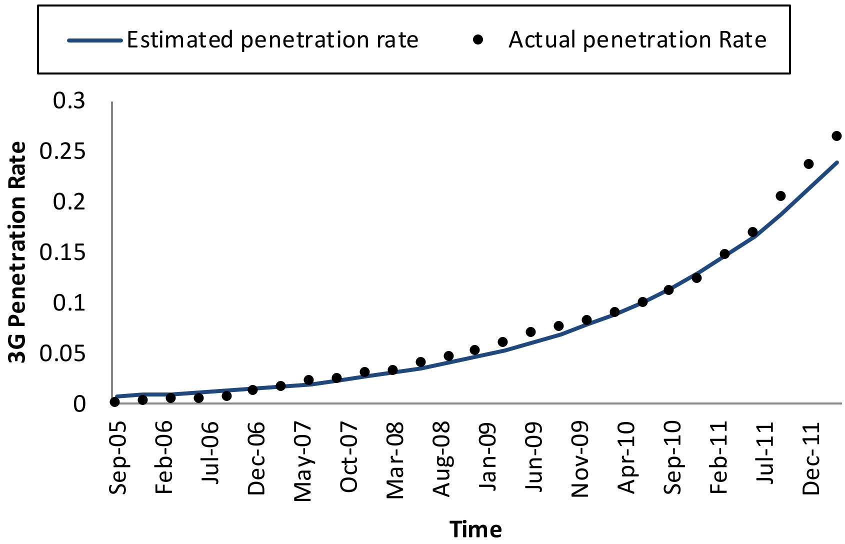


Figure 6-2 **Estimated 3G diffusion in Belgium**

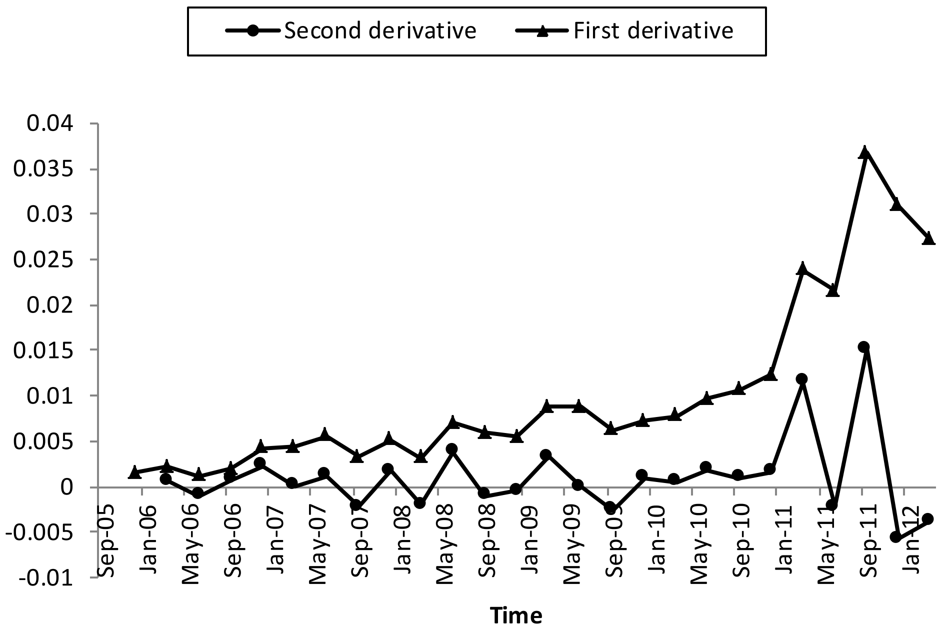


Figure 6-3 **First and second derivative of 3G diffusion in Belgium**

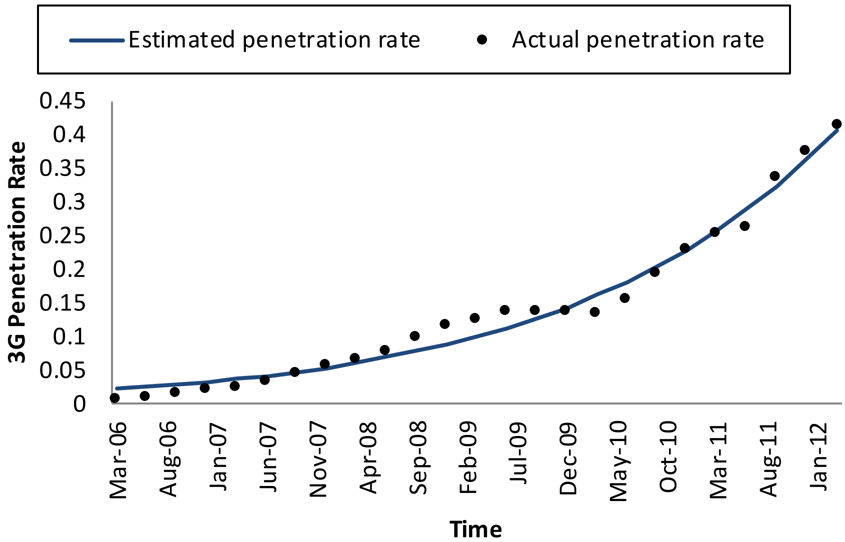


Figure 6-4 **3G diffusion in Lithuania**

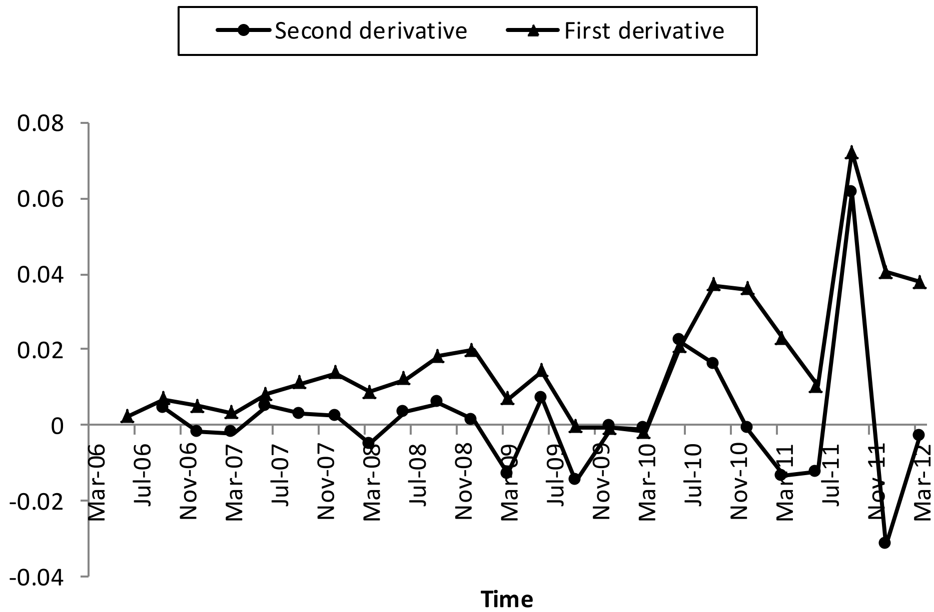


Figure 6-5 **First and second derivate of 3G diffusion in Lithuania**

The estimated saturation level of diffusion of 3G telephony in Hungary is not statistically significant at the 95% level. Although the estimated intrinsic growth rates and the coefficients of infection points are statistically significant, the reliability of the results is doubtful. It is likely that the Gompertz model is not suitable for describing the 3G diffusion pattern in Hungary.

Based on the discussion above, Belgium, Lithuania and Hungary are not included in the following study.

6.3 3G Diffusion Patterns of European Countries

In the previous chapters, the observed 3G diffusion in Albania, Azerbaijan, Belgium, Hungary, Lithuania, Macedonia and Montenegro are found inconsistent with the S-shaped diffusion model, and therefore are excluded in the following study. In order to keep the 3G diffusion pattern in the whole Europe comparable with that of each European country, the 3G diffusion pattern of 39 European countries as a whole is estimated again with the Gompertz model. The results are listed in Table 6-2.

***Table 6-7* NLS regression result of the Gompertz model with aggregated 3G penetration rate in 39 European countries**

Coefficient	Estimated value	Standard error
