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The pattern and externality effect of diffusion of mobile telecommunications: the case of the OECD and Taiwan

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Abstract

Through the adoption of a two-step methodology, this paper sets out to examine the pattern of diffusion of mobile telecommunications with the aim of identifying the key factors influencing the diffusion rate for 29 OECD countries and Taiwan between 1980 and 2001. We find that the pattern of diffusion of mobile telecommunications for all the sample countries is generally characterized by an S-shaped curve; nevertheless, significant differences exist in the spread of the S curve, largely due to differences in the magnitude of the network externality coefficient. Our results underline the importance, with regard to accelerating diffusion, of the switch to digital technology and market competition. Furthermore, the approach selected with regard to fee payment represents another critical factor affecting mobile telecommunications diffusion, while the fixed penetration rate has a significantly negative influence. Policy implications stemming from these results are also discussed.

Keywords: Mobile telecommunications; Diffusion pattern; Network externality coefficient

1. Introduction

Although mobile telecommunications technology has been available since the early 1960s, it is only in recent years that the widespread diffusion of mobile services

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has come about. By 2001, Luxembourg and Taiwan had the world's highest penetration rates for mobile telecommunications services, at 96%, whereas in contrast, the respective diffusion rates in the US and Canada were only 44% and 32%. With the notable exceptions of Gruber (2001), Gruber and Verboven (2001a,b), previous studies in this field have tended to lack any systematic investigation of the reasons why there is such a dramatic difference in diffusion rates between nations. Using a logistic model of diffusion, Gruber and Verboven simultaneously estimated the diffusion coefficients and the factors associated with technological change and regulatory policies in telecommunications services. However, since they simply defined the coefficient β as a measure of the rate of diffusion, they examined neither the causes of the different mobile telecommunications diffusion rates nor the economic implications of this coefficient.

By adopting a two-step methodology, this paper sets out to examine the pattern of diffusion of mobile telecommunications with the aim of identifying the key factors influencing the diffusion rate for 29 OECD countries and Taiwan between 1980 and 2001. Although, Taiwan is not a member of the OECD, we believe that the unique characteristics of the island's mobile telecommunications market warrant a study in its own right. Indeed, with the mobile telecommunications market having been fully competitive since its inception in 1996, Taiwan's mobile telephone diffusion rate is now the highest in the world. Furthermore, per capita gross domestic product (GDP) in Taiwan is comparable to many of the OECD members and even higher than eight of the emerging markets within the OECD. [1] Clearly, therefore, an international comparison of the market penetration rates in Taiwan and the OECD countries should yield interesting results.

Using a logistic function of the epidemic model, we begin by estimating the pattern of diffusion amongst subscribers in the sample countries, where we find that the S curves for Northern Europe, the US, Canada and Japan are relatively flat, whereas much steeper S curves are discernible for Western Europe, Southern Europe and Taiwan. By integrating the technology diffusion model and the network externality model, we explore the economic implications of network externalities for the diffusion coefficient β and find that most of the differences can be attributed to the differences in the magnitude of the network externality coefficient β.

The estimated diffusion coefficient is then regressed in OLS models to identify the key determinants of the diffusion rates for the 30 countries, which leads to our finding that socio-economic indicators, such as population density and per capita GDP, have no significant effect on mobile diffusion. However, the switch to digital technology does prove to be an important driving force for mobile telecommunications diffusion. Our study supports the hypothesis that competition accelerates innovation diffusion. We also find that the choice of payment programs and the penetration rate of fixed networks play critical roles in affecting diffusion. Policy implications derived from these results are discussed in the conclusion.

[1] The eight emerging markets are: the Czech Republic, Greece, Hungary, Korea, Mexico, Poland, Portugal and Turkey.

This paper is organized as follows: Section 2 traces the pattern of diffusion of mobile telecommunications services in the OECD countries and Taiwan, and analyzes the differences in the pattern of diffusion between the different economies. The penultimate section describes the econometric estimation model used to identify the major determinants of the rate of mobile telecommunications diffusion, followed by a discussion of the empirical findings and their implications. The Section 4 summaries the study with some concluding remarks.

2. Identifying the pattern of diffusion

The growth trends in mobile telecommunications subscriptions of all the countries within our study are S-shaped curves in general. The characteristic common to all of these nations is that annual growth in subscriptions starts out slow, stable and somewhat protracted in the introductory stage, the growth rate begins to take off once cumulative subscriptions have reached a critical mass, and then growth tapers off prior to reaching saturation. The benchmark for the take-off in most countries seems to have been around 1997, followed by roughly four years of expansion; a complete S curve then emerges around 2002, as most OECD countries entered their saturation stage. Although the S curve is a general characteristic of the growth rates, the pattern of diffusion is nevertheless different from one country to another. In the following section, we attempt to identify the precise patterns of mobile telecommunications diffusion.

