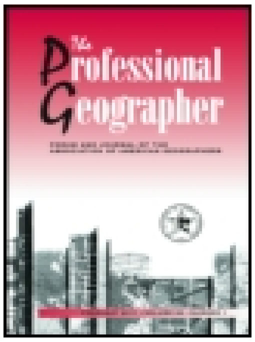

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Modeling the Spatial Diffusion of Mobile Telecommunications in China

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This article empirically evaluates factors contributing to spatial variations of cellular telephony adoption at the regional level in China. We estimate a logistic model using a variety of specifications for the spatial diffusion of cellular telephony. We find that regional disparity in the adoption and subsequent diffusion speed of cellular telephony is associated with different levels in economic development, economic structure, foreign investment, and the level of fixed-line telephony penetration. The results suggest that mobile communications diffusion starts first in regions with a higher potential demand density and economic development level. However, these characteristics play differential roles in determining the timing of initial adoption and diffusion speed within regions. **Key Words: China, mobile telecommunications, technology diffusion.**

对于移动电话在中国区域级别的空间变化，本文实证性地评估了它的影响因素。我们设计了一种逻辑模型，使用了多种规格以估算移动电话的空间扩散。我们发现，在区域水平上，移动电话的开始使用和其后的推广速度上存在差异，这种差异是与不同的经济发展水平，经济结构，外国投资，以及固定电话普及率相关联的。结果表明，移动通信的扩展一般开始于潜在的需求密度和经济发展水平都比较高的地区。然而，这些特点在决定首次采用的时间和其后区域内的推广速度上扮演了不同的角色。**关键词：中国，移动通信，技术推广。**

Este artículo evalúa empíricamente los factores que contribuyen a las variaciones espaciales de la adopción de telefonía celular en China, a nivel regional. Optamos por un modelo logístico que utiliza una variedad de especificaciones para la difusión espacial de este tipo de telefonía. Encontramos que la disparidad de la rapidez de adopción y subsiguiente difusión de la telefonía celular están asociadas con diferentes niveles de desarrollo económico, estructura económica, inversión extranjera y el nivel de penetración de la telefonía de línea fija. Los resultados sugieren que la difusión de comunicaciones móviles empieza primero en regiones con densidades más altas de demanda potencial y mayores niveles de desarrollo económico. No obstante, estas características juegas papeles diferentes para determinar los tiempos de adopción inicial y velocidad de difusión al interior de las regiones. **Palabras clave: China, telecomunicaciones móviles, difusión de tecnología.**

Historically in the analysis of the spatial diffusion of innovations the focus has been on the patterns and characteristics of early adopters and their behavior. Hence, Rogers (1995) characterized early adopters as knowledgeable risk takers. Griliches (1957) looked at the rate of return for early adopters and characterized them as profit maximizers. The geographer Hagerstrand (1967) was focusing on the character of early adopters in the transmittal process that produces follow-on participants in the process. Space was treated as a contiguity system with embedded characteristics producing barrier elements to the diffusion process. In the case of diffusion of hybrid corn, the new innovation needed to compete and become a substitute for an existing production system. Hence, the benefit differential between an existing system and the new innovation was an important determinant in the uptake of the new system. Much of the discussion on "initial advantage" and "first mover benefits" is derivative of these considerations and relates to the substitution effects of innovations in

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a competitive production process. Other analyses of the spatial diffusion process relate to either the spread of communicable disease in an epidemiological context or the spread of innovations to provide resistance to those spatial patterns such as tuberculosis inoculation of cattle among Swedish farmers and the relative efficiency and behavioral resistance to that process (Wolpert 1964). To the extent that the organization of space is treated, it is as a by-product with a particular concern for characteristics of physical space as reflective or absorbing barriers related to mountains, lakes, or road networks as pathways. In this context the space–process interaction had a simple two-dimensional contiguity context.

Mobile telecommunications has become a popular subject of diffusion studies in recent years as the cellular telephone was adopted at an astonishing rate across the world. This innovation process differs from earlier studies in the recognition of network externalities that impact the diffusion process by making the innovation more valuable both quantitatively and qualitatively as more users join the network. In other words, the diffusion of mobile telecommunications is a process that is dependent on a network that links spatially separated entities: telecommunication users. Further, in this particular case, the substitution effect of the new innovation of mobile telecommunications replacing a low-cost, effective, and existing alternative is minimized as the fixed-line telephony system in China was extremely small relative to the potential user population and had very limited access both spatially and economically. This is in contrast to the situation in many developed countries, where the new innovation had to compete with an effective alternative. Finally, this is a product consumption and service-based innovation diffusion process in contrast to an innovation that is product, output, or epidemiologically related.