k	91.4642**	3.9256
r	0.0610**	0.0021
m	32.3014**	0.7306
R-squared	0.9990	
RSS	0.6576	
RMSE	0.1953	

*Indicates the coefficient is significant at 95% confidence level.

**Indicates the coefficient is significant at 99% confidence level.

The distribution of saturation levels of the diffusions of 3G telephony in 39 European countries is presented in Figure 6-6, and relevant statistics are listed in Table 6-3. Saturation levels of diffusion of 3G telephony in the 39 European countries show great variability. Austria shows the largest market potential of 3G technology, measured with penetration rate (m=355.59).

In other words, the number of 3G subscriptions in Austria may eventually count 355.59% of its total population if the diffusion process continues under the assumption of the Gompertz model. On the other hand, the saturation level of the diffusion of 3G telephony in Ukraine is merely 6.69%. That is, 3G subscriptions may count merely 6.69% of its total population, even when the market is completely mature. For Europe as a whole, the maximum 3G penetration rate may reach 91.46% eventually. It is higher than the median level of the 39 European countries (m=86.82). The average absolute deviation from the overall saturation level in Europe is 63.78, and the median average deviation of the 39 European countries is 38.64. Both of these measures of dispersion show that the saturation levels of diffusion of 3G telephony in the 39 European countries also vary greatly.

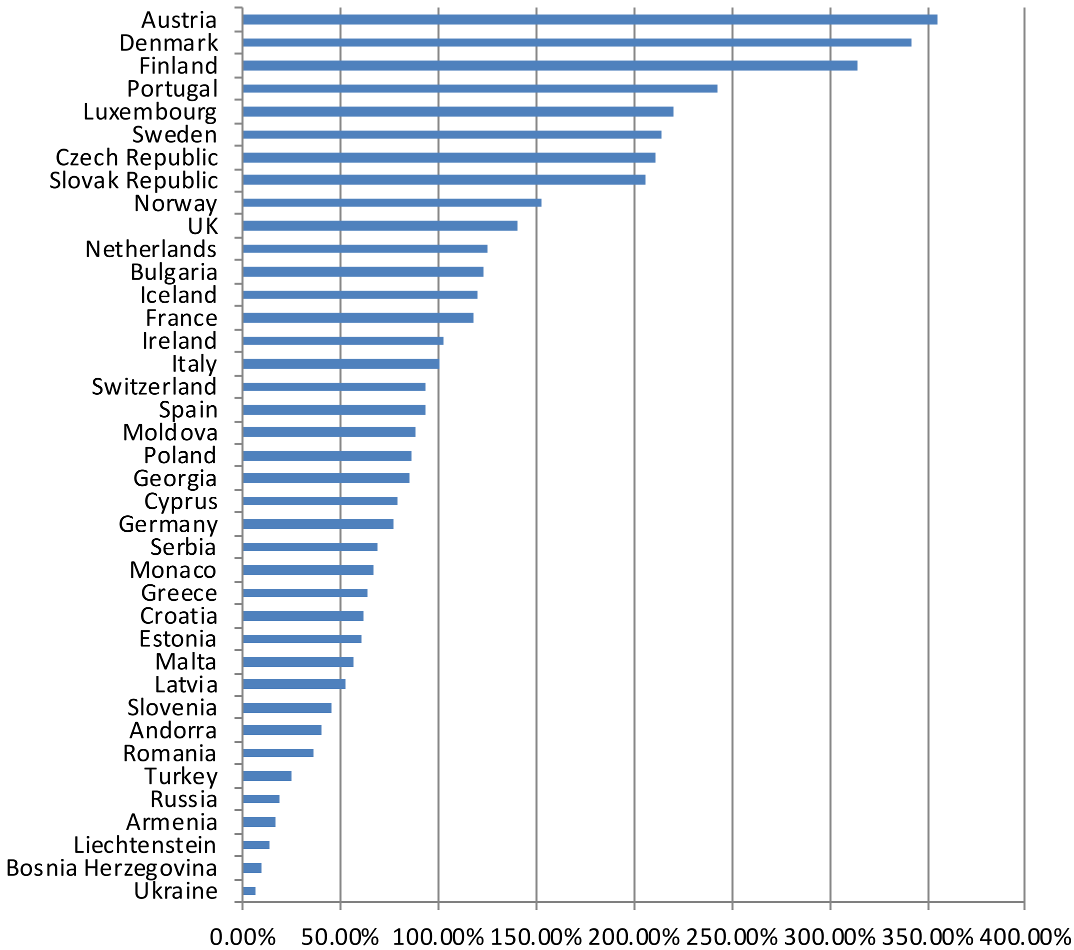


Figure 6-6 **Saturation level of diffusion of 3G telephony in European countries**