2.1. The theoretical model

As is generally the case in all new innovations, mobile telecommunications services are not immediately adopted by all potential subscribers when the new technology is first introduced – the absorption decision takes time. Many alternative diffusion models could be used to describe this process. For example, the theoretical grounding for the traditional 'modified exponential model' lies in an assumption that the temporal path of technology diffusion is made possible by the spread of information from a central source. A variant of the modified exponential model is the logistic model used by Karshenas and Stoneman (1993), Rogers (1995), Geroski (2000), Scitovski and Meler (2002), in which the authors modified the central information source theory by including the input of previous users so that a secondary information source, namely 'word-of-mouth', is incorporated into the model. Using the logistic function of the epidemic model, we attempt to identify the precise patterns of mobile telecommunications. The model contains the following assumptions:

(1) Non-users in time t have two information sources for new technology absorption – a central source and a word-of-mouth process. The absorption rate achieved by the central source is independent of the size of the existing user population, whereas the absorption rate achieved by word-of-mouth relies totally on the size of the current user population.

(2) The respective influences of central source and hands-on experience diffusion paths on non-users can be specified as [α] and [$\beta * y(t)/N$], with the actual effect of new technology dissemination being achieved by these additive influences. More specifically, the relationship is given by

$$\Delta y(t) = \alpha[N - y(t)] \cdot \Delta t + \beta \frac{y(t)}{N}[N - y(t)] \cdot \Delta t, \tag{1}$$

where the rate of diffusion in time t, $\Delta y(t)$, is a function of its two sources; and $[N - y(t)]$ is the non-user population.

Rearranging Eq. (1), we obtain

$$\Delta y(t) = \left[\alpha + \beta \frac{y(t)}{N}\right] \cdot [N - y(t)] \cdot \Delta t, \tag{2}$$

where α and β in the first square brackets on the right hand side of the equation represent the diffusion parameters; the second term, $[N - y(t)]\Delta t$, represents the number of non-users in time t. Assuming that there are $y(0) > 0$ initial users, taking the limit as $\Delta t \to 0$ and solving for the time path of usage yields

$$y(t) = N\left[1 - \mathrm{e}^{-(\alpha+\beta N)t}\right]\left[1 + \varphi \mathrm{e}^{\frac{-\beta(\alpha+\beta N)t}{\alpha}}\right]^{-1}, \tag{3}$$

where $\varphi = (N - y(0))/y(0)$. The diffusion of mobile services in this equation follows an S-shaped curve. Rogers (1995) and Scitovski and Meler (2002) demonstrated the analysis of the impact of the relative magnitude of the diffusion parameter α and β on the pattern of diffusion.

Taking the second derivative of Eq. (3) allows us to identify the location of the inflection point

$$y(t^*) = \frac{N}{2}\left(\frac{1 - \frac{2\alpha}{\alpha+\beta\cdot N}}{1 - \frac{\alpha}{\alpha+\beta\cdot N}}\right) \leqslant \frac{N}{2}. \tag{4}$$

It is clear from Eq. (4) that the value of $y(t)$ at the inflection point tends to be low if α is larger than β, or when the strength of the central source is greater than word-of-mouth. Conversely, when α is smaller than β, the inflection point ($y(t)$) tends to be high, in which case word-of-mouth has the dominant effect. The heavy line in Fig. 1 shows that a larger α/β value causes the S pattern to curve up early in time.

2.2. Data source and empirical analysis of the S curve

We track the diffusion paths of mobile telecommunications services using a database on 29 OECD member countries and Taiwan for the period from 1980 to 2001. The data on subscription volume for the end of each year for the period 1980–1997 are obtained from the OECD Telecommunications Database, 1999, while data for

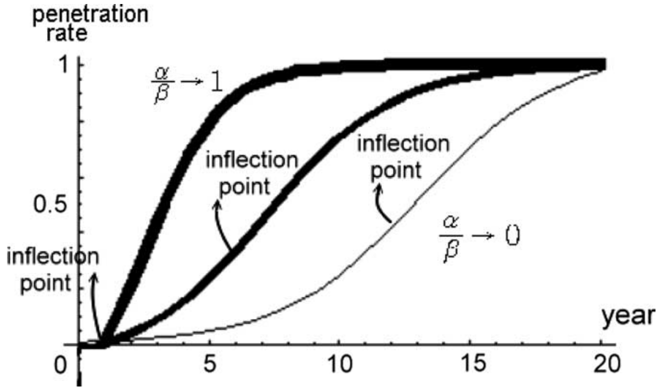

Fig. 1. Logistic model with different $\frac{\alpha}{\beta}$ values.