As a consequence of these issues there are competing hypotheses that we hope to understand more clearly. First we wish to understand what the role and character of first-move advantage to early adoption is and if that bestows a continued competitive advantage in the rate of adoption of this kind of innovation. This is brought to our attention because in another context Ding and Haynes (2009) have examined the production of a related new innovation, mobile handsets, in China. In that study they noted a successful "catch-up strategy" driven by demand, market coordination, and utilization of an existing distribution and technology support system, underwritten with favorable and effective government policy changes. Hence we are drawn to the assessment of these potentially conflicting hypothesized outcomes using the same innovative technology but in very different contexts. Finally, a complicating factor is that telephony, including mobile telephony, might be seen as an element of regional economic development, but at the same time it reflects the economic geography of consumption.

As a developing country, China has experienced unprecedented growth in its mobile telecommunications sector. Mobile telephony was first adopted in China in 1987[1] and fourteen years after the initial adoption, China started to boast the world's largest mobile subscriber base in 2001. Although there is a large regional disparity in the diffusion of mobile telecommunications in China, empirical research on China's rapid adoption of cellular telephony from a spatial diffusion perspective has yet to appear. In contrast to most recent diffusion studies focusing on the diffusion process across countries (e.g., Gruber 2001; Giovanis and Skiadas 2007; Comer and Wikle 2008), this research focuses on the diffusion of mobile telecommunications across regions over time in a single country using a spatial-temporal data set. The focus on one country implies some limitations but also provides some advantages. The relative homogeneity of these regions compared to other studies using worldwide country-level data sets is better suited for the customary assumption of common parameters of interest across different regions.

We find mobile communications diffusion starts first in regions with a higher potential demand density and economic development level. However, these characteristics play differential roles in determining the timing of initial adoption and diffusion speed within regions. Although regions with better economic conditions are found to adopt mobile telecommunications early, there is also some evidence that latecomers that have a higher share of state-owned economy, lower levels of foreign direct investment (FDI), or lower levels of fixed-line telephony have high diffusion speeds.

Results of this research have important policy implications. The level of telecommunications infrastructure of a region is believed to be closely related to economic and social welfare. With the rapid adoption of telecommunication services and with advancements in information technologies, new "network neighborhoods" could form with the relatively diminishing advantages of some forms of geographic proximity (Yilmaz, Haynes, and Dinc 2002). This geographical imbalance should be even more important in analyses conducted on developing and newly integrating economies like China. Such economies usually exhibit dramatic location-sensitive differences in terms of natural resource endowments and regional development. Better availability of telecommunication technologies, especially mobile telecommunications services, might liberate economic activities from some geographical restraints and allow them to decentralize from the core to the periphery while maintaining necessary connections.

Furthermore, a vast literature on telecommunications infrastructure investment and economic growth exists and identifies telecommunications service availability as a crucial element in the accumulation of factors boosting economic growth at both the regional and sector-specific levels (e.g., Ding and Haynes 2006; see also review in Poot 2000). As China tries to achieve universal service across the country, it is important to understand the factors that underlie the evolution of the market and to understand the success of leading regions and the inability of other regions to develop their mobile telecommunications sector. This empirical study helps identify the fundamental elements determining the spatial bias in the diffusion of that technology.

The article proceeds as follows. The next section reviews the literature and provides a brief overview of the development of mobile telecommunications sector in China. After that, we outline the logistic models of cellular technology diffusion. We then present and discuss the results. The final section concludes and points out directions for future research.

Literature Review

Technological Diffusion

In a study investigating the diffusion of hybrid corn, Griliches (1957) was among the first to employ diffusion models in empirical studies. After that the diffusion of technology and products has been approached from a number of different perspectives, including geography (Hagerstrand 1967; Haynes, Mahajan, and White 1977; Brown 1981), marketing and consumer behavior (Bass 1969; Mahajan, Muller, and Bass 1990), economics (Gurbaxani 1990), and sociology (Rogers 1995). As summarized by Perkins and Neumayer (2005), geographers were at the forefront of quantitative technological diffusion research but much of the recent quantitative research has been undertaken by economists, sociologists, and business researchers. Early empirical studies depicted the diffusion of an innovation as a generally slow process, wherein the intensity at which adoption of a new technology spread across an economy changed over time with an S-shaped logistic curve (Griliches 1957; Bass 1969). The evidence of the basic logistic model's success in fitting historical data lends credibility to the model's basic structural soundness. Numerous hypotheses and interpretations have been set forth to explain the S-shaped nature of the diffusion curve. Mansfield (1961) suggested the diffusion rate is a function of the extent of economic advantage of the innovation, the amount of investment required for the adoption, and the degree of uncertainty associated with the innovation. Sharif and Kabir (1976) used a technological substitution framework when interpreting diffusion processes based on the fact that an innovation typically replaces an existing product or service. The dynamics of this replacement process account for both the diffusion rate and the shape of the diffusion curve. Brown (1981) proposed a supply and demand rationale from a behavioral orientation and Sahal (1981) employed a learning perspective to explain diffusion patterns. Rogers (1995) offered a communications-based theory to interpret the diffusion of diverse phenomena. Rogers defines the innovation-decision process as the process through which an individual passes from first knowledge of an innovation to the formation of an attitude toward the innovation, to a decision to adopt or reject, to implementation and use of the new idea, and to confirmation of this decision.