Table 6-8 **Statistics for saturation level of diffusion of 3G telephony in European countries**

	Saturation level
Maximum	355.5924
Minimum	6.6925
Median	86.8202
Overall European level	91.4642
Average absolute deviation from the overall European level	63.7842
Median absolute deviation	38.6425

It is clear from the analysis above that the 3G diffusion pattern in each European country highly varies from one another. Previous studies show that such variation is likely to be influenced by specific external factors (Rouvinen, 2006; Jang, Dai, & Sung, 2005). In the next section, the external determinants of saturation level of 3G diffusion in European countries are analyzed in depth.

7 Determinants of 3G Diffusion in Europe

7.1 Control Scheme of the Gompertz Model

As discussed in Section 5, the Gompertz model was first developed as a model of human mortality. The rationale behind the model is that "the average exhaustions of a man's power to avoid death were such that at the end of equal infinitely small intervals of time, he lost equal portions of his remaining power to oppose destruction". In other words, the number of survivals at any given age is a function of the age variable, and the maximum "power to oppose destruction" and the rate at which such power declines are the major coefficients.

When the Gompertz model is used to describe a diffusion pattern, the process of human mortality becomes a metaphor of the process how one adopts a new technology. Equation (7.1) presents the fractional growth rate of the number of adopters of a new technology. It is clear that the value of fractional growth rate is completely controlled with the coefficient *r*. Therefore, the coefficient *r* is considered as the intrinsic growth rate of a diffusion pattern.

$$\frac{dN(t)}{N(t)dt} = re^{-r(t-m)} \tag{7.1}$$

The other major coefficient in the Gompertz model is the saturation level of diffusion. As shown in equation (5.4), although cumulative number of adopters at time t is determined by *K*, *r* and *m* simultaneously, coefficient *K* is independent from coefficients *r* and *m*. Therefore, the saturation level of diffusion is completely expressed by coefficient *K* in the Gompertz model. The saturation level is either measured by the number of adopters, or by the amount of revenues, or by the penetration rate of an innovation, as in this study.

The coefficient of infection point *m* is hardly considered as part of the control scheme of the Gompertz model. Assume that the time variable used in the Gompertz model ranges in $(-\infty, +\infty)$. As the time variable approaches negative infinity, the dependent variable approaches 0. In other words, the introductory phase of a diffusion process is infinitely long, which is clearly inconsistent with reality. The coefficient m is therefore added in the model to adjust the length of the introductory phase of a diffusion pattern.

In the next chapter, the nature and possible determinants of the saturation level of diffusion of 3G telephony are discussed in depth.

7.2 Influential Factors of Saturation Level of Diffusion

As discussed in Section 4, the saturation level of diffusion is determined by both the demand and the supply of an innovation. For an individual, his/her decision to adopt an innovation is determined by the extent to which the characteristics of an innovation match his/her own characteristics. For a whole social system, the cumulative demands to an innovation are partially determined by the socioeconomic characteristics and communication behaviors of the whole society. Meanwhile, the characteristics of an innovation are mainly determined by the suppliers of the innovation. The saturation level of diffusion of an innovation is therefore determined by the equilibrium of the demands and the supplies.

It is clear that the supplies and demands determine the saturation level of an innovation simultaneously. However, neither the supplies nor the demands can be measured accurately in empirical studies. Therefore, it is more practical to study the factors that influence the demands and the supplies, and to find out how these factors influence the saturation level of the diffusion eventually.

Possible determinants of the demands and the supplies of 3G telephony are discussed respectively.

7.2.1 Possible Determinants of the Demands to 3G Telephony

For an individual, his/her decision to adoption is determined by three factors: personality, socioeconomic characteristics and communication behaviors. For a whole society, on the other hand, unique characteristics of each individual are likely to be offset by that other individuals and are of minimal significance. Only the commonly shared characteristics and the average behaviors can be observed. Rogers (1983) reviewed previous studies in innovation adoption and listed 29 Generalizations about the characteristics of adopters in different categories. Those characteristics that can be generalized in a whole social system are discussed below.

1. **Education:** It is assumed that the overall demand to a new technology is higher for a social system with a higher level of education than that with a lower level of education. In this study, the level of education of each country is measured by the percentage of labor force with secondary education or tertiary education.
2. **Literacy:** For a country with higher literacy rate, the demand for a new technology is likely to be higher than those countries with lower literacy rate.
3. **Social status:** Demand for a new technology is likely to be higher for those countries where average social status is higher. Social status is likely to be indicated by such variables as income, level of living, possession of wealth, occupational prestige and so on. In most occasions, those who have higher income may enjoy higher social status. Therefore, it is convenient to use income measures to describe social status. In this study, the measure of income is GDP per capita.
4. **A commercial economic orientation:** For a society with a commercial instead of a subsistence economic orientation, the demand to a new technology is relatively high. However, there are no quantitative measures to this characteristic. Since this characteristic does not play a direct or significant role in the demand for a new technology, it is not included in this study.
5. **A more favorable attitude toward credit:** It is assumed that for those countries where overall attitude toward credit is more favorable, the demand for a new technology is likely to be higher. This characteristic is measured by domestic credit to private sector as a percentage of GDP in this study.