the period 1998–2001 are obtained from the latest publication posted on the ITU website. Since some of the data for the period 1980–1985 are missing for a few countries, such as Turkey and Greece, the total number of observations is 454 instead of 630. Subscription data on Taiwan are available from information published on the Taiwan Directorate-General of Telecommunications Office website. Since our collected data are discrete annuals rather than continuous, as opposed to using Eq. (1), we use the following equation for our regression analysis:

$$\Delta y(t) = y_t - y_{t-1} = \alpha(N_{t-1} - y_{t-1}) + \beta \frac{y_{t-1}}{N_{t-1}} (N_{t-1} - Y_{t-1}). \tag{5}$$

Eq. (5) is subsequently estimated for the pooled sample data of thirty countries using the ordinary least squares (OLS) method, with the estimation results being presented in Table 1.

The estimated coefficient of α is 0.002, and insignificant, implying that the central source generally had a negligible effect on the diffusion of mobile telecommunications in all thirty countries. However, at around 0.63, the estimated β coefficient is statistically significant, which suggests that between 1990 and 2001, the spread of user testimonials has emerged as an important source of mobile telecommunications diffusion. Substituting the estimated values of α and β into Eq. (5), and solving the

Table 1
Regression results for Eq. (5)

Coefficient	Estimated value	Standard error
α	0.002	0.002
β	0.627[a]	0.020
No. of observation	454	
R-squared	0.755	

[a] Indicates the coefficient is significant at 95% confidence level.

equation for $y(t)$, we obtain the average growth pattern of penetration rates for the sample countries as:

$$y(t) = 10^{-2} - \frac{0.629}{0.627 + 0.002e^{0.629t}}. \tag{6}$$

Fig. 2 shows the computation results of Eq. (6) with the average growth rates for the thirty countries in the earlier years being generally low and gradual, and penetration achieving a level just below 10%. The take-off stage starts at around the fifth year, and continues until penetration approaches saturation.

We also estimate the values of mobile telecommunications diffusion coefficients α and β in Eq. (5) for each country separately, using the same methodology. Since the values of α in all of the countries were insignificant, we list only the average values of the diffusion coefficient β in Fig. 3 for a country comparison.

Fig. 3 shows that β is the highest in the Western and Southern European regions, and lowest in North America. In terms of individual countries, Taiwan and Luxemburg have the highest diffusion rates, while Canada, the US and Japan have the lowest. Sorting the growth patterns of the thirty nations according to their β values, we identify three types of growth patterns: the 'complete S type', the 'growth-in-process type' and the 'low diffusion type'.

2.2.1. The complete S type

Nations with complete S path growth patterns can be further divided into two groups: the slow-growth and rapid-growth nations. Relative to the average OECD penetration rates shown in Fig. 4, Northern European countries are characterized as the slow-growth group. The countries of Northern Europe, those that have led the development of mobile telecommunications technology for over 25 years, naturally have high penetration rates averaging between 70% and 80%. Nevertheless, their β values are generally low in the first part of their S curves, with a protracted, and close to zero, growth rate in the beginning. This is because at the time when mobile telecommunications were introduced to these nations, the related technology was

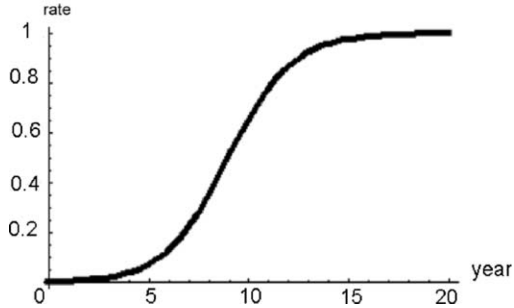

Fig. 2. Mobile diffusion pattern for OECD countries and Taiwan.

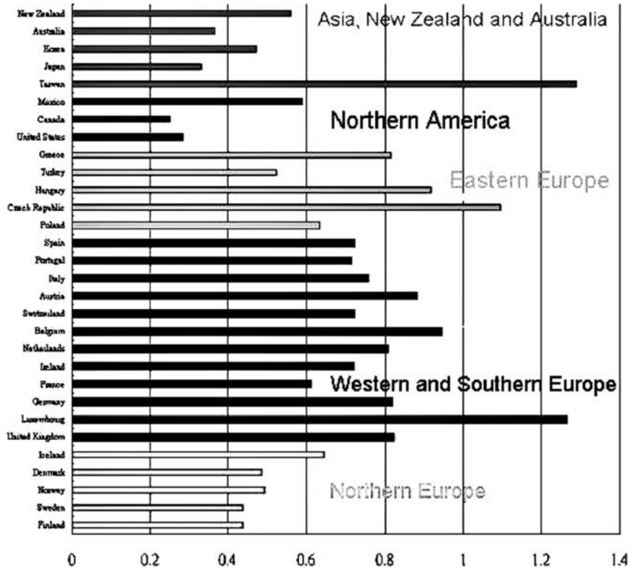

Fig. 3. The average β value for individual country.