A number of attempts have been made to extend or improve the application of the basic logistic model. For example, instead of assuming a fixed value the market potential could be estimated using exogenous sources of innovation. Maximum likelihood and nonlinear estimation procedures have been used to estimate the model parameters (Mahajan, Muller, and Bass 1990). Extensions of the basic logistic model have also attempted to account for the dynamic ceiling on the number of potential adopters (Mahajan and Peterson 1985), the effect of competition within a market (Gruber and Verboven 2001; Marcu 2004), the effect of supply restrictions (Islam and Fiebig 2001), and the diffusion of successive generations of one technology (Islam and Meade 1997). Few of these extensions have been subject to extensive replication, however, and the basic logistic model remains in widespread use.

Determinants of Mobile Telecommunications Diffusion

An innovation is defined as "an idea, practice, or object that is perceived as new by an individual or other unit of adoption" (Rogers 1995, 11). Treating the mobile phone or other telecommunications technology as an innovation has been widely accepted. As use of the cellular telephone has grown at an astonishing rate across the world, researchers have conducted empirical studies on its diffusion (Gruber 2001; Gruber and Verboven 2001; Marcu 2004; Giovanis and Skiadas 2007; Buys et al. 2008; Comer and Wikle 2008), where the reasons and dynamics behind the differences in the adoption or diffusion speed across a set of countries are examined in a cross-country framework. Another group of studies investigate the diffusion of mobile telecommunications within a single country using time-series data (Wright, Upritchard, and Lewis 1997; Frank 2004; Lee and Cho 2007).

Numerous econometric studies have also investigated the impact of various other factors on the diffusion of mobile telecommunications across countries, such as economic conditions or income, sociocultural attributes, national industry structure, the cost and features of the mobile telecommunications, the availability and cost of alternative communication mediums, and regulatory policies (e.g., Riordan 2001; Frank 2004; Wareham, Levy, and Shi 2004). A recent review can be found in Buys et al. (2008). Consistently, economic conditions have been perceived to be the most important predictor of diffusion level. In a recent study, Comer and Wikle (2008) examined the worldwide diffusion of the cellular telephone during the period from 1995 to 2005. They found that gross domestic product (GDP) per capita explains more than 75 percent of the variation. Because of important policy implications, many empirical studies have examined the role of competition and privatization in the diffusion of mobile telecommunications. Generally, the empirical evidence supports the argument that more vigorous competition and deregulation lead to rapid diffusion of mobile telecommunications in a country (Petrazzini 1996; Wallsten 2001; Buys et al. 2008). Perkins and Neumayer (2005) found that trade openness significantly influences the rate of diffusion positively, but they failed to find significant evidence for the impact of FDI on the diffusion rate of new technologies. A few studies have investigated the complementarity and substitution between cell phone diffusion and the presence of other communications technologies (Haynes et al. 2006). Whereas some suggested the existence of different degrees of complementarity of cell and fixed phones (Hamilton 2003), many others found a predominance of substitutability (see a review in Couri and Arbache 2006).

Many researchers have found countries that adopted telecommunication technologies later had a faster diffusion speed. Using event-history models, Perkins and Neumayer (2005) examined whether latecomers have a higher diffusion rate of three technologies including digital telephone mainline. The authors presented evidence that the latecomer advantage allows late adopters, primarily developing countries, to diffuse new technologies faster than developed countries. This is consistent with Gruber's (2001) work, where he found the later a country adopted mobile telecommunications the faster its diffusion speed was.

Diffusion of Mobile Telecommunications in China

Since the mobile telecommunications network was introduced into China in Guangdong Province in 1987, China has had unprecedented growth in its mobile telecommunications sector. In the early stage of adoption, the number of adopters increased slowly. Before the mid-1990s, owning a mobile phone was a rare luxury reserved only for wealthy businessmen or