6. **Exposure to mass media:** In a society where people are more exposed to mass media, the information about a new technology spreads more widely, which increases the demand for the innovation. The level of exposure is also hard to measure with a quantitative measure. A possible proxy of this characteristic is the penetration rate of Internet, because Internet is gradually becoming one of the mainstream media, especially in relatively developed countries.
7. **Interconnectedness:** Information spreads faster in a society with higher level of interconnectedness. It may also lead to higher demands for an innovation. The level of interconnectedness can hardly be measured by a single quantitative indicator. The proxy measure used in this study is the population living in the largest city as a percentage of total population of a country.
8. **Others:** Rogers also concluded other characteristics of adopters that may have a positive influence on the demand for an innovation, including the ability to cope with uncertainty, a more favorable attitude toward changes, less dogmatic personality and so on. Although these characteristics are not likely to be measured with a single quantitative indicator, they may in accordance with features of relatively young persons. In this study, population aged from 15 to 64 as a percentage of population is used as a proxy of these characteristics.

7.2.2 Possible Determinants of the Supply to 3G Telephony

An individual's decision to adopt an innovation is also influenced by the supply of the innovation. More specifically, the quality and quantity of supply determines the intrinsic characteristics of an innovation, and further influences the decision of adoption. The determinants of the supply of an innovation may influence the saturation level of an innovation indirectly.

Most determinants of the supply of an innovation are industrial-level factors. Several possible determinants are discussed below.

1. **Competition:** In a highly competitive market, an innovation tends to be imitated rapidly after it is released to the market. As a result, the price of the new technology reduced to a

level which is only marginally higher than the cost. More people can afford the adoption, and the saturation level of the diffusion tends to be higher. Meanwhile, in a highly competitive market, firms devote themselves in creating differential advantages over each other. One of the major strategies is to improve the innovative product to better meet the demands. Therefore, fierce competition in a country may lead to a relatively high saturation level of the diffusion. In order to describe the competition within a country with higher accuracy, two measures are used in this study: one is the Herfindahl-Hirschman index (HHI) in the telecommunication market of a country, the other is the number of mobile network operators in a country.

2. **Resources:** When resources used for an innovation is limited, the supply of the innovative product or service is also limited in quantity, and the price of the innovation is driven high. As a result, the saturation level of the diffusion of the innovation is relatively low. In mobile telecommunication industry, the major resources are radio spectrum and network license. In this study, the auction prices for 3G licenses and the band size of released radio spectrum in each country are used as measures of resources.
3. **Substitution:** If an innovation can be substituted by an alternative, or if part of the functions of an innovative product is the same as that of its previous generation, people may choose to adopt the alternative product, or remain as users of the previous generation. Therefore, the saturation level of the diffusion is lower for an innovation that can be easily substituted. The major substitutions to the 3G telephony include 2G telephony and fixed Internet, since 3G technology functions as both mobile voices and mobile broadband. In this study, the penetration rate of 2G telephony and the penetration rate of Internet in each country are used as measures of substitution. It is noteworthy that the penetration rate of Internet is also used to measure the extent to which people are exposed to mass media. Therefore, the influence that Internet penetration rate has on the saturation level of 3G diffusion is blurred.

7.3 Model

Possible determinants of the saturation level of diffusion and corresponding indicators are discussed in Chapter 7.2. In following chapters, the saturation level of 3G diffusion in 39 European countries are modeled with the above mentioned indicators to determine the influence of each determinant.

The saturation level of the diffusion of 3G technologies in a country is determined by the demand and supply of 3G telephony simultaneously. Assume that both the demand and the supply have a linear effect on the saturation level. The saturation level of diffusion can be expressed with the following equation:

$$K_i = f\left(D_i, S_i\right) = \mathrm{A} + \mathrm{B}_1 D_i + \mathrm{B}_2 S_i \tag{7.2}$$

where D_i refers to the level of demand in country *i* and S_i refers to the level of supply. B_1 and B_2 are coefficients of demand and supply respectively. A is a constant.

As discussed in Chapter 7.2, the demand and supply of an innovation is determined by several exogenous factors. Further assume that each factor has a linear effect on the demand or the supply. The saturation level of diffusion can be expressed with equation (7.3):

$$\begin{aligned} K_i &= \mathrm{A} + \mathrm{B}_1\left[g\left(X_{i,d}\right)\right] + \mathrm{B}_2\left[h\left(X_{i,s}\right)\right] \\ &= \mathrm{A} + \mathrm{B}_1\left(\alpha_d + \beta_d X_{i,d}\right) + \mathrm{B}_2\left(\alpha_s + \beta_s X_{i,s}\right) \\ &= (\mathrm{A} + \mathrm{B}_1\alpha_d + \mathrm{B}_2\alpha_s) + \mathrm{B}_1\beta_d X_{i,d} + \mathrm{B}_2\beta_s X_{i,s} \end{aligned} \tag{7.3}$$

where $X_{i,d}$ is a vector of variables that influence the demand in country i, $X_{i,s}$ is a vector of variables that influence the supply. β_d and β_s are vectors coefficients of the demand and that of the supply respectively.

In order to determine the influences of the factors discussed in Chapter 7.2, the model is specified as equation (7.4):

$$
\begin{aligned}
K_i &= \alpha + \beta_1 EDU + \beta_2 LR + \beta_3 GDPPC + \beta_4 CR + \beta_5 POPILC + \beta_6 POPY \\
&+ \beta_7 PRI + \beta_8 HHI + \beta_9 NUM + \beta_{10} APL + \beta_{11} BAND + \beta_{12} PR2G + \varepsilon_i
\end{aligned} \tag{7.4}
$$

where ε_i is the error term.

Model (7.4) is estimated with an appropriate econometric method in the following chapters.

7.4 Data

Table 7-1 presents the definitions and descriptive statistics of the variables that are usable in the regression analysis.

Table 7-2 presents the correlation matrix of the variables. The dependent variable K is statistically significantly correlated with the level of credit usage, the population aged from 15 to 64, the penetration rate of Internet and the band size of radio spectrum used for mobile telecommunication. The dependent variable K is not significantly correlated with the rest of independent variables. Meanwhile, the correlation coefficient between K and the population from 15 to 64 is negative, which is opposite to the expectation. Although the pairwise correlation between the dependent variable and part of independent variables are insignificant, these variables are not excluded from the model based on two reasons: Firstly, there are strong theoretical reasons to include these variables; secondly, the real effects these variables have on the dependent variable can only be detected when the influences from other variables are controlled.