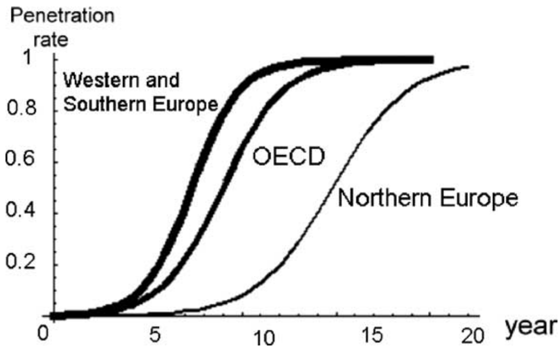

Fig. 4. The diffusion patterns in Europe and OECD.

somewhat immature and the cost of cellular telephone usage was high. Since the barriers to entry were rather substantial, penetration took quite some time.

By the time cellular telephones had been introduced to Western Europe, Southern Europe and Taiwan, cellular telecommunication costs had fallen dramatically and it was therefore easier to achieve critical mass. This is underlined by the fact that within a very short period of time, the growth in subscription rates in Western and Southern Europe outpaced the rate of growth in Northern European countries. In other words, as mobile telecommunications were introduced from Northern Europe into Western and Southern Europe, technology maturation and economies of scale had resulted in significant price falls. The difference between manufacturers' suggested prices and the sort of price that consumers were willing to pay began to widen, resulting in sharp increases in mobile telephone growth rates. As a result, those countries that introduced mobile technology late in the process experienced shorter penetration periods and much more rapid growth rates after successful penetration. For these countries, the take-off stage of the S curves came on much more quickly than it did for the pioneers.

2.2.2. The growth-in-process type

The use of mobile telephones began in many Eastern European nations some ten years after the Northern European nations had gained access to the technology. Although per capita income levels are not high in the European Union (EU) nations, at the time of their initial introduction, cellular telephone usage fees were much lower than the fees being paid by their counterparts in Northern Europe. Therefore, as Fig. 5 shows, although the penetration periods are much shorter, all of the S curves are currently still at the early stage of development.

2.2.3. The low diffusion type

Nations with low diffusion rates include the US, Mexico, Canada and Japan. The North American nations charge call recipients for the service a payment system, which we later discover significantly impairs diffusion. In addition, the availability of digital technology might be a factor contributing to their low diffusion rates. While digital systems were widely used in Northern European nations, operating systems in North America remained at the AMPS stage. The US was two years behind the NE countries. Canada and Mexico had no digital system until as late as 1997. Japan, on the other hand, pursued a self-reliance research policy to develop her mobile telecom technologies and systems, in contrast to the concerted effort by the Northern European nations in developing uniform standards and means for technology sharing. The incompatibility of her systems with the systems of their neighboring countries might have postponed the diffusion of mobile tech-

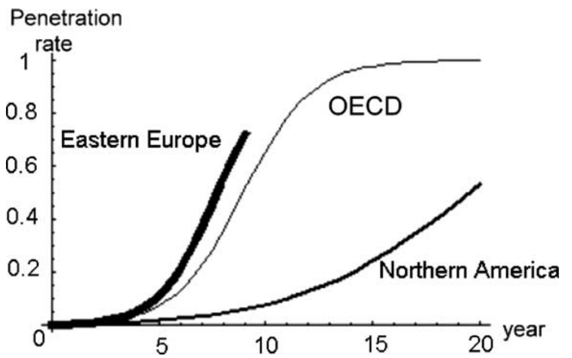

Fig. 5. The diffusion patterns in Eastern Europe and Northern America.

nology. Further study on Japan may be required for a fuller understanding of why Japan's diffusion rate is low.