Table 1 *Growth of mobile subscribers in China, 1989–2004*

Year	Total mobile subscribers (millions)	Annual increase (millions)	Cellular vs. total telephone users (%)	Share of digital (%)	Teledensity (including cellular subscribers)
1989	0.01	—	0.09	0.0	0.97
1990	0.02	0.01	0.15	0.0	1.08
1991	0.05	0.03	0.33	0.0	1.26
1992	0.18	0.13	0.95	0.0	1.59
1993	0.64	0.46	2.43	0.0	2.22
1994	1.57	0.93	3.96	0.1	3.30
1995	3.63	2.06	6.30	4.3	4.76
1996	6.85	3.22	8.86	24.0	6.32
1997	13.23	6.38	13.09	48.3	8.18
1998	23.86	10.63	18.18	72.3	10.51
1999	43.30	19.44	24.65	88.4	13.97
2000	84.53	41.23	33.01	97.0	20.20
2001	145.22	60.69	41.10	99.7	27.69
2002	206.01	60.78	48.93	100.0	32.78
2003	268.69	62.69	50.51	100.0	41.15
2004	334.82	66.13	51.73	100.0	50.80

Source: National Statistical Bureau (NSB) (2001–2005); Ministry of Information Industry (2006b).

senior bureaucrats. Only after the mid-1990s have technological advancements in telecommunications and increased purchase power due to rapid economic growth made it possible for China to develop its telecommunications infrastructure rapidly at a relatively low cost (Table 1). By the end of 2005, this number increased to more than 393 million and 31 out of 100 inhabitants in China on average were mobile phone subscribers (Ministry of Information Industry [MII] 2006b). The annual net increase of cellular subscribers has been around 60 million in recent years. Now China boasts the world's largest mobile telecommunications network in terms of subscriber base and the number of cellular subscribers is greater than the number of fixed-line users. However, in China's rapidly growing economy, the interregional digital gap seems to be even bigger than its huge income gap (Hu and Zhou 2002). Different regions exhibit a wide array of cellular penetration levels, ranging from less than 11.4 percent in Guizhou Province to 92 percent in Beijing at the end of 2004 (MII 2006a). The unprecedented growth in this sector and the huge regional disparity in the diffusion rates allow us to empirically evaluate factors contributing to spatial variations in cellular telephony adoption at the regional level.

One study focusing on fixed-line telephony penetration in China showed that income levels, tariffs, educational levels, and levels of FDI all had significant impacts on the penetration rate (Hu and Zhou 2002). In a qualitative study, Sangwan and Pau (2005) summarized a set of key factors driving the adoption of mobile service in China: rapid economic growth, the emergence of strong local manufacturers, rapid technological advancements, and liberation and deregulation of the mobile market. All these factors at global, industry, and market levels support the understanding of the adoption rate of mobile telecommunications services in China. In a study focusing on the mobile handset manufacturing sector, Ding and Haynes (2009) documented how China's domestic manufacturers caught up with foreign competitors. However, there has been no systematic study focusing on the spatial diffusion of mobile telecommunications at the regional level in China.

Methodology and Data

As noted by Rogers (1995), the adoption of cellular technology, similar to that of other new technologies, is slow at the early stage of development because the network is relatively small, the average cost of subscription is high, and the value added from accessing a limited network is low. As the number of cellular subscribers increases, more and more people adopt the technology, leading to an exponential increase in the number of adopters. When the penetration achieves a certain high level, the diffusion rate will slow down because of reduced potential adopters. Following the literature (e.g., Bass 1969), the basic logistic growth model can be written as:

$$Y_{it} = \frac{N_{it}}{[1 + e^{-(a_{it}+b_{it}t)}]} \tag{1}$$

where Y_{it} is the number of wireless subscribers in region i at time t. Three important elements determine the shape of this function in this equation: the market ceiling level N_{it}, the location parameter a_{it}, and the diffusion speed parameter b_{it}. Assuming N_{it} represents a proportion of the total population ($N_{it} = \gamma_{it}*POP_{it}$) we have:

$$m_{it} = \frac{\gamma_{it}}{[1 + e^{-(a_{it}+b_{it}t)}]} \tag{2}$$

where γ_{it} is the proportion of the population that eventually will adopt a mobile phone and m_{it} is the cellular penetration rate ($m_{it} = Y_{it}/POP_{it}$).

One-Stage Estimation Procedure

For the one-stage estimation procedure in aggregate models of diffusion, the three parameters of an S-shaped diffusion curve, a, b, and γ, are considered as functions of a set of variables. The model can be estimated simultaneously by nonlinear estimation procedures or maximum likelihood methods (Gruber and Verboven 2001; Frank 2004). However, our nonlinear regression in the one-stage procedure does not converge. A solution to this problem is to pool the data and estimate a common fraction of potential adopters for a group of regions, assuming that different regions are in different stages of adoption. We estimated a common fraction of potential adopters for each region group using nonlinear least squares, without including regional characteristics in the estimation. Once estimated, we treat the fraction of potential adopters as a "known" parameter, as in Marcu (2004).

Based on the location of different regions and heterogeneity in socioeconomic characteristics among different regions, we classify regions in China into three broad groups and assume regions in each region group have the same ceiling level of potential adopters. These region groups are identified to reduce the heterogeneity arising from both observable and unobservable factors: the large metropolitan regions (LMR), the east China region (ECR), and the central and western China region (CWCR). Regions in each group and their related statistics are listed in Table 2.