It is also noteworthy that pairwise correlation coefficients between some independent variables are statistically significantly large, as shown in Table 7-2. For example, the correlation coefficients between GDP per capita and credit usage, population aged from 15 to 64 and penetration rate of Internet are 61.09, -61.49 and 79.83 respectively. Therefore, it is predictable that the multiple linear regression may suffer from multicollinearity.

***Table 7-1* Descriptions of variables**

Variable	Description	Unit	Source	Obs.	Mean	Minimum	Maximum	Std. Dev.
EDU	Labor force with secondary education or above	%	WB	35	73.4973	11.0000	94.4000	19.4720
LR	Literacy rate	%	WB	36	98.3612	99.7942	90.8167	1.9177
GDPPC	GDP per capita	constant 2000 $	WB	39	19950.8955	540.5997	99399.6029	21403.1350
CR	Credit to private sector to GDP	%	WB	36	100.7666	25.1536	249.2818	59.3433
POPILC	Population living in the largest city to total population	%	WB	38	31.3160	5.6480	100.9178	21.6702
POPY	Population aged from 15 to 64 to total population	%	WB	36	68.3077	65.0177	72.4672	1.9439
PRI	Users of Internet per 100 habitants	N/A	ITU	39	56.7122	10.7550	92.9240	21.6679
HHI	Herfindahl-Hirschman index for mobile telecommunication	N/A	WCIS	39	3966.1103	2255.3951	10000.0000	1575.3411
NUM	Number of mobile network operators	N/A	WCIS	39	3.74356	1.0000	8.0000	1.2715
APL	Accumulated auction prices for 3G licenses	Mil. $	IC	39	3020.1851	0.0000	51707.1000	10073.8192
BAND	Accumulated band size of radio spectrum	MHz	WCIS	37	141.8351	20.0000	348.3000	88.1477
PR2G	Subscriptions of 2G telephony per 100 habitants	N/A	WCIS	39	81.9012	9.8097	120.4418	21.9399

Source: WB refers to World Bank's world development indicator, ITU refers to International Telecommunication Union's ICT Indicators Database 2012, WCIS refers to World Cellular Information Service, IC refers to Informa's Intelligence Center

Table 7-2 **Pairwise correlations (correlation coefficients multiplied by one hundred)**

	K	EDU	LR	GRPPC	CR	POPILC	POPY	PRI	HHI	NUM	APL	BAND	PR2G
K	100.00												
EDU	10.68	100.00											
LR	12.73	71.28**	100.00										
GDPPC	18.12	2.07	18.27	100.00									
CR	33.76*	-20.92	-3.99	61.09**	100.00								
POPILC	-15.43	-15.64	-15.74	-6.02**	3.27	100.00							
POPY	-34.67*	2.46	-6.57	-61.49**	-35.26*	-6.34	100.00						
PRI	45.30**	-1.40	17.57	79.83**	50.51**	-9.34	-50.03**	100.00					
HHI	-20.69	-11.48	-11.95	-12.27*	-20.59	30.84*	18.47	-15.67	100.00				
NUM	0.34	40.15*	31.72	-19.87	-22.39	-32.54*	29.87	-17.47	-60.50**	100.00			
APL	-1.65	5.75	8.91	18.02	13.91	-34.76	-32.68	18.77	-40.56	1.01	100.00		
BAND	57.88**	15.40	19.23	43.46	34.04	-29.94*	-56.17*	53.08**	-39.79*	12.85	43.22**	100.00	
PR2G	20.99	-2.24	5.27	34.95	24.86	-3.29	-5.83	33.78*	6.17	-14.72	-5.63	-7.73	100.00

*Indicates the coefficient of correlation is significant at the 95% confidence level.

**Indicates the coefficient of correlation is significant at the 99% confidence level.

7.5 Estimation

Table 7-2 shows that the correlation coefficients between the independent variable and 8 out of 12 possible variables are not statistically significant. Meanwhile, some variables show significantly strong correlation between other variables, which may result in multicollinearity in the regression. Therefore, it is predictable that regression coefficients of some variable are statistically insignificant. The regression result of model (7.4) is listed in Table 7-3.

Table 7-3 **Regression result of the full model**

Coefficient	Estimated value	Standard error
C	207.7666	1090.6774
EDU	1.7471	1.0318
LR	-5.6747	8.3551
GDPPC	0.0035+	0.0018
CR	-0.1988	0.3041
POPILC	0.4565	0.8726
POPY	8.8189	11.1138
PRI	-0.7538	1.0092
HHI	-0.0695*	0.0293
NUM	-38.7057+	19.7725
APL	-0.0047**	0.0014
BAND	0.7188**	0.2230
PR2G	1.0218	0.7279
Observations	34	
R-squared	0.6966	
F-statistic	3.8326	

**Indicates the coefficient is significant at 99% confidence level.

*Indicates the coefficient is significant at 95% confidence level.

+Indicates the coefficient is significant at 90% confidence level.

The regression result of shows that only 5 out of 12 variables in model (7.4) are statistically significant. Meanwhile, the signs of the coefficients of literacy rate, credit usage and penetration rate of 2G telephony are opposite to expectations. These results are likely to result from multicollinearity. In order to detect the real influence of each variable, it is necessary to remedy the model to reduce multicollinearity.

One effective solution to the problem of multicollinearity is stepwise regression. As discussed in Chapter 7.2, all of the listed variables are likely to influence the saturation level of the diffusion. But the level of influence of each variable highly varies with that of one another. Therefore, the variable that is most likely to influence the demand and the one that is most likely to influence the supply are selected as initial variables, and the rest variables are selected by the automatic procedure of the stepwise regression. Among all the variables that influence the demand to 3G telephony, the income variable is likely to have the highest influence. Those who have higher income generally have higher affordability to an innovation, which leads to higher demand to the innovation. The most important factor that influences the supply is competition. Fierce competition generally leads to lowered prices and more advantageous products. The consequences in turn stimulate the demand, and result in a higher level of saturation. Therefore, the stepwise regression starts with two variables: GDPPC and HHI.