2.3. Interpretation of the diffusion coefficient

The estimated β values are important in terms of providing an understanding of the differences in mobile telephone diffusion rates between nations. In this section we revise the external network model proposed by Shy (2001) to explain the economic implications of the β value, adding a parameter to Shy's externality consumer utility function in order to measure the strength of network externalities. We also substitute a logistic probability distribution function for Shy's a priori assumption of a union distribution since the cumulative probability density function fits the diffusion patterns of our sample data (the S curve) better than Shy's straight line distribution. The revised externality network model can then be represented by the following equation:

$$U_x = \begin{cases} (1-x)\beta \cdot q^{e} - p & \text{if subscribing,} \\ 0 & \text{if not subscribing,} \end{cases} \tag{7}$$

where U_x is the utility of a type-x consumer and x is a proportionality index assuming values between zero and one; q^{e} is the expected number of users in the end, and p is the vendors' price. The utility of each consumer exhibits network externality since it increases with q^{e}. $(\beta * q^{e})$ can thus be used to represent the effects of external networks.

Following Shy's mathematical logic, we derive a new inverse demand function to include the influence of β:

$$p = \left(1 - \hat{x}\right)\beta \cdot \eta \cdot \hat{x}. \tag{8}$$

Assume a group of a η continuum of potential telecommunications customers uniformly indexed by x on $[0, 1]$. The consumers indexed by $x > \hat{x}$ will not subscribe

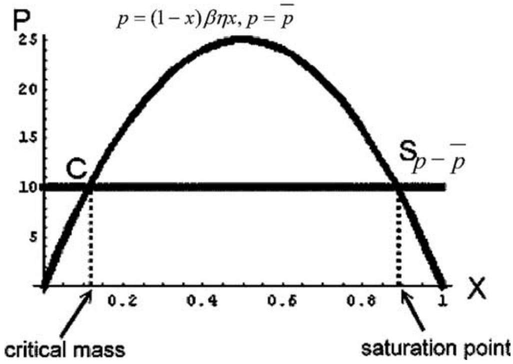

Fig. 6. Demand curve of telecommunications services.

to the service, whereas consumers will subscribe if they are indexed by $x \leqslant \hat{x}$. It follows that q^{e} is equal to $\eta \cdot \hat{x}$. The graphical representation of Eq. (8) is shown in Fig. 6, from which it is clear that when the demand curve is hyperbolic, and if the vendors offer a price at $\overline{p}$, two solutions emerge for the value of x, point C and point S, but only point S is a stable equilibrium solution.

Fig. 7 shows that the larger the value of β, the higher the price that consumers will be willing to pay, and thus, the more rapid the rate of network expansion. β may therefore be interpreted as an index of external force.

For the countries under observation, since we attribute the different diffusion growth patterns to the differences in the value of β, the magnitude of β determines the size of the critical mass and the location of the saturation point, which explains why take-off and saturation points differ between different nations.

The intersection between the demand curve and price line in Fig. 7 may be represented by

$$P = \beta\eta\chi - \beta\eta\chi^{2}. \tag{9}$$

Following this, the two solutions of the quadratic Eq. (9) are critical mass (C) and saturation point (S), as follows:

$$C = \frac{\beta\eta - \sqrt{\beta^{2}\eta^{2} - 4P\beta\eta}}{2\beta\eta}, \tag{10}$$

$$S = \frac{\beta\eta + \sqrt{\beta^{2}\eta^{2} - 4P\beta\eta}}{2\beta\eta}. \tag{11}$$

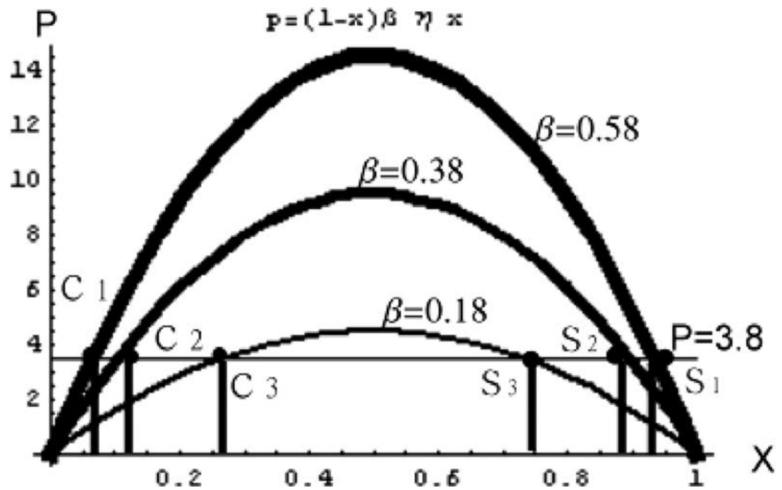

Fig. 7. Demand curves of telecommunications services with different levels of β. This figure is drawn under the assumptions that $\eta = 100$, $P = 3.8$.

