ISSN 1791-3144

DEPARTMENT OF ECONOMICS

DISCUSSION PAPER SERIES

Modelling and Forecasting Mobile Telecommunication Services: The case of Greece

Theologos Dergiades and Apostolos Dasilas

Discussion Paper No. 13/2009

Department of Economics
University of Macedonia
156 Egnatia str
540 06 Thessaloniki
Greece
Fax: + 30 (0) 2310 891292
http://econlab.uom.gr/econdep/

Modelling and Forecasting Mobile Telecommunication Services: The case of Greece

By

Theologos Dergiades[a,1] and Apostolos Dasilas[b]

[a] University of Macedonia, Department of Economics, 156 Egnatia Str., 54006 Thessaloniki, Greece.
[b] University of Macedonia, Department of Accounting and Finance, 156 Egnatia Str, 54006, Thessaloniki, Greece.

Abstract

In this paper we try to model the adoption pattern of mobile telecommunication services into the Greek market for the period from 1993 to 2005. Two separate sigmoid curves, the Gompertz and the Logistic, are fitted to the observed number of subscribers by means of non-linear least squares. The in-sample fit to data favoured the use of the Logistic curve in describing the diffusion process, fact which is further supported by Frances' parametric test (1994b). The dominance of the Logistic curve over the Gompertz is also verified via a pseudo out-of-sample forecasting exercise. Furthermore, an attempt is made to predict the expected number of subscribers up to 2015, solely based on the Logistic curve. Taking into account the prediction's uncertainty, the variance of the forecast errors is calculated utilising the non-parametric bootstrap method. Our empirical results reached to three conclusions. First, the introduction of the pre-paid mobile telephony in 1997 along with the entry of the third mobile operator in 1998 has boosted the diffusion process in Greece; second, the levelling-off process in the diffusion of mobile phones has already begun; finally, the average expected growth rate in new subscribers is less than half percent for the period between 2006 and 2015.

Keywords: Mobile telecommunications; diffusion modelling; forecasting; bootstrap.

JEL classification: O33; L96; C53; C15.

1. Introduction

The history of mobile telephony goes back to radio telephony experiments in the US in the 1920s (Kargman, 1978 and Agar, 2003). The first mobile phones were launched in 1947 as a highway service between Boston and New York after the success of the first mobile telephone network in St. Louis introduced by the American Telephone and Telegraph (AT&T) Company (Agar, 2003). The first American cellular (mobile) phone system came into operation in 1979 on a trial basis and went into commercial operation in 1983.

[1] Corresponding author: Department of Economics, University of Macedonia, 156 Egnatia Str, 54006, Thessaloniki, Greece, Tel:+30-6932768932, E-mail: dergiades@uom.gr

In Europe, mobile telephony developed in a slightly different manner. Sweden was the first European country that launched a fully operational mobile telephone network in 1981. In Greece, the services of mobile telephony have been provided since 1993. Telestet – predecessor of TIM and recently renamed Wind – was founded in 1992 and was the first company in Greece which was granted a GSM license for the development of a nation-wide network for the provision of mobile telephony services. Telestet's investment on the acquisition of the license and building up the network reached 30 billion drachmas and is considered one of the largest post-war investments in Greece. The company initiated its activities in the Greek market under the commercial brand name Telestet on 29 June 1993, when the first call from a mobile phone, in Greece, was made.[2] In the same year a second mobile company, Panafonet, which later acquired by Vodafone Plc, entered the market.

Up to 1997, the Greek mobile telephone sector was a pure duopoly with only two companies operating, Telestet and Panafone (predecessor of Vodafone). By the end of 1997 the penetration of mobile phones, according to the International Telephone Union (ITU), was less than 50% of the population. The competition was not so intense, something that was reflected to the expensive mobile charge rates and the low-quality services. As regards that period, Greek mobile phones consumers are characterised by low average spend usage among Europeans. In April 1998 Cosmote, a subsidiary of the Greek telecom incumbent Hellenic Telecommunications Organization (OTE), launched commercial operations – five years later than its competitors Telestet and Panafone – and in the middle of 2002 a fourth operator, Q-Telecom, entered the market. At first sight, it could be argued that the Greek mobile telephone sector is an oligopoly with only four players. However, the deregulation of the Greek telecommunications market has spurned the growth and competition among the mobile phone companies resulting in the reduction of handset

[2] Telestet changed hands in 2004 and was renamed TIM. Recently, a private Egyptian fund, Weather Investments, acquired TIM and renamed to Wind.

prices and mobile charge rates. Moreover, the fierce competition among the companies led to the provision of new services as for example i-mode, phone banking and broadband services.

