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DETERMINANTS OF MOBILE PENETRATION TO FORECAST NEW BROADBAND ADOPTION: OECD CASE

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Abstract

This paper aims to analyze relationship between Mobile penetration and various indicators of communication infrastructure throughout OECD countries. Panel data is utilized for the purpose of this study. In order to control network effects as well as the endogeneity of variables, the Arellano–Bond dynamic panel estimation is adopted. In particular, this paper attempts to identify what are the factors to promote the 3G mobile phone by using dynamic panel data analysis. In constructing an estimation model, Cellular mobile penetration is taken as a dependent variable, while various technical and economic variables are selected as independent variables. The obtained results can be used to forecast adoption of New Broadband Penetration technology.

Keywords: Mobile Penetration, New Broadband Adoption, Panel Data, Communication, Forecast, OECD

Jel Code: C53

YENİ GENİŞ BANT ADAPTASYONUNU TAHMİNLEMEDE MOBİL PENETRASYONUN BELİRLEYİCİLERİ: OECD ÖRNEĞİ

Özet

Bu makalede mobil penetrasyon ile iletişim altyapısının çeşitli göstergeleri arasındaki ilişki OECD ülkeleri genelinde analiz edilmektedir. Bu amaçla panel data yöntemi kullanılmıştır. Değişkenlerin içsellik sorunu ve ağ etkilerini kontrol edebilmek için Arellano-Bond dinamik panel tahmini uygulanmıştır. Özel olarak bu makale, ilerideki çalışmalarda 4G kullanımını tahminleyebilmek için dinamik panel data analizini kullanarak 3G kullanımı etkileyen faktörleri belirlemeye çalışmaktadır. Bu amaçla bir tahmin modeli oluştururken cep telefonu penetrasyonu bağımlı değişken olarak, çeşitli teknik ve ekonomik değişkenler de bağımsız değişkenler olarak alınmıştır. Elde edilen sonuçlar yeni geniş bant penetrasyon teknolojisinin adaptasyonunu tahmin etmek için kullanılabilecektir.

Anahtar Kelimeler : Mobil Penetrasyon, Yeni Geniş Bant Adaptasyonu, Panel Veri, İletişim, Tahmin, OECD

Jel Kodu : C53

1. INTRODUCTION

The world has witnessed a dramatic improvement in telecommunications technologies during the past couple of decades. A wide range of telecommunication services have emerged in parallel with an increasing competition among the service providers. It has not been long since the introduction of third generation (3G) technologies even in OECD countries, yet some countries have already started to use 4G technology and some other are in the process of

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doing the required investment. 2G technology which is still widely used globally was based on voice technology to meet the basic demand of consumers. But the improving telecommunication technologies have enabled the video services as well, thus leading to 3G technologies. Now, Worldwide Interoperability for Microwave Access (WiMAX) 802.16 m and Long-Term Evolution (LTE)-Advanced were recognized as the foundation of fourth generation (4G) technology at the end of 2009 (Tseng, 2014). In this context, this study aims to explore the relationship between the level of such technologies and various factors that are argued to be related to them. Specifically, we attempt to identify the factors promoting the 3G mobile phone by using panel data analysis. In constructing an estimation model, Cellular mobile penetration is taken as a dependent variable, while various technical and economic variables are selected as independent variables. The obtained results are intended to be used to forecast adoption of 4G technology in the following studies.

Such a forecast is especially vital for telecommunications businesses. It is important to understand the development tendency of the 3G market and the growth of the 3G phones penetration rate to allocate their investments in base station settings and launched services. Therefore, an accurate forecast of 3G phones demand is important to help telecommunications companies with making operational, tactical marketing strategic decisions, such as business scheduling, staff training-on-job, the preparation of 3G added-value services, base stations investments, and so on. The benefits of accurate forecasting are undisputed (Chen, 2014).

Abu (2010) attempts to present a view of the effect of technological innovations for the diffusion of 3G mobile phone in Japan using panel data analysis. Suki (2011) examines the relationship between perceived usefulness, perceived ease of use, perceived enjoyment, attitude and subscribers' intention towards using 3G mobile services.

The purpose of this paper is to analyze factors promoting the 3G mobile phone from these two viewpoints. Regarding the research method, this paper applies a dynamic panel data model which performs an analysis with telecommunication data for OECD countries.