The effect of β on C and S can be measured by partially differentiating Eqs. (10) and (11), respectively as follows:

$$\frac{\partial C}{\partial \beta} = \frac{\sqrt{-4P\beta\eta + \beta^2\eta^2} - \beta^2\eta^2}{4\beta^2\eta\sqrt{-4P\beta\eta + \beta^2\eta^2}} < 0, \tag{12}$$

$$\frac{\partial S}{\partial \beta} = \frac{\sqrt{-4P\beta\eta + \beta^2\eta^2} + \beta^2\eta^2}{4\beta^2\eta\sqrt{-4P\beta\eta + \beta^2\eta^2}} > 0. \tag{13}$$

As clearly indicated in the above two equations, the larger the value of β, the smaller the value of the critical mass, and therefore, the larger the value representing the saturation point.

3. Determinants of the diffusion coefficients

The discussion in the previous section should have fully demonstrated the critical role of β with regard to its influence on the path of diffusion of mobile telecommunications. In this second part of the study, we now proceed with an examination of the factors determining the strength of β.

3.1. Possible determinants

The literature on patterns of diffusion of mobile telecommunications is particularly scant, mainly because it was not until recent years that mobile telephone subscriptions began to reach the top of the S curve. In his analysis of the determinants of the speed of mobile telephone diffusion in Central and Eastern European (CEE) between 1990 and 1997, Gruber (2001) found several major determinants of rapid diffusion, among them, the timing of a country's adoption of mobile telephones and the total number of vendors were significant. Also, complete market liberalization was more effective than partial liberalization of the market over time. The scope of fixed mainline telecommunications was another factor that contributed to the speed of diffusion.

Gruber and Verboven's further study of 15 EU nations (2001a) over the period from 1984 to 1997 found that digital technology achievement, open competition and the timing of the awarding of licenses to countries had a pronounced effect on diffusion). In yet another parallel global study, involving 205 countries, a major finding was that uniform and standardized regulations had an important impact on the expansion of subscriptions (Gruber and Verboven, 2001b).

Using the findings of the previous studies and observed practices in our sample countries, we identify seven variables as possible determinants of the differences in the pattern of diffusion between these countries. They are: (i) population density;

(ii) per capita income; (iii) the availability of digital technology; (iv) market competition; (v) the number of new vendors in the market; (vi) the proposed payment options; and (vii) penetration rates in the fixed network.

In countries where population density is high, we expect a high level of human interactions. In these countries, mobile telephones stand out as the most appropriate tool for facilitating the frequent integration. Taiwan has the highest population density in our sample, it comes as no surprise that the island also has the highest β value and the highest penetration rate of all the nations studied.

Real per capita GDP is clearly another variable capable of describing country characteristics. Since consumers in countries with higher income levels are more likely to use mobile telephones, we expect a positive correlation between per capita income and the mobile telephone penetration rate of that country.

The transition from analogue to digital technology facilitated dramatic increases in the overall capacity of the radio spectrum. Furthermore, digital communications enhance the effect of network externalities, thanks to the ease of convertibility from one system to another. We therefore expect the availability of digital technology in a country to play an important role in terms of increasing subscriber numbers.

The healthy growth of an industry is largely determined by the openness of its markets, and the trend in most mobile telecommunications markets in recent years has indeed been towards gradual liberalization. In 1990, for example, with the exceptions of eight duopolies, all of the mobile telecommunications markets of the OECD nations were monopolized; however, just eight years later, in 1998, no monopolies remained in any of the OECD nations. Note that it is not necessary for all vendors in a competitive market to establish their own network, since the networks of most countries are integrated through an access charge system, which enables vendors to realize economies of scale while society benefits from competition.

The variable for new firms was added in this study because we noticed that in Australia, in 2000, when the number of firms increased from three to six, the penetration rate jumped noticeably from the previous year. We include the number of new firms in the model as a proxy for competition and measure the effect of competition on the value of β.

Two major payment options have emerged in this market, namely, calling party pays (CPP) and receiving party pays (RPP). Of the OECD nations, the most representative users of the RPP system are the US, Canada and Mexico. Within this region, as long as consumers have a mobile telephone, regardless of whether they are the calling party or receiving party, the owner bears part of the cost. Given such a payment system, an inevitable consequence is that many mobile telephone users may simply turn off their telephones or choose not to answer selected incoming calls in order to reduce their telephone bills. Such behavior will substantially discount the existing externality effect of the network while also retarding the speed of diffusion of mobile telecommunications. We find that the β value and penetration rate are generally lower for countries using the RPP system.