The business segment of mobile telephony is one of the highest growth segments of the country, since the companies involved in the provision of mobile telephony services have made considerable investments of high value, both in the development of telecommunications and technological infrastructure and in human resources. Penetration in Greece now exceeds 110%, much above the average of the European Community, an index that reveals the dynamics of the segment in Greece. What powered this rapid growth was undoubtedly the high level of demand for mobile phone services. However, the first signs that the market had matured appeared in 2004 when the mobile phone market saw its profits increase by 14% compared to 16% in 2003 and 29% in 2002. According to the results announced by the companies for 2005, it appears that 2005 was, even in the best case, the first year of single-digit growth and, in the worst case, the first year of declining revenue. Wind showed a 1.9% drop in revenue in the nine-month period of 2005, while at the same time Cosmote recorded its lowest growth ever, at just 2%. Similar are the figures for Vodafone.

The fall in growth rates is seen as normal, given that mobile phone companies in Greece have now run out of customers. In such a competitive environment, a price-war for mobile telecommunication services is bound to begin. Another implication of the fierce competition in the mobile telecommunications arena is the search of incumbent companies to offer new and more advanced mobile services to their customers. In line with this, all mobile phone companies operating in Greece have already tried to launch the operation of the first 3rd generation network (3G) for mobile services. This development is expected to mark a new era in Greek telecommunications, promoting the technological growth of the country at international level. According to ITU, during 2007 consumers will be offered even more added value services via their mobile phones and, at the same time, they will be able to exploit even further the new opportunities offered by the of 3G mobile telephony.

The rest of the paper is organised as follows. Section 2 presents a brief literature review regarding the diffusion of the mobile phones. Section 3 outlines the data and methodology employed in this study. Section 4 presents the empirical findings of the study and Section 5 contains the main conclusions and discusses their implications as well as suggesting some avenues for further research in the area.

2. Prior Research on the Diffusion of Mobile Telephony.

It is well established that through time a successful innovation follows a typical sigmoid curve (Bothelo and Ligia, 2004). The stylised diffusion process for an innovation described by an S-shaped curve goes through four phases: the introductory phase, the growth phase, the maturity phase and the decline phase. These four phases are approximated by an S-shaped curve as shown in the seminal studies by Griliches (1957), Mansfield (1968) and Romeo (1977). There are several studies in the literature where sigmoid curves are used to describe the diffusion of an innovation and afterwards forecasting is performed in order to assess future market developments (Meade, 1984).

Botelho and Pinto (2004) were among the first researchers who tried to model diffusion patterns of mobile phones in Portugal. According to the authors, the Portuguese mobile telecommunications sector had experienced a number of technological and regulatory developments over the last decade as a result of the EU Directives 90/388 and 91/287, both aiming at deregulating and liberalising telecommunications markets within the EU. In the light of such an institutional environment, Botelho and Pinto (2004) analysed the pattern and rate of adoption of mobile phones by the Portuguese population between 1989 and 2000. The authors assumed that the diffusion pattern of mobile phones in Portugal is mostly approximated by a sigmoid or S-shaped curve. They used two forms of S-curves, that is, the Logistic or Pearl-Reed curve and the

Gompertz curve. However, they found that only the Logistic adequately describes the path of mobile phone diffusion in Portugal. Furthermore, Botelho and Pinto (2004) found that the high-growth rate phase of the diffusion of cellular phones ended in 1999, when the growth rate of the number of subscribers began to decline.

Massini (2004) investigated the mobile-telephony diffusion pattern in Italy and the UK, two countries that display similar characteristics with respect to size, wealth, population and geographical characteristics. The author employed a multivariate regression analysis taking also into account economic and technological factors that can explain differences in the diffusion speed between Italy and the UK. Massini (2004) found that the introduction of digital technology led to a significant boost in the number of Italian subscribers. On the other hand, a more general trend variable provided better results for explaining the reasons behind the diffusion process in the UK. The economic variables considered as determinants of the diffusion process displayed statistical significance either in the diffusion speed or in the saturation level in both Italy and the UK. Irrespective of the specification model, the handset price was shown to have the greatest impact on diffusion speed or in the saturation level. Finally, the tariff was considered as another important economic factor explaining the diffusion process, especially in the case of the UK. According to Massini (2004), these findings are mostly explained by the fact that the handset price was highly subsidised in the UK and, therefore, British mobile users paid more attention to the tariff, the impact of which on the diffusion process was clearer in Italy.