One of the major advantages of using the dynamic model is the opportunity to introduce network externalities or network effects into the analysis. In particular, subscribers can receive greater benefits in accordance with the growth of the network. Thus, a mobile carrier's network size or number of subscribers plays an important role when users choose the particular carrier they want to subscribe to. Mobile carriers, for example, offer discount rates for calls among their own subscribers, and accordingly subscribers to larger networks receive greater benefits. Network effects are significant when competition among mobile carriers is fierce. Another benefit of applying a dynamic panel data model has something to do with the endogeneity problem of the data. Endogeneity problem occurs quite often in empirical analyses, thus appropriate ways of dealing with this problem need to be utilized. A parameter or variable is said to be endogenous where there is a correlation between the parameter or variable and the error term. When correlations between explanatory variables and error terms exist, estimated coefficients of variables are not true values, and an endogenous bias occurs. One way of dealing with the problem of endogeneity bias is to use instrumental variables. The reason of using such variables is that they are not correlated with alternative factors, instead they are only correlated with the independent variable of interest. Thus, such variables will be correlated with the dependent variable only indirectly. They work through the independent variable to affect the dependent variable. This paper provides a solution to such an endogeneity problem by applying the Arellano–Bond estimator which enables the calculation of an unbiased estimator by using an exogenous or predetermined endogenous variable. In addition to this, the system generalized method of moments (GMM) is used (Akematsu, 2012).

2. METHODOLOGY AND MODELS

2.1. Methodology

A study consisting 34 OECD countries during the years of 2001-2011 (11 years) is conducted. Total number of observations is 330. Panel data analysis is used because both cross-section and time-section dimensions exist. Mobile penetration (the number of subscription per 100 inhabitants) which is used as the independent variable is dependent on the number of subscribers in the previous years, thus a dynamic panel data is used rather than static panel data. The Arellano–Bond linear dynamic panel data estimation model (Arellano& Bond, 1991) is used in order to solve the endogenuity, heteroskedasticity, and autocorrelation problems that exist among the variables. Arellano-Bond (1991) and Arellano-Bover (1995)/Blundell-Bond (1998) are models developed for this purpose. Both of them are especially designed for situations with small T, large N panels. Their usage on datasets of such characteristics is safe (Roodman, 2006). In our study, since T = 11 and N = 34, these conditions are satisfied.

Conducting the unitroot tests of the variables, it is detected that unitroot problem does not exist since the H_0 hypothesizes which states that it exists are rejected for each variable.

On the other hand, the Arellano–Bond linear dynamic panel data estimation model is executed by using xtabond2 command which was developed in 2003 in Stata12 to solve all these problems detected. This command also provides that endogenous and autocorrelation tests as well. H_0 hypothesis stating that instruments used in Sargan test are valid. Sargan is applied to test the instrumental variables used for the solution of endogeneuity problem (endogenous). If the number of observations is enough, as many lag values of endogenous variables as wanted can be used as instrumental variable (Roodman, 2006). The fact that number of observations is enough in our study makes it possible to use the 6th lag values of endogenous variables and pass the Sargan test successfully.

On the other hand, Arellano–Bond tests AR(1) and AR(2) are executed to test the auto correlation problems. In the AR (1) test, the lagged value of the dependent variable used in the model causes the rejection of H_0 hypothesis which states that there is no auto correlation. (The presence of the lagged dependent variable MP_{it-1} gives rise to autocorrelation). Thus, AR(2) test needs to be viewed (Roodman, 2006). Our model is resulted as expected, as the H_0 hypothesis stating that there is no autocorrelation in AR(2) test is accepted. Moreover, Wald test has resulted statistically meaningful. All these test results are provided in the tables below. Thus, our model has passed all the tests with success.

2.2. Models

Gombertz and logistic models have been the best models in explaining the S graphics (S-curve of innovation diffusion) of the most innovative trends (Lee & Lee, 2010). Using the Gombertz model is more appropriate as stated by Lin and Wu (2013) and Gruber and Verboven (2001) in their studies. Because in the Logistic model, the number of all the potential users (adopters) in a specific time and country needs to be forecasted and this is very difficult if it is an early stage for diffusion or there is heterogeneity among the countries (Lin and Wu, 2013); (Gruber and Verboven, 2001). This number (the number of potential adopters) is determined in Gombertz model as a function of supply and demand side variables. The formulas below are developed by this approach. The Gomberts model has a wide range of applications in forecasting the transition processes into the new communication and service technologies (Stoneman, 1983; Estache, Manacorda, and Valletti, 2002; Lee and Lee, 2010; Kiiski and Pohjola, 2002; Singh, 2008; Trappey and Wu, 2008; Andres et al., 2010; Lin and Wu, 2013).