Once mobile telecommunications became a widely available service and their tariffs were comparable to those of fixed line telecommunications, those subscribers who wished to add an additional line could then choose between mobile and fixed networks. In 1987, of all Northern European subscribers, 21% used mobile telephones while 79% used fixed networks. By 1990, however, 60% of all subscribers were mobile telephone users, with the remaining 40% using fixed networks, and there was an increasing tendency towards the choice of mobile telephones by new subscribers. As such, very strong substitutability between mobile telephones and fixed line networks now characterizes the telecommunications market.

3.2. Data sources and estimation results

We specify the following regression model to test the above hypotheses:

$$\begin{aligned}\beta_{it} =& a_0 + a_1 \cdot \mathrm{POP}_{it} + a_2 \cdot \mathrm{GDP}_{it} + a_3 \cdot \mathrm{DIG}_{it} + a_4 \cdot \mathrm{MARKET}_{it} \\ &+ a_5 \mathrm{NEW}_{it} \cdot + a_6 \cdot \mathrm{CPP}_{it} + a_7 \cdot \mathrm{FIX}_{it} + \varepsilon_{it},\end{aligned} \tag{14}$$

where POP represents population density and GDP is per capita income; MARKET is a dummy variable which assumes a value of one if markets are open to more than two competitors, otherwise its value is zero; NEW is the number of new firms in a given year; DIG is a dummy variable equal to one if a nation has access to digital technology, otherwise zero; CPP is also a dummy variable, which is inactive unless a ‘calling party pays’ plan is used; FIX_{it} is the penetration rate of the fixed network for country i in year t, measured as the number of fixed telecommunication lines per head of population; ε_{it} **is** the stochastic error term.

In order to estimate the relative effects, we have to take account of unobserved heterogeneity between countries. If the value of β also depends on factors other than our specification, the model suffers from omitted variable bias. One way to solve this problem is to assume that the specific factors determining the value of β (for example, the various styles of government management amongst the countries in our sample) cannot be measured. This unobserved heterogeneity can be explicitly modeled by a country-specific constant in Eq. (14) for the fixed effects, while country-specific factors are uncorrelated with the regressors in the random effects model. We use the ordinary least squares (OLS) method to facilitate separate estimation of both the random- and fixed-effects models.

Due to the incomplete data for the early period (specifically 1980–1989), we estimate the regression model of Eq. (14) for the 29 OECD countries and Taiwan for the period 1990–2000 only. Data for the explanatory variables is derived mainly from the ITU and OECD websites. Most of the OECD data are historical, whereas current data are more readily available from the ITU. For Taiwan, most of the data are taken from the Directorate-General of Telecommunications website, with an additional small amount being provided by the ITU website. The dependant variable, β_{it}, is computed from Eq. (5) as follows: [2]

[2] According to the empirical results in the first part of our regression analysis in the previous section, the estimated coefficient of α in Eq. (5) is not significantly different from zero. Therefore, $\alpha(N_{t-1} - y_{t-1})$, the first item of Eq. (5), is ignored.

$$\beta_{it} = \left[\frac{y_{t-1}}{N_{t-1}}(N_{t-1} - y_{t-1})\right]^{-1} \cdot (y_t - y_{t-1}), \tag{15}$$

where β_{it} refers to the β value of the ith nation at time t. Eq. (14) is estimated on 330 observations in our sample using STATA software.

According to the results of the Hausmen test, a random effects model, rather than a fixed effects model, is the more appropriate model for the sample data. The regression results of the random effects models, i.e. Models 1 and 2, are presented in Table 2. The specifications of these two models are quite similar; there is however one major difference, since Model 2 has an extra interactive term, D*FIX.

The estimated results of Model 1 in Table 2 show that population density and per capita GDP levels do not significantly affect the speed of diffusion. This finding is consistent with the results obtained by Gruber (2001) for Eastern Europe and Gruber and Verboven (2001a) for the EU as a whole.

As expected, the coefficient of DIG is positive (0.18) and significant, implying that when all other control variables are held constant, a large increase in spectrum capacity, due to the introduction of digital technology, apparently at tracts a sizable number of new users. The variables pertaining to competition, such as MARKET and NEW, turn out to have positive and considerably strong effects on the speed of diffusion, their respective estimated coefficients being approximately 0.16 and 0.13. The results support the hypothesis that competition, measured by market opening and the number of new firms, contributes to the rate of diffusion. Opening up the market to more than two competitors significantly speeds up the rate of diffusion, indeed, the greater the number of new firms the more rapid the diffusion rate.