Frank (2004) studied the diffusion of mobile telecommunication services in Finland. His objectives were to find factors which have influenced the diffusion process and to forecast the diffusion of mobile telecommunication services. To achieve his objectives, Frank (2004) used data from Finland that was fitted in a logistic model by means of nonlinear least squares. He considered GDP per capita, digitalisation and the number of fixed phones as the variables affecting the diffusion process of wireless telecommunications in Finland. The results concerning the first objective were that the economic situation, as measured by the GDP per capita, has affected the relative growth rate of the diffusion process and the number of potential adopters has been a constant fraction of the population covered by the wireless network. In addition, the final penetration rate was estimated at 91.7% in 2009.

The Portuguese mobile telecommunications market has received further attention from Pereira and Pernias-Cerrillo (2005) who proposed a nonlinear method to estimate diffusion process different from the standard S-curves, namely the Logistic and the Gompertz. The researchers asserted that the Logistic and the Gompertz curves display two serious shortcomings. "The first and more important problem of these curves is their lack of flexibility with respect to two important characteristics of the diffusion process: (i) the inflection point, and (ii) the asymmetry around the inflection point. For the Logistic and the Gompertz curves, the inflection point always occurs at a fixed fraction of the saturation level; 50% for the Logistic and, approximately, 37% for the Gompertz. The second problem of these curves is the difficulty of discriminating empirically between them" (Pereira and Pernias-Cerrillo, 2005, pp. 1). Pereira and Pernias-Cerrillo (2005) used the Richards curve, also known as generalised Logistic curve, to model the diffusion trend employing quarterly data from 1994 to 2003. They found that the Logistic curve is a valid representation of the diffusion process in Portugal, but only as a long-term trend. Furthermore, they identified significant effects of increased competition on the diffusion process. They also observed that there were seasonal fluctuations that accounted for much of the variation in the early stages of diffusion. Interestingly enough, the authors found that the saturation level of the diffusion process implies a penetration rate around 100% and the slowdown in the adoption of mobile telephony began in 2001, shortly after the full liberalisation of the Portuguese telecommunications market.

More recently, Lee and Cho (2007) used and extended Frank's (2004) Logistic model to estimate the diffusion mobile telecommunication services in Korea. In addition to the logistic model of diffusion, the authors used a time series autoregressive moving average (ARMA) model to determine the diffusion adoption process. The results showed that the Logistic model fitted better than the ARMA model. Moreover, the economic situation as measured by the GDP per capita had a positive impact on the diffusion process and the final penetration rate was estimated to be 71.3% of the population. Finally, the more interesting finding was that mobile telecommunications was a substitute to fixed telecommunications rather than a complement.

3. Data and Methodology

Annual data covering the number of mobile phone subscribers in Greece during the period 1993-2005[3] are used in this paper. Figure 1 illustrates the year-by-year cumulative adoption of mobile telecommunication services in Greece and it can be easily seen that the observed diffusion process up to the end of the sample is much like a typical S-shaped curve.

(Insert Figure 1, about here)

Among a wide range of S-shaped curves, those commonly used to describe the diffusion process of an innovation are the Gompertz and the Logistic. The functional forms of the Gompertz and the Logistic curves are given by Equations (1) and (2), respectively.

$$x_t = a_1 \exp[-b_1(\exp(-c_1 t))] \quad (1)$$

$$x_t = a_2(1 + b_2 \exp(-c_2 t))^{-1} \quad (2)$$

where x_t is the variable measuring the diffusion process in period t (the number of mobile subscribers), a_i, b_i and c_i ($i = 1,2$) are positive parameters for estimation.