We allow each region group to have its own fraction of potential adopters. The fraction of potential adopters of the total population in a certain region group is derived by pooling the data and estimating a common fraction of potential adopters for each group.

The location and speed factor in the diffusion model can be specified as:

$$a_{it} = \alpha_i^0 + X_{it}\alpha + \varepsilon_{it} \tag{3}$$

$$b_{it} = \beta_i^0 + X_{it}\beta + \varepsilon_{it} \tag{4}$$

The vector X_{it} includes continuous variables affecting both the timing and the speed of adoption. The parameters α_i^0 and β_i^0 are region-specific timing and speed fixed effects,[2] which capture differences in the timing and speed of adoption due to regional characteristics that are not covered in this model. Note that Equation 2 can be rewritten in terms of cellular penetration rates as:

$$z_{it} = Ln\left(\frac{m_{it}}{\gamma_{it} - m_{it}}\right) = a_{it} + b_{it}t \tag{5}$$

where the dependent variable, z_{it}, is the natural logarithm of the fraction of potential adopters that did not adopt by time t but that adopt in time t, and m_{it} is the per capita mobile penetration rate.

Replacing the parameter in Equation 5 with 3 and 4, we get:

$$z_{it} = \alpha_i^0 + X_{it}\alpha + (\beta_i^0 + X_{it}\beta)t + \varepsilon_{it} \tag{6}$$

The level and speed of adoption vary with regional socioeconomic characteristics. The choice of variables in this study is under the guidance of spatial diffusion theories and follows the empirical literature on spatial diffusion of new technologies (Riordan 2001; Hu and Zhou 2002; Frank 2004). The regional characteristics included in this analysis are the income level as approximated by GDP per capita

Table 2 *Classification of regions and descriptive statistics*

Region group	Regions	γ_i	Mobile (1995)	GDP PC (1995)	FDI (1995)	SOE (1995)	FTELE (1995)	Urban (1995)	a[a]	b[a]	γ[a]
Large metropolitan region	Beijing	0.81	1.22	11,909	13.5	54	19.4	75.3	−10.90	0.76	1.04
	Shanghai	0.81	1.13	19,073	17.0	37.9	18.5	85.8	−10.94	0.76	0.88
	Tianjin	0.81	0.59	11,163	32.1	31	14.0	69.9	−10.13	0.69	0.52
East China region	Fujian	0.44	0.48	7,646	49.4	17	6.0	33.3	−8.05	0.55	0.42
	Guangdong	0.44	1.31	7,657	36.7	17.6	8.4	44.1	−9.76	0.63	0.93
	Hainan	0.44	0.43	5,200	48.4	35.5	5.0	32.2	−8.04	0.52	0.31
	Heilongjiang	0.44	0.37	6,105	7.2	65.2	4.3	41.3	−9.28	0.63	0.33
	Hubei	0.44	0.17	4,647	6.6	38.1	3.0	32.2	−9.88	0.61	0.30
	Jiangsu	0.44	0.33	8,090	22.6	21.4	6.6	33.3	−10.20	0.69	0.38
	Jilin	0.44	0.34	4,895	10.4	62.1	5.8	39.8	−9.32	0.60	0.41
	Liaoning	0.44	0.48	7,347	13.6	33.8	6.4	43.5	−9.47	0.67	0.34
	Shandong	0.44	0.24	6,423	16.6	29.4	3.8	30.5	−9.18	0.58	0.32
	Zhejiang	0.44	0.57	8,921	7.1	13.9	7.9	39.0	−9.57	0.64	0.64
Central and western region (CWCR)	Anhui	0.25	0.10	3,776	8.5	29.6	2.5	22.3	−9.66	0.63	0.19
	Gansu	0.25	0.08	2,500	3.7	64.3	1.7	19.3	−11.03	0.72	0.18
	Guangxi	0.25	0.22	3,727	13.9	39.8	1.9	22.6	−10.30	0.64	0.27
	Guizhou	0.25	0.10	1,999	2.9	67.2	1.1	19.1	−10.45	0.68	0.15
	Hebei	0.25	0.21	4,988	7.2	39.2	3.7	20.9	−10.88	0.70	0.31
	Henan	0.25	0.14	3,788	5.1	31.9	1.9	18.6	−9.17	0.55	0.28
	Hunan	0.25	0.17	3,913	7.8	39.4	1.9	23.9	−9.59	0.61	0.23
	Inner Mongolia	0.25	0.10	4,069	0.1	63.4	2.8	34.2	−10.80	0.70	0.35
	Jiangxi	0.25	0.40	3,391	8.5	50.7	1.9	22.2	−9.95	0.65	0.21
	Ningxia	0.25	0.19	3,848	4.3	67.6	4.0	26.0	−12.95	0.83	0.35
	Qinghai	0.25	0.05	3,679	1.1	83.7	2.9	27.9	−13.82	0.94	0.25
	Shaanxi	0.25	0.18	3,082	8.7	46.8	2.5	25.9	−10.68	0.69	0.30
	Shanxi	0.25	0.21	3,900	2.0	34.7	1.9	28.0	−10.25	0.65	0.33
	Sichuan	0.25	0.18	4,752	3.2	36.9	1.7	21.4	−10.22	0.67	0.23
	Xinjiang	0.25	0.16	4,983	1.7	77.7	2.3	27.1	−14.32	0.97	0.28
	Yunnan	0.25	0.19	3,296	4.8	68.2	2.0	18.7	−10.13	0.67	0.22