In our study, the empirical model below is used for mobile penetration similar to the way Lin and Wu (2013) used for fixed broadband penetration.

$$lnMP_{it}\text{-}lnMP_{it\_1}=\alpha_i\ (lnMP^*_i\text{-}lnMP_{it\_1}) \qquad (1)$$

whereas MP stands for mobile penetration, MP_{it_1} mobile penetration of the previous year, and MP* total potential subscribers which is defined as a function of supply and demand side variables. Adding the changes of these variables by time, the model takes the form below:

$$\ln MP^*_i=\beta_{i0}+\ \beta_i 1lngdp_{it}+\ \beta i2lnarpu_{it}+¥_iZ_{it} \qquad (2)$$

Z_{it} is used to explain the other explanatory variables possible. If we place this second formula into the first, it takes the below form:

$$lnMP_{it}=\alpha_i\beta_{i0}+\ \alpha i\beta_{i1}\text{-}lngdp_{it}+\alpha_i\beta_{i2}lnarpu_{it}+\alpha_i¥_iZ_{it}+(1\text{-}\ \alpha_i)\ \ln MP_{it\_1} \qquad (3)$$

Writing this formula for the panel data analysis with our other variables:

Model 1:

$$lnMP_{it}=\ \alpha_0+\ \beta_1 lngdp_{it}+\beta_2 lnarpu_{it}+\beta_3 lntraf_{it}+\beta_4 lntelinv_{it}+\beta_5 lninternet_{it}+\beta_6 lnedu_{it}+\beta_7 lnHHi_{it}+\beta_8 lnmobrevenue_{it}+¥_3Z_{it}+\beta_9 \ln MP_{it\_1}+\mu_{it} \qquad (4)$$

Model 2:

$$lnMP_{it}=\ \alpha_0+\ \beta_1\ \ln MP_{it\_1}+\beta_2 lnarpu_{it}+\beta_3 lntraf_{it}+\beta_4\ lngdp_{it}+\beta_5 lninternet_{it}+\beta_6 lnedu_{it}+\beta_7 lnHHi_{it}+\beta_8 lnmobrevenue_{it}+¥_3Z_{it}+\mu_{it} \qquad (5)$$

Model 3:

$$lnMP_{it}=\ \alpha_0+\ \beta_1\ \ln\ MP_{it\_1}+\beta_2 lnarpu_{it}+\beta_3 lntraf_{it}+\beta_4 lntelinv_{it}+\beta_5 lninternet_{it}+\beta_6 lnedu_{it}+\beta_7 lnHHi_{it}+\beta_8 lnmobrevenue_{it}+¥_3Z_{it}+\mu_{it} \qquad (6)$$

$\mu_{it,}$ shows the regression bias.

2.3. Variables and Data

Four of the 34 OECD countries are excluded from the analysis due to the lack of data availability (Israel, Australia, Slovenia, and Chile). Mobile penetration which is measured as the mobile phone subscribers per 100 people (mobile subscribersper 100 inhabitants) is used as the dependent variable in the study conducted over 30 countries. Nine independent variables used in the developed model are: mobile penetration rate in previous year, GDP per capita, mobile traffic, ARPU (average monthly revenue per user), public telecommunication investment per capita, internet host per domain, education, HHI (Herfindahl-Hirschman Index for mobile and other platforms), and mobile telecommunication revenue. In order to obtain the values of these variables, OECD Communications Outlook 2013 is used (OECD, 2013).

Moreover, import and export variables are used as the instrumental variables in the study. The logarithms of all the variables are used in the model as a way of minimizing the skewness problem that might have otherwise occurred.

The revenue is used to explain the broadband diffusion. Akematsu and Shinohara et al. (2012), Garcia-Murillo (2005) and Bouckaert et al. (2010) in their studies state that the revenue has a significant positive effect in broadband diffusions. Lin and Wu(2013), using the technique developed by Rogers (2003), have applied the approach of dividing the broadband usage periods into the innovator and early adopter stage, the early majority stage and the late majority and laggard stage. With this approach they have not been able to detect a meaningful relationship between the broadband diffusion and GDP per capita which they have used to represent the revenue in total time. On the other hand, they have found a positive meaningful relationship in the periods of the innovator and early adopter stage and the late majority and laggard stage. GDP per capita is used for this purpose in our study.