To estimate the Gompertz curve, we start by taking logarithms on both sides of Equation (1), which results to:

$$\ln x_t = \ln(a_1) - b_1(\exp(-c_1 t)) \quad (3)$$

Applying first differences and logarithms to Equation (3) and adding the stochastic term e_t (assuming the usual properties), we get the following specification:

[3] Source of our data is OECD's Telecommunication Database.

$$\ln(\Delta \ln x_t) = -a_1 t + \ln(b_1 \exp(c_1) - b_1) + e_t \tag{4}$$

In specification (4) only b_1 and c_1 out of the three initial parameters are subject to estimation. The third parameter a_1 (saturation level or potential users) is assumed to be time-varying, something which is, of course, much more realistic than taking its value for granted for the whole sample period (Frank, 2004). A plus point coming out from the time varying assumption for the saturation level is that it permits the identification of possible structural breaks that took place during the diffusion process (Frances, 1944a). The series of the saturation level can be obtained exogenously based on the following expression:

$$\hat{a}_{1t} = \exp(\ln x_t + \hat{b}_1 \exp(-\hat{c}_1 t)) \tag{5}$$

To write the Logistic curve in a similar fashion as in Equation (4), the initial step is to take logarithms on both sides of Equation (2), yielding to:

$$\ln x_t = \ln a_2 - \ln(1 + b_2 \exp(-c_2)) \tag{6}$$

Accordingly, taking first differences in Equation (6), we receive the subsequent expression:

$$\Delta(\ln x_t) = \ln((1 + b_2 \exp(-c_2 t + c_2)) / (1 + b_2 \exp(-c_2 t)) \tag{7}$$

Adding and subtracting at the same time the $b_2 \exp(-c_2 t + c_2)$ term in Equation's (7) numerator and after same rearranging, Equation (8) is obtained:

$$\Delta(\ln x_t) \approx b_2 \exp(-c_2 t)(\exp(c_2 - 1) / (1 + b_2 \exp(-c_2 t)) \tag{8}$$

Applying again logarithms on both sides of Equation (8) and adding the stochastic term h_t (assuming the usual properties), the Logistic curve is transformed to:

$$\ln(\Delta(\ln x_t)) \approx \ln b_2 + \ln(\exp(c_2) - 1) - c_2 t - \ln(1 + b_2 \exp(-c_2 t)) + h_t \tag{9}$$

Finally, the third non-determined parameter from Equation (9) is provided exogenously via Equation (10). Again it is assumed that a_2 is time varying over the sample.

$$\hat{a}_{2t} = \exp[\ln x_t + \ln(1 + \hat{b}_2 \exp(-\hat{c}_2 t))] \tag{10}$$

4. Empirical Results

4.1. Preliminary results

Before we proceed to the estimation of the two curves, it is of great importance to clarify whether the data support the use of the Logistic or the Gompertz curve. It is known that a symmetric process is better described by the Logistic curve, while an asymmetric process is better described by the Gompertz curve. A simple way to clarify the diffusion pattern of mobile phones in Greece with respect to its symmetry is to apply Frances' (1994b) parametric test. The idea for the selection between these two diffusion models is based on a simple linear regression. Frances' (1994b) proved that the $\ln(\Delta \ln x_t)$ transformation is a non-linear function of time in the case of the Logistic model and a linear function of time in the case of the Gompertz model. Consequently, by regressing the $\ln(\Delta \ln x_t)$ term on a constant, on time and on a non-linear transformation of time, a simple test for selecting between these two models is established. Frances' (1994b) specification is the following:

$$\ln(\Delta \ln x_t) = \delta + \gamma t + \theta t^2 \qquad (11)$$

The selection between the two curves is made by merely checking the significance of the coefficient that corresponds to the non-linear transformation of time. In case of significance, the diffusion pattern seems to be described more accurately by the Logistic model, while in the contrary case by the Gompertz model. To apply the test, specification (11) was estimated by OLS and the estimation results are illustrated in Table 1. From the associated *p*-value of the θ coefficient, it is inferred that the use of the Logistic model is strongly supported.

(Insert Table 1, about here)

Turning now to the estimation procedure, specification (4) (Gompertz model) can be computed through the use of the non-linear least squares estimation technique, providing appropriate starting values. Estimates of the parameters and the corresponding standard errors are illustrated in Table 2. In accordance with Table 2, it is inferred that both coefficients are significant, their signs are those expected and, finally, more than ¾ of the dependent variable's total variability is explained by the model. To ensure the overall quality of the estimated equation it is crucial to test the residuals for normality, heteroscedasticity and serial correlation using the Jarque-Bera statistic, the White's test and the Breusch-Godfrey LM test, respectively. The associated *p*-values for each of the tests verify that normality, homoscedasticity and no serial correlation hold for the residuals.