Note: Mobile = the number of mobile subscribers per 100 inhabitants; GDPPC = log value real gross domestic product per capita in 1995 values (in Renminbi [RMB], official currency in mainland China); FDI = share of foreign direct investment divided by total fixed investment; SOE = share of state-owned enterprise in total industrial output; FTELE = number of fixed-line subscribers per 100 inhabitants; Urban = urbanization level.
[a] a, b, and γ represent the location parameter, diffusion speed parameter, and potential adopters parameter, respectively, and the values are estimated based on mobile diffusion data during 1990 to 2005 using PROC NLIN in SAS.
Source: Based on China National Statistical Bureau (NSB; 2001–2005).

($Ln(GDP)$), economic structure as approximated by the share of state-owned enterprise in total industrial output (SOE), and foreign direct investment (FDI) in particular regions.[3] The cost of the mobile communication service was not considered because the prices of mobile services had been regulated by the Ministry of Posts and Telecommunications (later MII) and had generally been uniform in China during the study period. In theory, penetration of alternative communication mediums, such as fixed-line telephony, may have a positive or a negative effect on fixed network expansion, depending on whether adopters view mobile telecommunications as a complement or a substitute for fixed-line telecommunications. To consider the effect of fixed-line telephony penetration level, this study employs an instrumental variables estimation (two-stage least square regressions [2SLS]) to address the endogenous nature of the relationship between fixed-line and mobile telecommunications. Because literature suggests that mobile telephony generally serves as a substitute for fixed-line telephony (Ward and Woroch 2005), the level of fixed-line telephony penetration may have a negative effect on the diffusion mobile telecommunications.

The regression model can be specified as:

$$\begin{aligned} Z_{it} = {} & \alpha_i^0 + \alpha_1 Ln(GDP)_{it} + \alpha_2 SOE_{it} \\ & + \alpha_3 FDI_{it} + \beta_i^0 t + (\beta_1 Ln(GDP)_{it} \\ & + \beta_2 SOE_{it} + \beta_3 FDI_{it})t + \varepsilon_{it} \end{aligned} \quad (7)$$

Two-Stage Estimation Procedure

The two-stage procedure to estimate the parameters in the diffusion model has been widely used in early studies (Griliches 1957; Mansfield 1961; Capello 1994). In the first stage, a logistic curve is imposed on the data of a proportion of the adopters to estimate the parameters a, b, and γ in Equation 2. The second stage uses a linear regression to explain the slope coefficient of the fitted curves in terms of various exogenous factors. In this stage, the interpretation of the spatial differences in the diffusion process occurs due to interregional cross-section regression analysis between the logistical parameters a_{it}, b_{it}, and γ_{it}, and the variables representing the structural and spatial-economic characteristics of the region $(X, Y, Z \ldots)$, thus explaining the spatial dispersion of the technology on the basis of the spatial determinants. In other words, the parameters of the S-curve for different regions are estimated and then the determinants of those parameters are identified by a set of ordinary least squares (OLS) regression models

$$Z_i = \alpha_0 + \beta_1 Ln(GDP)_i + \beta_2 SOE_i + \beta_3 FDI_i + \varepsilon_i \tag{8}$$

where Z_i represents a_i, b_i, or γ_i. Using the same set of regional socioeconomic characteristics as in the one-stage estimation, the independent variables in Equation 8 contain continuous variables affecting the timing, the speed of adoption, and the ceiling level, including the following: *Ln*(*GDP*), *SOE*, and *FDI*. We also consider the effect of fixed-line telephone as an endogenous variable and use the urbanization level as an instrumental variable.

Spatial Dependence Issue

Spatial autocorrelation exists whenever errors are correlated across space. If the adoption of mobile telecommunications is spatially clustered, then it will also be spuriously correlated with many unobserved neighborhood characteristics. Thus, the coefficients will reflect the effects of independent variables as well as other neighborhood characteristics.