The coefficient of CPP is positive and statistically significant, having the highest value of all the explanatory variables (0.24). The large coefficient suggests that using a 'receiving party pays' approach, as opposed to a 'caller party pays' approach, has a

Table 2
OLS regression with β as dependent variable

Variable	Model 1	Model 2
CONSTANT	0.940** (0.172)	0.836* (0.176)
POP	0.0003 (0.0003)	0.00005 (0.0003)
GDP	−0.651 (6.690)	−1.683 (6.409)
DIG	0.176** (0.091)	0.156** (0.092)
MARKET	0.156* (0.093)	0.154* (0.092)
NEW	0.126** (0.057)	0.124** (0.057)
CPP	0.237** (0.121)	0.330** (0.128)
FIX	−0.015** (0.005)	−0.012** (0.005)
D*FIX	–	−0.004* (0.002)
R^2	0.524	0.585
No. of observations	330	330

Numbers in parentheses are standard errors. Regressions are estimated by ordinary least squares using heteroskedastic-consistent covariance matrix.

* and ** Represent statistical significant at 5% and 10%, respectively.

significant negative impact on the rate of diffusion of mobile telephones. This is an effect which has not previously been identified in the literature.

The estimated coefficient of fixed network penetration rate is significantly negative, which suggests the existence of a substitution relationship between fixed networks and mobile penetration rates within these countries. As noted earlier, when considering the addition of a new line, consumers have a choice between a fixed network line and a mobile telephone line. An earlier study (Kelly, 1995) noted that, for most of the OECD countries, with the notable exceptions of Northern European countries, there was discernible complementarity in mobile and fixed network penetration rates for most of the 1980s. Since 1988, however, such complementarity has transformed itself into substitutability.

In order to verify the relationship between mobile and fixed network penetration rates in more recent years, we divide our sample into two groups, the Northern European (NE) countries and the non-Northern European (NNE) countries. A new dummy variable, D*FIX, is added to Eq. (14) as shown in Model 2 of Table 2. The dummy variable takes on a value of one if a nation is an NE nation; otherwise zero. As compared to the results obtained from Model 1, the empirical results from Model 2 show that the estimated coefficients for all of the explanatory variables retain the same signs as those in Model 1, but that in Model 2, the estimated coefficients of both FIX and D*FIX are significantly negative. Moreover, the value of R^2 in Model 2 is slightly higher than in Model 1. These results indicate that the substitution effect was much stronger in the Northern European countries than in the non-Northern European countries during the period 1990–2001.

Considering the difficulties and costs involved in the restructuring of traditional fixed telecommunications networks, and with consumers in recent years having come to view mobile telephones as an acceptable substitute for fixed line services, mobile telecommunications have clearly become a convenient and essential communications tool. Moreover, the introduction of advanced digital technology into the telecommunications market appears to be crucial to mobile telephone adoption; thus, a clear policy implication is that continual investment in advanced technology could be the key to a company's success in this market. Furthermore, the increased capacity and better compatibility made possible by digital technology also allows more firms to operate in this market. The growing intensity of competition, as highlighted in our study, will clearly further accelerate the rate of mobile telephone diffusion. Companies should recognize and seek to capture the opportunities created by economies of scale so as to expand their growth potential. Finally, the selection of an appropriate payment plan, which does not retard the motives for mobile telephone adoption, also represents an important strategy for the successful expansion of the telecommunications market.

4. Conclusions

Using the logistic function of the epidemic model, we find that amongst the OECD countries and Taiwan, discernibly different mobile technology diffusion patterns existed during the period from 1980 to 2001, although the diffusion patterns of all the sample countries exhibited an S-shaped curve. We find relatively flat S curves in Northern Europe, the US, Canada and Japan, but contrasting sharper S curves for Western Europe, Southern Europe and Taiwan.

The observation that some countries had slower growth rates while there has been remarkable expansion of some of the other markets can be explained by the differences in the magnitude of the network externality coefficient, β. In this study we integrate a technology diffusion model with the network externality model to explore the economic implications of network externalities for the diffusion coefficient β and find that the larger the value of β, the smaller the critical mass and the shorter the time taken to reach saturation point.

Once the estimated β values are obtained, we use an OLS regression model to identify the determinants of the telecommunications diffusion rate. Our empirical results underline the importance of the switch to digital technology and market competition with regard to the acceleration effect on diffusion rates. Furthermore, the choice of fee payment method represents another critical factor affecting the rate of diffusion of mobile telephones, while the fixed network penetration rate has a significantly negative influence on mobile telephone diffusion rates.

Some important strategic policy implications following on directly from our results are also discussed in this paper. Future research should focus on the effects of regulatory policies in various regions. This should provide additional insights into the reasons for the differences in diffusion patterns across different countries.

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