(Insert Table 2, about here)

To estimate specification (9) (Logistic model), the technique applied is the same as previously. Estimates and diagnostic tests are presented in Table 3. Again, it is realized that the two coefficients are significant, their signs are those expected as well as normality and serial correlation are not a problem. Some interesting features are the remarkably higher value of the adjusted coefficient of determination and the presence of heteroscedasticity in the residuals.

(Insert Table 3, about here)

Therefore, specification (9) should be corrected for heteroscedasticity. The method used for this purpose is the weighted least squares (WLS). The assumption made about the error variance is that it varies reciprocally along the time squared. The re-estimated specification (see Table 4) yields a model where all previous merits remain, without, however, heteroskedasticity constituting a problem.

(Insert Table 4, about here)

To sum up, the Logistic model is qualified in describing the diffusion process on the basis of fitting the data and Frances' test (1994b). However, any definite conclusions cannot be derived if both models' predictive performance is not initially assessed.

4.2. Forecasting

As argued in the previous sub-section, a stronger piece of evidence is needed to verify the predominance of one model over the other. Therefore, a pseudo out-of-sample forecasting exercise is being performed, since it is well known that two models appearing to fit the data equally well can perform quite differently in a pseudo out-of-sample forecasting exercise (Stock and Watson, 2003).

Pseudo out-of-sample forecasting is being carrying-out using the Logistic and the Gompertz models for a sample spanning the period from 2000 to 2005. The criteria used to assess the forecasting ability of the two models are: the root mean squared error (RMSE), the mean absolute error (MAE), the mean absolute percentage error (MAPE) and, finally the Theil inequality coefficient (TIC). The values for all these criteria are reported in Table 5. Clearly, each criterion separately lends support to the use of the Logistic model.

(Insert Table 5, about here)

It is well established fact that lower forecast errors for a model, when it is compared with others, does not necessarily imply forecasting superiority, given that the difference in the forecast errors may be statistically insignificant from zero. For this purpose, two tests which are considered the most appropriate to this task have been applied: the Diebold-Mariano (1995) test for equal predictive accuracy and the Harvey et al. (1998) encompassing test. The null hypothesis for the Diebold-Mariano (1995) test is that the forecasting performance between the two competing models is equal and the null hypothesis for the Harvey et al. (1998) test is that first model's forecasts encompass second model's forecasts. Both tests results are illustrated in Table 6. For the Diebold-Mariano (1995) test the null hypothesis is rejected at the 0.1 level of significance, while for the Harvey et al. (1998) test the null hypothesis of forecast encompassing is rejected at any conventional level of significance. It is actually concluded that the difference in forecasting performance is deemed significant and, therefore, the forecasting supremacy of the Logistic model is confirmed.

(Insert Table 6, about here)

In the light of three alternative assessment methods which qualify the use of the Logistic model as the one describing better the diffusion process, we proceed by carrying out out-of-sample forecasting based solely on the Logistic model. From the estimated specification (9) it is trivial to predict the number of the expected mobile phone users for the period 2006 to 2015 (see Table 7). Taking into account forecasts uncertainty, the variance for each time period forecast is approximated through the non-parametric Bootstrap method, initially advanced by Efron (1979). More specifically, given the sum of the squared residuals it is easy to find residuals variance ($\hat{\sigma}^2$). Having as starting point Equation (12), it is now feasible through random sampling coming from the normal distribution with zero mean and variance $\hat{\sigma}^2$, to create observations for x_t^*.

$$x_t^* \approx \ln \hat{b}_2 + \ln(\exp(\hat{c}_2) - 1) - \hat{c}_2 t - \ln(1 + \hat{b}_2 \exp(-\hat{c}_2 t)) + \hat{h}_t^* \quad (12)$$

For the newly created dependent variables (thousands in number), Equation (9) is re-estimated and forecasting is performed for each separate estimation. A result is to receive a thousand forecasts $\hat{\pi}_i$ (i=1…1000), for the period 2006 to 2015. The variance of our initial forecasts $\hat{\pi}$, is given by the following formula:

$$Var(\hat{\pi}) = \frac{1}{n}\sum_{i=1}^{n}[\hat{\pi}_i - \hat{\pi}][\hat{\pi}_i - \hat{\pi}]^T \quad (13)$$

The asymptotic saturation level of the Logistic model can be approximated through forecasting for a long horizon. The reason to act in such a manner is that as time goes to infinity the Logistic model converges to its saturation level.[4] Hence, by forecasting hundred years ahead the number of mobile users, the value of 11,951,837 is obtained as an approximation to the saturation level.