To test the robustness of the results, we tried an adjustment to the second-stage regression model following Rey and Montouri (1999), where the error term in Equation 8 becomes

$$\varepsilon^* = \lambda W \varepsilon + u \tag{9}$$

W is the predetermined spatial weight representing the spatial relationship between residuals and λ is a coefficient to be estimated that acts as a scalar "weighting" the spatial structure, where a small λ (close to zero) signifies a weak spatial relationship. We chose the most commonly used first-order contiguity matrix as the spatial weight matrix.

Data

Data on cellular subscribers for twenty-nine regions of China, from 1990 to 2005, are utilized to estimate the parameters of the S-curves for different regions in both methods. China has thirty-one provinces, autonomous regions, and cities under direct guidance of the central government. Although Hong Kong and Macao are parts of China, they are not under direct guidance of the central government now and hence are not included here. Due to missing data, Tibet has been excluded from the statistical analysis. Moreover, as the Chongqing area was given municipality status and separated from Sichuan Province from 1997 onward, we managed to adjust data for the new Sichuan Province from the old one, which included only the new Sichuan area. As a result, the total number of units in this study is twenty-nine because two regions, Tibet and Chongqing, have been excluded from the analysis. For the second stage of the cross-sectional regression, data for 1995 are used because most of the regions started to adopt cellular technologies in the early 1990s and data in 1995 can be used as an approximation of the socioeconomic characteristics during that period. Data are drawn from officially published sources such as MII (2006b) and the National Statistical Bureau (NSB). Descriptive statistics are presented in Table 2.

Empirical Results

Spatial Patterns of Mobile Telecommunications Diffusion

Before interpreting the estimation results, we need to assess the spatial dependence issue of mobile phone diffusion in China. We computed the values of the global Moran's I statistics and p values for the mobile telecommunications adoption rates, measured by the number of subscribers per 100 inhabitants,

Table 3 *Moran's I statistics of mobile adoption rate in China*

Year	Moran's I	*p* value
1990	−0.076	−0.45
1991	0.095	0.110
1992	0.090	0.121
1993	0.105	0.110
1994	0.155	0.056
1995	0.234	0.018
1996	0.319	0.010
1997	0.317	0.006
1998	0.321	0.008
1999	0.331	0.009
2000	0.317	0.007
2001	0.287	0.008
2002	0.248	0.015

Note: Calculated by the authors based on the data on mobile adoption rates listed in Table 1. Five provinces or cities (Tibet, Chongqing, Hong Kong, Macao, and Taiwan) are not considered in this analysis.

across the twenty-nine provinces for the years from 1990 to 2002 (Table 3). As Table 3 shows, the global Moran's I statistics for the years from 1995 to 2002 are greater than 0.2 and are significant at the 0.05 level. The results suggest that the spatial distribution of mobile adoption rates in China is not completely independent, and the spatial agglomeration of similar value (high or low) is particularly clear in the years after 1995.

As Table 2 shows, we derived the values of the location parameter, diffusion speed parameter, and potential adopters parameters (a, b, and γ in Equations 1 and 2) from the first-stage estimation. We computed the global Moran's I statistics and p values for these estimated diffusion parameters and the results are presented in Table 4. The global Moran's I statistics for the location and speed parameter are greater than 0.3 and are significant at the 0.01 level, suggesting the existence of spatial autocorrelation. However, the Moran's I statistics for the ceiling level of adoption (γ) are insignificant and therefore there is no significant spatial autocorrelation for this parameter. To check for spatial error dependence for different models, Moran's I tests were carried out on the residuals for the one-stage and two-stage regression models and the test statistics are generally significant for the location and speed parameters and insignificant for the ceiling level parameter. To test the robustness of our results, we ran spatial dependence models to address the spatial autocorrelation problem explicitly. The Lagrange multiplier test shows that the spatial error model can better account for the nature of spatial autocorrelation than a spatial lag model. Thus, only the results from spatial error models are discussed.

Table 4 *Moran's I statistics of diffusion parameters*

	Moran's I	*p* value
Location parameter (a)	0.3776	0.006
Diffusion speed parameter (b)	0.3854	0.008
Potential adopters parameter (γ)	−0.1532	0.167

Note: Calculated by the authors using data of diffusion parameters listed in Table 1. Five provinces or cities (Tibet, Chongqing, Hong Kong, Macao, and Taiwan) are not considered in this analysis.