The estimation result of stepwise regression is presented in Table 7-4. Four variables are selected in the stepwise regression procedure besides GDPPC and HHI, including EDU, NUM, APL and BAND. Coefficients for all variables, including the constant, are statistically significant. Coefficients for APL and BAND are significant at the 99% confidence level, and coefficients for GDPPC, EDU, HHI and NUM are significant at the 95% confidence level. The R-squared value is 0.6452, showing that about 64.52% of the saturation level of 3G telephony diffusion in European countries can be explained by the 6 variables mentioned above. F-statistic shows that the coefficients of all variables in the stepwise regression are jointly significant at the 99% level.

Table 7-4 **Stepwise regression result**

Coefficient	Estimated value	Standard error
C	322.3820*	139.3430
GDPPC	0.0022*	0.0009
EDU	1.5288*	0.7237
HHI	-0.0631*	0.0254
NUM	-36.7525*	14.3463
APL	-0.0044**	0.0012
BAND	0.5021**	0.1659
Observations	34	
R-squared	0.6328	
F-statistic	7.7554**	

**Indicates the coefficient is significant at 99% confidence level.

*Indicates the coefficient is significant at 95% confidence level.

Since each European country varies with one another in observation, it is likely that the regression suffers from heteroscedasticity, and the estimators are not efficient. It is necessary to test if heteroscedasticity exists and, if it does exist, remedy the problem. The residuals and squared residuals from the stepwise regression are respectively plotted against predicted dependent variable $\widehat{K}$ in Figure 7-1(a) and Figure 7-1(b). It is apparent from Figure 7-1(a) that the residuals spread wider around zero as $\widehat{K}$ increases. Figure 7-1(b) further shows an explicit pattern between the squared residuals and the predicted K. It indicates high possibility that heteroscedasticity exists.

Formal tests show solid evidence of heteroscedasticity. Table 7-5 shows the results of White test of the stepwise regression. The White statistic exceeds the critical χ^2 value at the 95% confidence level, indicating there is heteroscedasticity in the regression.

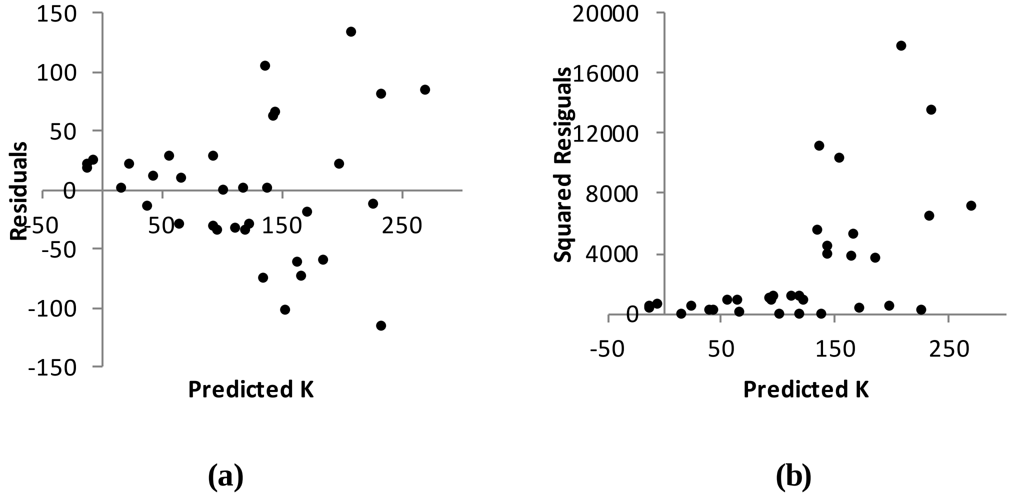


Figure 7-1 **Residual Plots**

Table 7-5 **Results of White Test**

	Coefficient	Standard Error
Constant	2766.6604	2892.4696
$GDPPC^2$	-8.9907e-07	9.9338e-07
EDU^2	0.0011	0.4036
HHI^2	-6.6490e-05	0.0001
NUM^2	-75.0563	63.5387
APL^2	-5.2518e-06**	1.3472e-06
$BAND^2$	0.1189**	0.0232
Observations	33	
n*R-squared	18.6518**	

**Indicates the coefficient is significant at 99% confidence level.

$\chi^2_{0.05}(6) = 12.59516$

Since there are multiple variances in the model, it is hard to determine the structural relationship between the error variance and a single variable explicitly. Therefore, the weighted least square (WLS) method is not applicable. The solution to heteroscedasticity in the regression is to estimate robust standard errors. Table 7-6 shows the result of regression with White's heteroscedasticity-consistent variances and standard errors. White's heteroscedasticity-corrected standard errors are different from the result of OLS estimation. As a result, the statistical significance of the coefficient of EDU is reduced, and that of the coefficient of HHI is enhanced. The coefficients of GDPPC, HHI, NUM, APL and BAND are significant at the 95% level, and the coefficient of EDU is still significant at 90% level.

Table 7-6 **Regression result with White's heteroscedasticity-consistent variances and standard errors**

Coefficient	Estimated value	Standard error
C	322.3820*	120.6255
GDPPC	0.0022*	0.0009
EDU	1.5288+	0.7646
HHI	-0.0631**	0.0196
NUM	-36.7525*	13.2889
APL	-0.0044**	0.0010
BAND	0.5021*	0.2207
Observations	34	
R-square	0.6328	
F-statistic	7.7554**	

**Indicates the coefficient is significant at 99% confidence level.

*Indicates the coefficient is significant at 95% confidence level.

+ Indicates the coefficient is significant at 90% confidence level.

7.6 Analysis

The regression result indicates that the saturation level of diffusion of 3G telephony in European countries are influenced by six variables, including GDP per capita, population with secondary education or above, concentration rate of mobile industry, number of mobile operators, auction price of mobile licenses and released band size of radio spectrum.