(Insert Table 7, about here)

[4] $\lim_{t\to\infty} x_t = \lim_{t\to\infty} [a_2 (1+b_2 \exp(-c_2 t))^{-1}] = a_2$

4.3. Analysis of the Diffusion Process

Figure 2 illustrates the observed number of subscribers, the out-of-sample forecasts of the Logistic model, the estimated series for the time varying saturation level (equation 10) and the long-run value of the saturation level.

(Insert Figure 2, about here)

In Figure 2, what is attention-grabbing is the serious upward adjustment for the time varying saturation level, started taking place in 1997. Such an adjustment is attributed to the introduction of the pre-paid mobile telephony services, as well as to the shockingly successful entrance of Cosmote into the market. It is also observed that the forecasts have already been made move close to the saturation level. More specifically, based on the forecasts have been made, it is expected that the average growth rate in new subscribers up to 2015 will be less than half percent. Facts as the approximation of the saturation level and the slow down in the growth of new subscribers signify that the levelling-off process in the diffusion has already begun, something which is also verified by visually inspecting Figure 3.

(Insert Figure 3, about here)

In Figure 3, subscribers' velocity (right scale) and acceleration (left scale)[5] are plotted together in an effort to distinguish the four phases of a stylised diffusion process chronologically. The main feature of the first phase is that only few individuals adopt the innovation and the growth rate of the diffusion remains at the same level. According to this definition, the end of the first phase is located in 1995. The characteristic of the second phase is that the number of adopters increases rapidly and the innovation becomes very popular. Therefore, the termination of the second phase coincides with the velocity's global maximum in 2000. The most distinctive attribute of the third phase is the gradually declining rate of adoption. It could be argued that possible years signalling the end of the phase are the 2002 and 2004, during which acceleration's global and local

[5] Velocity is approximated by the fist difference in the number of subscribers, while acceleration by the second difference.

minimum respectively are observed. Adopting, *ad hoc*, as a cut-off year, the year that signifies a wider phase, 2004 is selected as the end of the phase. Finally, during the fourth phase the number of adopters decline dramatically. Hence, the four phases took place in the following periods, respectively: 1993-1995, 1995-2000, 2000-2004 and, finally, 2004-onwards.

5. Conclusions

Two S-shaped curves, the Gompertz and the Logistic, were fitted to the observed number of subscribers by means of non-linear least squares in order to model the diffusion process of mobile telecommunication services in Greece. The comparison showed that the Logistic model fares better in describing the diffusion process of adoption. Therefore, annual out-of sample predictions and their approximated variances through the bootstrap method were estimated on the basis of the Logistic model. The analysis undertaken revealed that the introduction of the pre-paid mobile services in 1997, along with the entry of Cosmote into the market in 1998, played a catalytic role in accelerating the diffusion. Moreover, it appears that the diffusion process has already passed into the last phase, implying that Greek mobile operators have started running-out of new customers.

Given the daunting results of our analysis and the low average usage of Greek subscribers, three major implications for the mobile operators have arisen. First, the sustainability of high profitability margins will not depend any more to the increase of the existing subscribers' base and a fierce competition on a price level is about to begin. Second, the Greek mobile operators should seek new profitability sources (e.g. increasing average usage via new products and services), if they want to remain competitive and not become acquisition targets. Third, a potential decline in the financial figures of the Greek mobile operators may provoke decline in investments, layoffs and restructurings in the sector hurting the quality of mobile services offered.

Finally, there are several caveats to our study and directions for future research. For example, future research could be directed to the identification of those economic (i.e. GDP per capita) and technological variables (i.e. digitality, the number of fixed telephone lines) that can explain the growth rate of the diffusion process in Greece.

References

Agar, J. (2003) *Constant touch, a global history of the mobile phone*, Icon Books, Cambridge, UK.

Botelho, A. and L. Pinto (2004) The diffusion of cellular phones in Portugal, *Telecommunications Policy*, **28**, 427-437.

Carvalho, A. (2006) Diffusion of mobile phones in Portugal: Unexpected success?, *Presentation at the Innovation Pressure International ProACT Conference*, 15-17 March, 2006, Tampere, Finland.

Dekimpe, M. G., P. M. Parker, and M. Sarvary (1998) Staged estimation of international diffusion models- an application to global cellular telephone adoption, *Technological Forecasting & Social Change*, **57**, 105-132.