Although a meaningful positive relationship between the education and broadband diffusion is expected theoretically, this could not be detected in many studies (Garcia-Murillo, 2005; Cava-Ferreruela and Alabau-Muˇnoz, 2006; Lee and Lee,2010; Lin and Wu, 2013). Lin and Wu (2013) have faced with a similar situation but they have been able to show this positive relationship for some periods of the life cycle.

We have used the Students as a percentage of the population of 15-19 year-olds as education variable.

The number of subscribers is expected to increase as the competition increases resulting in improved services and convenient prices. HHI (Herfindahl-Hirschman Index for mobile and other platforms) is used in this study to measure the factor of competition. It is calculate as the sum of the squared .market share of mobile and other platforms. This positive relationship is detected in some studies using HHI. (Bouckaert et al., 2010; Distaso et al., 2006; Lin and Wu, 2013; Lee and Lee, 2010).

Telecommunication investments (public telecommunication investment per capita) and increase in services provided through internet are expected to increase the mobile penetration. Various variables are used for this purpose. Internet host as a proxy (Garcia-Murillo, 2005), internet host per 100 inhabitants (Lee and Brown, 2008) and internet hosts per 1 million people (Lin and Wu, 2013) have detected the existence of this relationship. Internet host per domain and public telecommunication investment per capita is used for this purpose in our study.

On the other hand, the effects of the changes in mobile traffic (cellular mobile traffic per mobile subscriber per year) on mobile penetration is looked into during the study. In their study over Japan, Akematsu and Shinohara et al. (2012) have shown that the increase in need for talk has increase the use of new techniques developed (iphone, onesec, and felica), thus having a positive effect on the usage of 3G.

Penetration rate in previous periods can be expressed as the factor causing the model to be a dynamic panel. In other words, the number of mobile subscribers in previous periods effects the current number of subscribers. There are various studies in the literature showing that the high penetration in previous periods increases current penetration (Akematsu and Shinohara et al., 2012; Bouckaert et al., 2010; Lee and Lee, 2010; Lin and Wu, 2013; Church and Gandal, 2005; Andres et al., 2010). In these studies it is stated that the network developed by the subscribers in previous periods plays an important role in adding new subscribers, thus showing the network effect with a positive relationship on current penetration.

Although a meaningful negative relationship between the price and broadband diffusion is theoretically expected, in many studies conducted this could not be detected (Cava-Ferreruela and Alabau-Muˇnoz, 2006; Lee and Lee, 2010; Garcia-Murillo, 2005; Akematsu and Shinohara et al., 2012). Lin and Wu (2013) have shown the existence of this relationship only in certain stages of the life cycle. ARPU and mobile telecommunication revenue are used for this purpose in our study.

3. RESULTS OF ESTIMATION AND DISCUSSION

Analyzing the correlation between the variables, a high correlation of 72.89% between GDP per capita and public telecommunication investment per capita is detected in the table 1. For this reason, used together, one of these variables always loses meaning statistically. Public telecommunication investment per capita is meaningful, while GDP per capita is not when they are used together. But both of them are meaningful when they are used separately. In the table 2, the three cases where (i) they are used together, (ii) GDP per capita used only, and (iii) public telecommunication investment per capita used only are shown by mopen1, mopen2, and mopen3 models respectively. Based on the statistics provided in the table 2, all three models have valid values. As of the other variables, the situation does not change.

In this case, the three models can be evaluated together. A positive meaningful relationship between mopen and GDP per capita is detected when considering the revenue variable. This situation shows similarity with the relationship between the revenue and broadband diffusion found in the studies of Lin and Wu (2013), Garcia-Murillo (2005), and Bouckaert et al. (2010). Since the increase in the revenues of individuals will increase their purchasing power, the positive relationship between GDP per capita and mobile penetration is an expected situation.

The negative relationship between the price and broadband diffusion observed in previous researches, is similarly observed between ARPU and mobile penetration. It is seen that the increase in the prices of provided services due to the increase in average revenue per capita results in decrease in the mobile penetration. A meaningful relationship between mobile penetration and other variable of mobile telecom revenue has not been detected.