Holding the other variables constant, if GDP per capita in a country increases by $1, the maximum market potential of 3G telephony in the country increases by 0.0022 percentage points. When GPD per capita in a country increases, the overall affordability of people in the country tends to be higher. As a result, more people are able to replace their 2G handsets with 3G ones and meanwhile subscribe 3G services. Therefore, the market potential of 3G telephony is larger for a country with relatively higher GDP per capita.

Similarly, if the population with secondary or higher education in a country increases by 1 percentage point, the saturation level of 3G telephony diffusion increases by 1.5288 percentage point. 3G technology enables mobile broadband, which makes smartphones and mobile applications more functional and more complex. These innovative products are more likely to be accepted by people with higher education. Therefore, the saturation level of 3G telephony is higher for a country where people are more educated.

Competition level of mobile telecommunication industry in a country also influences the market potential of 3G telephony in the country. It is noteworthy that both the concentration rate and the number of mobile network operators influence the market potential of 3G telephony. These two variables together describe the structure of competition, and each variable reflects one aspect of the industry. Therefore, these two variables are described together. When the other variables are kept constant, especially when the number of network operators is constant, a higher HHI indicates that the market share of the largest operators increases. On the other hand, when the concentration rate of the industry is constant, the more operators exist in the market, the higher market share the largest operators enjoy. In both cases, leading operators enforce stronger control over the market. Telecommunication industry is featured with monopolistic competition all around the world. In most European countries, the market share of the leading operators is higher than 40%. As a result, the market leaders are able to price 3G telephony to maximize their economic benefits. On the other hand, market followers tend to price 3G telephony at similar level in order to survive in the game. Therefore, in a market where leading operator has higher power, price of 3G telephony tends to be higher, and the market potential of 3G telephony is lower. The coefficients of both HHI and NUM are negative, which jointly supports the argument.

The last two variables, APL and BAND determine the price and amount of radio spectrum, the major resource of 3G telephony. As the accumulated auction price of mobile licenses increases by \$1 million, the saturation level of 3G telephony decreases by 0.0044 percentage points. For mobile operators, it is natural that the license fee is part of their costs. Such costs are likely to be transfer to be part of the subscription prices. Therefore, higher price of licenses leads to lower market potential of 3G telephony. Meanwhile, if the spectrum band size increases by 1MHz in a country, holding other variables constant, the saturation level of 3G telephony increases by 0.5021 percentage points. When spectrum resources are sufficient, 3G subscribers usually enjoy high quality voice and high-speed mobile surfing. Therefore, if more spectrum resources are released in a country, keeping other variables constant, the saturation level of 3G telephony is usually higher.

7.7 Policy Implications

The study in the saturation level of diffusion of 3G telephony is of great practical importance for governments, network operators and handset manufacturers.

Government activities directly influence the development of telecommunication industry. In most countries, radio spectrum resources are inherently owned by the government. For any mobile network operator deciding to provide mobile services, it is necessary to obtain the rights to dispose a specific band of spectrum and, in some cases, to obtain the license for operating with a specific telecommunication standard. For a country where the price of license is relatively low and the released spectrum resources are sufficient, more operators are encouraged to provide 3G services. As the intensity of competition increases, it is likely that consumers gain more benefits. Therefore, the governments are suggested to promote competition by actively releasing resources and lowering the barriers to entry for network operators.

The saturation level of 3G telephony diffusion is of great importance for mobile network operators. Given the fact that the market structure of telecommunication is relatively stable, an operator can predict its future revenues based on the prediction to the maximum market potential of mobile services. Similarly, an operator may also use the saturation level as a reference in pricing its services. Therefore, mobile network operators may benefit from the accurate prediction of saturation level of the diffusion of 3G telephony.

Once the penetration rate of 3G telephony exceeds 100%, the incremental subscriptions onwards are likely to have more than one handset. Some consumers may subscribe more than one contract of mobile services to meet the needs of massive communication, while the others do so to "activate" their second or even third handset. Nowadays people desire to communicate and to surf Internet regardless to the limitations of time and space. As a result, mobile handsets such as smartphones, tablets and USB modems become more popular. In a country where market potential of 3G services is relatively high, mobile handset manufacturers see clear potential for more advanced and functional products. The determinants of saturation level of the diffusion of 3G telephony also serve as important references for marketing strategies of handset manufacturers.

8 Conclusion

This study investigated the diffusion of 3G telephony in European countries and studied the external factors that influence the saturation level of the diffusion. Two major innovative topics were discussed in this study. The first was focusing on the diffusion of 3G telephony, which was not involved in previous studies. The second and the most important, was studying the external factors that influence the saturation level of diffusion of 3G telephony.

In this study, the Logistic model, the Gompertz model and the Bass model were compared and the Gompertz model was selected as the best-fitting model for diffusion of 3G telephony in Europe from 2003 to 2012. The Gompertz model was also applied to estimate the diffusion of 3G telephony in 39 European countries.

In the study of external factors that influence the saturation level of diffusion, six determinants were found theoretically and empirically relevant. It was found that the overall income level and education level had positive impacts on the saturation level of diffusion. Intensive competition also positively impacted the diffusion of 3G telephony. Appropriate telecommunication regulations were crucial for diffusion of 3G telephony. Both sufficient spectrum resources and relatively low price of licenses promoted the diffusion of 3G telephony and led to a high saturation level of diffusion.

For policy makers, this study serves as reference for pricing licenses and releasing spectrum resources. For mobile operators and handset manufacturers, the study is also helpful in making pricing decisions, product portfolios and marketing strategies.

Nowadays, the 4G technology has been deployed in many European countries. It is predictable that 4G will gradually substitute 3G. Therefore, two questions are crucial for market players: firstly, will the diffusion of 3G telephony proceed to saturation? And if not, secondly, what will the saturation level of 3G telephony be in the context of 4G deployment? These questions are of great importance in practice, and are likely to be one of the directions of future studies.

Bibliography

Bass, F. M. (1969, 1). A New Product Growth for Model Consumer Durables. *Management Science, 15*(5), pp. 215-227.