Diebold, F. and R. Mariano (1995) Comparing predictive accuracy, *Journal of Business and Economic Statistics,* **13**, 253-263.

Dunnewijk, T. and S. Hulten (2006) A brief history of mobile telecommunication in Europe, working paper no 034, United Nations University.

Efron, B. (1979) Bootstrapping Methods: Another look at the Jackknife, *Annals of Statistics,* **7**, 1-26.

Frances, P.H. (1994a) Fitting a Gompertz Curve, *Journal of the Operational Research Society*, **45**, 109-113.

Frances, P.H. (1994b) A Method to Select Between Gompertz and Logistic Trend Curves, *Technological Forecasting and Social Change*, **46**, 45-49.

Frank, L.D. (2004) An analysis of the effect of the economic situation on modelling and forecasting the diffusion of wireless communications in Finland, *Technological Forecasting & Social Change*, **71**, 391-403.

Geroski, P. (2001) Models of technology diffusion, *Research Policy*, **29**, 603-625.

Griliches, Z. (1957) Hybrid corn: An exploration of the economics of technological change, *Econometrica*, **48**, 501-522.

Gruber, H. (2001) Competition and innovation: The diffusion of mobile telecommunication services in the Central and Eastern Europe, *Information Economics and Policy*, **13**, 19-34.

Gruber, H. and F. Verboven (2001) The diffusion of mobile telecommunications services in the European Union, *European Economic Review*, **45**, 577-588.

Harvey, D.I., S.J. Leybourne and P. Newbold (1998) Tests for forecast encompassing, *Journal of Business and Economic Statistics*, **16**, 254-259.

Kargman, H. (1978) Land mobile communications: The historical roots, In Bowers, R., A.M. Lee and C. Hersey, *Communications for a mobile society. An assessment of new technology*, Sage Publications, Beverly Hills, London.

Lee, M. and Y. Cho (2007) The diffusion of mobile telecommunication services in Korea, *Applied Economics Letters*, **14**, 477-481.

Mansfield, E. (1968) *Industrial research and technological innovation. An econometric analysis.* London: Longmans, Green and Co Ltd.

Massini, S. (2004) The diffusion of mobile telephony in Italy and the UK: An empirical investigation, *Economics of Innovation & New Technology*, **13**, 251-277.

Meade, N. (1985) Forecasting using growth curves-An adaptive approach, *Journal of Operational Research Society*, **36**, 1103-1115.

Meade, N. and T. Islam (2006) Modelling and forecasting the diffusion of innovation-A 25-year review, *International Journal of Forecasting*, **22**, 519-545.

Pereira, P. and J. Pernias-Cerrillo, (2005), The diffusion of cellular telephony in Portugal before UMTS: A time series approach, working paper no 08, Portuguese Competition Authority.

Romeo, A. (1977) The rate of imitation of a capital embodied process innovation, *Economica*, **44**, 63-69.

Stock, J. and M. Watson (2003) *Introduction to Econometrics*, International Edition, Addison Wesley.

Appendix 1: Tables

Table 1. Frances Test

	Parameters		
	δ	γ	θ^*
Estimate	-0.0640	0.0596	-0.0274
p-value	(0.849)	(0.618)	(0.011)

Note:* Significance of the θ coefficient supports the use of the Logistic Curve

Table 2. Estimation of the Gompertz Model

Parameter	Coefficient	Standard Error	t-value	*p*-value
b_1	6.231877	0.984753	6.328368	0.0001
c_1	0.297101	0.036516	8.136075	0.0000
Regression Statistics				
R^2	0.868759		J.B. (p-value)**	0.720730
$\bar{R}^2$	0.855635		White (p-value)***	0.891019
SSR*	1.906838		LM (p-value)****	0.188085

Notes: *SSR: Sum of the Squared Residuals, ** Jarque-Bera statistic for residuals normality, ***White Heteroskedasticity Test (F-statistic), ****Breusch-Godfrey Serial Correlation LM Test (F-statistic).

Table 3. Estimation of the Logistic Model

Parameter	Coefficient	Standard Error	t-value	*p*-value
b_2	75.67267	23.15700	3.267810	0.0085
c_2	0.628697	0.039222	16.02913	0.0000
Regression Statistics				
R^2	0.943401		J.B. (p-value)**	0.183958
$\bar{R}^2$	0.937741		White (p-value)***	0.002723
SSR*	0.822341		LM (p-value)****	0.749617

Notes: *SSR: Sum of the Squared Residuals, ** Jarque-Bera statistic for residual normality, ***White Heteroskedasticity Test (F-statistic), ****Breusch-Godfrey Serial Correlation LM Test (F-statistic).