Table 1: Correlations

	mopen	traf	arpu	pubtel~p	gdpcap	inthos~m	educ	hhi
traf	0.1637	1						
arpu	0.1277	0.5477	1					
pubtelinvcap	0.3043	0.392	0.6341	1				
gdpcap	0.5297	0.4713	0.6776	0.7289	1			
inthostdom	0.6523	0.2934	0.3472	0.4187	0.5943	1		
educ	0.4814	0.2704	0.3691	0.4521	0.449	0.4585	1	
hhi	-0.4008	-0.2133	-0.2029	-0.1235	-0.2117	-0.2983	-0.4672	1
motelrev	-0.0941	0.3128	0.3433	0.1212	0.0656	-0.1514	-0.0709	0.0824

Between cellular mobile traffic per mobile subscriber per year and mobile penetration, a meaningful negative relationship is observed. If the increase in mobile traffic reflects the fact that the market is about to reach its peak, this negative relationship is an expected situation because it might have resulted from the narrowing potential market share.

Table 2: Arrellano Bond Dynamic Panel Data Estimation Models of Mobile Penetration

	Model 1	Model 2	Model 3
	b	b	B
L.mopen	1.129859***	1.267539***	1.141039***
L2.mopen	-.335095***	-.439966***	-.3542452***
traf	-.0272314***	-.0243563***	-.0236675***
arpu	-.0904169***	-.057524***	-.0771358***
pubtelinvcap	.0556482**		.0529736**
gdpcap	0.0310059	.0639558***	
inthostdom	.0080408*	.0077373*	.0135067**
educ	.0571577**	.0794254***	.0734505**
hhi	-0.0561548	-0.0251569	-0.0566201
motelrev	0.0034965	0.0024224	0.0036879
_cons	1.294525**	0.4963797	1.474469***
Wald test	6729.65***	6021.977***	5592.234***
ar2	-1.317913	-1.30131	-1.236199
sargan	37.45361	27.05501	34.39133
N	270	270	270

*, **, ***indicate significance at the10%, 5%, 1% level, respectively.

As found in earlier studies, increase of internet use and services provided through internet with telecommunication investments, have resulted in positive effect on mobile penetration. Currently, many services can be provided through the internet. Using techniques such as voip, tango, skype, viber, and face time which enables cheaper communication through smart phones and e-trade opportunities increase this positive relationship.

The network effect shown by Akematsu and Shinohara et al., (2012); Bouckaert et al., 2010; Lee and Lee, 2010; Lin and Wu, 2013; Church and Gandal, 2005; and Andres et al., 2010 in their studies has been detected in our study as well. The number of subscribers in previous years had a positive effect on the current number of subscribers.

An expected positive relationship between education and broadband diffusion could not be proved statistically in most of the studies in the literature. However, existence of a statistically meaningful positive relationship between education and mobile penetration is detected in our study. Mobile penetration has increased in relation with the growth in the level of education, reflecting that technological services are used more in the societies with high education levels.

Although mobile penetration is expected to increase in relation with increasing competition, a statistically meaningful relationship between them could not be detected in this study. However, analyzing the periods of the life cycle as discussed in Lin and Wu (2013), the existence of such a relationship is expected to be observed because the effects of the competition for each stage of product life cycle can be different.

4. CONCLUSION

The relationship between 3G penetration and various indicators of communication infrastructure throughout OECD countries is analyzed throughout this paper. Panel data is utilized for this purpose. In order to control network effects and endogeneity problem, the Arellano–Bond dynamic panel estimation is adopted. This estimator enables the calculation of an unbiased estimator by using an exogenous or predetermined endogenous variable. In addition to this, the system generalized method of moments (GMM) is used. In constructing an estimation model, the number of subscribers to 3G mobile phone services is taken as a dependent variable, while various technical and economic variables are selected as independent variables.

A study consisting 34 OECD countries during the years of 2001-2011 is conducted. Total number of observations is 330. Panel data analysis is used because both cross-section and time-section dimensions exist. Mobile penetration which is used as the independent variable is dependent on the number of subscribers in the previous years, thus a dynamic panel data is used rather than static panel data.

The findings reported in the earlier section can be summarized as follow:

Analyzing the correlation between the variables, a high correlation of 72.89% between GDP per capita and public telecommunication investment per capita is detected.

A positive meaningful relationship between mobile penetration and GDP per capita is detected when considering the revenue variable.

The negative relationship between the price and broadband diffusion observed in previous researches, is similarly observed between ARPU and mobile penetration.

Increase of internet use and services provided through internet with telecommunication investments, have resulted in positive effect on mobile penetration. The detected network effect indicates that the number of subscribers in previous years has a positive effect on the current number of subscribers.

Existence of a statistically meaningful positive relationship between education and mobile penetration is also detected.

The obtained results are intended to be used to forecast adoption of 4G technology in future research.

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