Bass, F. M., Krishnan, T. V., & Jain, D. C. (1994). Why the Bass Model Fits without Decision Variables. *Marketing Science, 13*(3), pp. 203-223.

CDG. (2012). *Worldwide Deployment Search*. Retrieved 8 31, 2012, from CDMA Development Group: http://www.cdg.org/worldwide/

Chu, W.-L., Wu, F.-S., Kao, K.-S., & Yen, D. C. (2009). Diffusion of Mobile Telephony: An Empirical Study in Taiwan. *Telecommunications Policy, 33*, pp. 506-520.

Fisher, J. C., & Pry, R. H. (1971). A Simple Substitution Model of Technological Change. *Technological Forecasting and Social Change, 3*, pp. 75-88.

Geroski, P. A. (2000). Models of technology diffusion. *Research Policy, 29*(4), pp. 603-625.

Gompertz, B. (1825). On the Nature of the Function Expressive of the Law of Human Mortality, and on a New Mode of Determining the Value of Life Contingencies. *Philosophical Transactions of the Royal Society of London, 115*, pp. 513-583.

Gruber, H., & Verboven, F. (2001, March). The Diffusion of Mobile Telecommunications Services in the European Union. *European Economic Review, 45*(3), pp. 577-588.

Gruber, H., & Verboven, F. (2001, July). The Evolution of Markets under Entry and Standards Regulation — the Case of Global Mobile Telecommunications. *International Journal of Industrial Organization, 19*(7), pp. 1189-1212.

Gupta, R., & Jain, K. (2012). Diffusion of Mobile Telephony in India: An Empirical Study. *Technology Forecasting and Social Change, 79*, pp. 709-715.

ITU. (2012). *All About the Technology.* Retrieved 9 19, 2012, from International Telecommunication Union: http://www.itu.int/osg/spu/ni/3G/technology/index.html

Jang, S.-L., Dai, S.-C., & Sung, S. (2005). The Pattern and Externality Effect of Diffusion of

Mobile Telecommunications: the Case of the OECD and Taiwan. *Information Economics and Policy, 17,* pp. 133-148.

Meade, N., & Islam, T. (1998, August). Technological Forecasting—Model Selection, Model Stability, and Combining Models. *Management Science, 44*(8), pp. 1115-1130.

Meade, N., & Islam, T. (2006). Modelling and Forecasting the Diffusion of Innovation - A 25-year Review. *International Journal of Forecasting, 22*, pp. 519-545.

Michalakelis, C., Varoutas, D., & Sphicopoulos, T. (2008). Diffusion models of mobile telephony in Greece. *Telecommunications Policy, 32*(3-4), pp. 234-245.

Rogers, E. M. (1983). *Diffusion of Innovations* (Third Edition ed.). New York, N. Y., the United States of America: The Free Press.

Rouvinen, P. (2006). Diffusion of Digital Mobile Telephony: Are Developing Countries Different? *Telecommunication Policy, 30,* pp. 46-63.

Schmittlein, D. C., & Mahajan, V. (1982). Maximum Likelihood Estimation for an Innovation Diffusion Model of New Product Acceptance. *Marketing Science, 1*(1), pp. 57-78.

Sridhar, K. S., & Sridhar, V. (2007). Telecommunications Infrastructure and Economic Growth: Evidence from Developing Countries. *Applied Econometrics and International Development, 7*(2).

Srinivasan, V., & Mason, C. H. (1986). Nonlinear Least Squares Estimation of New Product Diffusion Models. *Marketing Science, 5*(2), pp. 169-178.

Waverman, L., Meschi, M., & Fuss, M. (2005). *The Impact of Telecoms on Economic Growth in Developing Countries.*

Winsor, C. P. (1932, 1 15). The Gompertz Curve as a Growth Curve. *Proceedings of the National Academy of Sciences, 18,* pp. 1-8.

Wu, F.-S., & Chu, W.-L. (2010). Diffusion Models of Mobile Telephony. *Journal of Business Research, 63,* pp. 497-501.

Appendix

Table A1-1 **Summary of 3G telecommunication market in each European country**

Country	Start time	Current penetration rate
Albania	2011Q1	10.72%
Andorra	2008Q1	20.12%
Armenia	2008Q4	15.10%
Austria	2003Q2	114.79%
Azerbaijan	2007Q2	8.97%
Belgium	2005Q3	26.29%
Bosnia Herzegovina	2009Q2	4.46%
Bulgaria	2006Q1	75.17%
Croatia	2005Q4	55.25%
Cyprus	2004Q4	35.10%
Czech Republic	2004Q3	67.41%
Denmark	2003Q4	80.70%
Estonia	2005Q4	36.97%
Finland	2004Q4	112.24%
France	2004Q4	49.73%
Georgia	2006Q3	44.59%
Germany	2004Q2	47.72%
Greece	2004Q1	50.94%
Hungary	2005Q3	18.53%
Iceland	2007Q3	70.51%
Ireland	2004Q4	58.29%
Italy	2003Q1	75.23%

Table A1-2 **(Continued)**

Country	Start time	Current penetration rate
Latvia	2004Q4	40.14%
Liechtenstein	2007Q1	11.90%
Lithuania	2006Q1	41.28%
Luxembourg	2003Q2	62.82%
Macedonia	2008Q3	20.95%
Malta	2006Q3	46.98%
Moldova	2003Q1	13.26%
Monaco	2006Q2	42.05%
Montenegro	2007Q2	15.95%
Netherlands	2004Q2	54.49%
Norway	2004Q4	76.66%
Poland	2004Q3	76.29%
Portugal	2004Q2	108.89%
Romania	2001Q1	27.05%
Russia	2003Q1	13.48%
Serbia	2006Q4	30.47%
Slovak Republic	2006Q1	63.52%
Slovenia	2003Q4	30.04%
Spain	2004Q2	76.65%
Sweden	2003Q2	103.57%
Switzerland	2004Q4	66.39%
Turkey	2009Q3	18.03%
Ukraine	2007Q1	4.56%
UK	2003Q1	64.77%