Table 4. Re-estimation of the Logistic Model (WLS)

parameters	Coefficient	Standard Error	t-value	p-value
b_2	68.73481	11.22502	6.123355	0.0001
c_2	0.615360	0.019994	30.77668	0.0000
Regression Statistics				
R^2	0.988034		J.B. (p-value)**	0.559919
$\bar{R}^2$	0.986838		White (p-value)***	0.884057
SSR*	0.188764		LM (p-value)****	0.806422

Notes: *SSR: Sum of the Squared Residuals, ** Jarque-Bera statistic for residual normality, ***White Heteroskedasticity Test (F-statistic), ****Breusch-Godfrey Serial Correlation LM Test (F-statistic).

Table 5. Pseudo Out-of-Sample Forecasting Exercise (2000-2005)

Gompertz model		Logistic model	
Criterion*	Value	Criterion	Value
RMSE	477189.4	RMSE	114899.3
MAE	366684.1	MAE	90520.25
MAPE	4.828176	MAPE	1.036289
TIC	0.025097	TIC	0.006012

Note: *Abbreviations for the criteria are referred to: Root Mean Squared Error, Mean Absolute Error, Mean Absolute Percentage Error and Theil Inequality Coefficient, respectively. The lowest the criterion value (for any criterion), the better is for the forecasting performance.

Table 6. Difference in the Forecasting Performance

Test*	Statistic Value
Diebold-Mariano (D-M)	1.712372
Harvey encompassing**	3.007744

Notes: *Both tests under the null hypothesis follow the standard normal distribution, **The null hypothesis is that forecasts from the Logistic model encompass forecasts from the Gompertz model.

Table 7. Forecasts and associated standard errors for the Logistic model

Time	Subscribers forecasts	Future subscribers growth rate	Standard deviation of forecast errors
2006	11,681,476	0.0194	16708.08
2007	11,804,415	0.0105	22806.76
2008	11,871,777	0.0057	27021.51
2009	11,908,455	0.0031	29148.15
2010	11,928,358	0.0017	30594.48
2011	11,939,138	0.0009	31263.21
2012	11,944,971	0.0005	31710.34
2013	11,948,126	0.0003	32011.88
2014	11,949,831	0.0001	32161.72
2015	11,950,753	0.0001	32244.24

Appendix 2: Figures

Figure 1

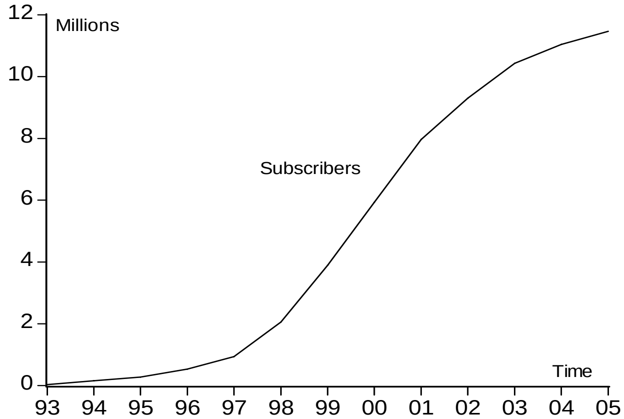

Figure 2

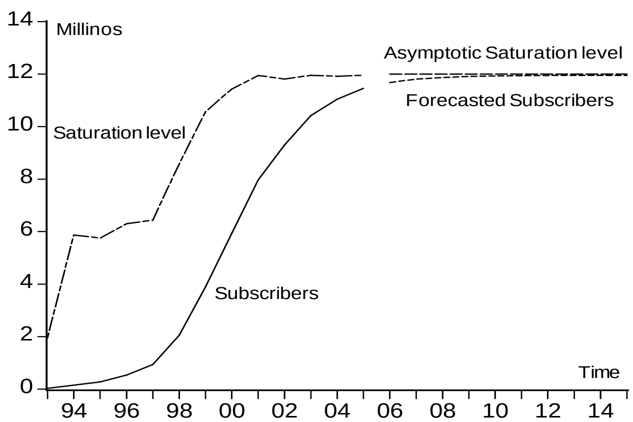

Figure 3