The local index of spatial association (LISA) cluster map illustrates the local spatial autocorrelation functionality, which is done via GeoDA (Anselin 2005). The cluster maps of location and diffusion speed parameters, illustrated in Figure 1 and Figure 2, show the locations with significant local Moran statistics in different symbols coded by types of spatial autocorrelation. The four categories (high-high, low-low, high-low, low-high) correspond to the four quadrants in the Moran scatter plot. The high-high and low-low locations (positive local spatial autocorrelation) are typically referred to as *spatial clusters*, whereas the high-low and low-high locations (negative local spatial autocorrelation) are termed *spatial outliers*. As Figure 2 shows, there are no high-high clusters or high-low locations. As an island, Hainan is a low-high outlier. Xinjiang, Qinghai, and Gansu in northwestern China are the core of the low-low cluster in terms of the location parameter of mobile telephony diffusion. However, Xinjiang and Gansu become the core of a high-high cluster of the mobile diffusion speed. The results suggest that while provinces in northwestern China adopt mobile telephony at a later stage, their diffusion speed is relatively high and this is consistent with the contention of latecomer "catch up" advantage (Perkins and Neumayer 2005).

Regression Results and Interpretations

We are interested in identifying the drivers of the mobile telecommunications diffusion in

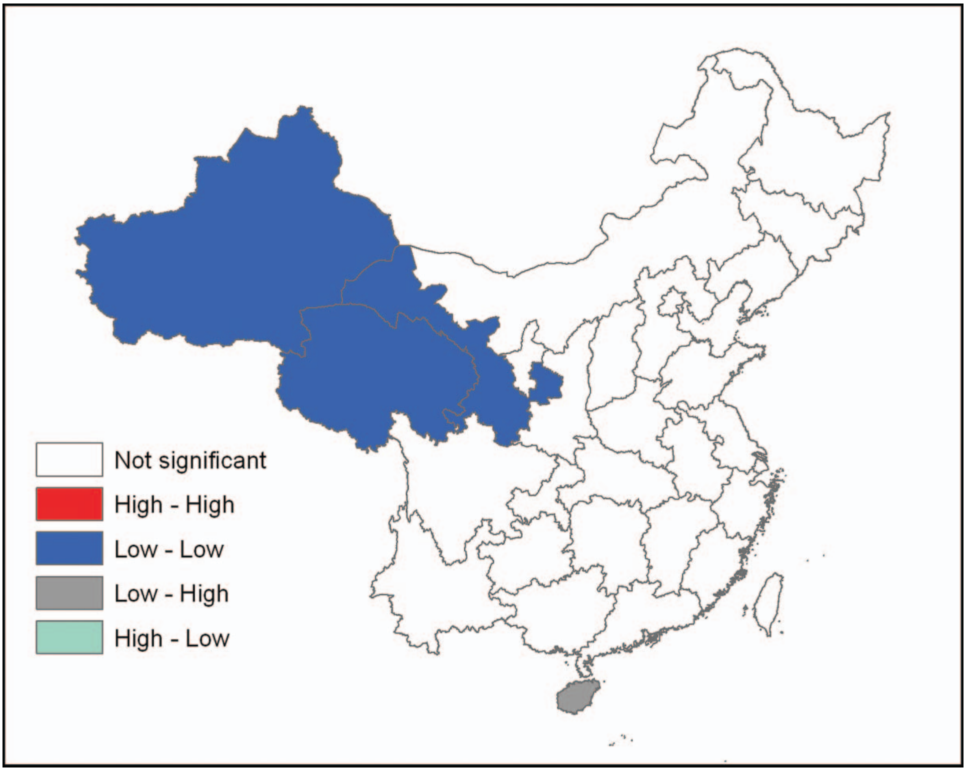

Figure 1 *The local index of spatial association (LISA) cluster map of location parameter (a). Note: Tibet, Chongqing, Hong Kong, Macao, and Taiwan are not considered in this analysis.*

China. The results from the one-stage estimation are presented in Table 5 and results from the two-stage estimation are presented in Table 6. For each estimation method, Model 2 further considers the endogenous fixed-line variable in addition to the three independent variables considered in Model 1. Model 3 considers the spatial dependence issues in the regression. The major difference between the two methods is the saturation level, which is assumed to be "fixed" for each region group in the one-stage estimation. Another difference is that the two-stage estimation uses cross-sectional data (in 1995) in the second stage of estimation, whereas the one-stage estimation method utilizes a panel data set. Both methods are employed to validate the results, although the coefficients cannot be compared directly. The R^2 values are acceptable, ranging from 0.51 to 0.91 for different models. Results from the two estimation methods are generally consistent and the coefficients from the one-stage estimation are more significant due to the increased degrees of freedom. The results from the two-stage estimation method seem to be less significant and less stable because the number of observations is quite small in the second-stage cross-sectional regression (twenty-nine observations).

As expected, the values of λ, or the coefficients of the spatial weighting matrix, were found to be highly significant in Model 3, which suggests there is significant spatial autocorrelation for the diffusion parameters. The results reported from the spatial error model (Model 3) and those from the OLS regression (Model 1), however, are quite similar in that coefficients for the explanatory variables are of the same signs and similar sizes. The results suggest that even though there is significant spatial autocorrelation we have sufficient confidence to draw conclusions based on regression results from the models in which

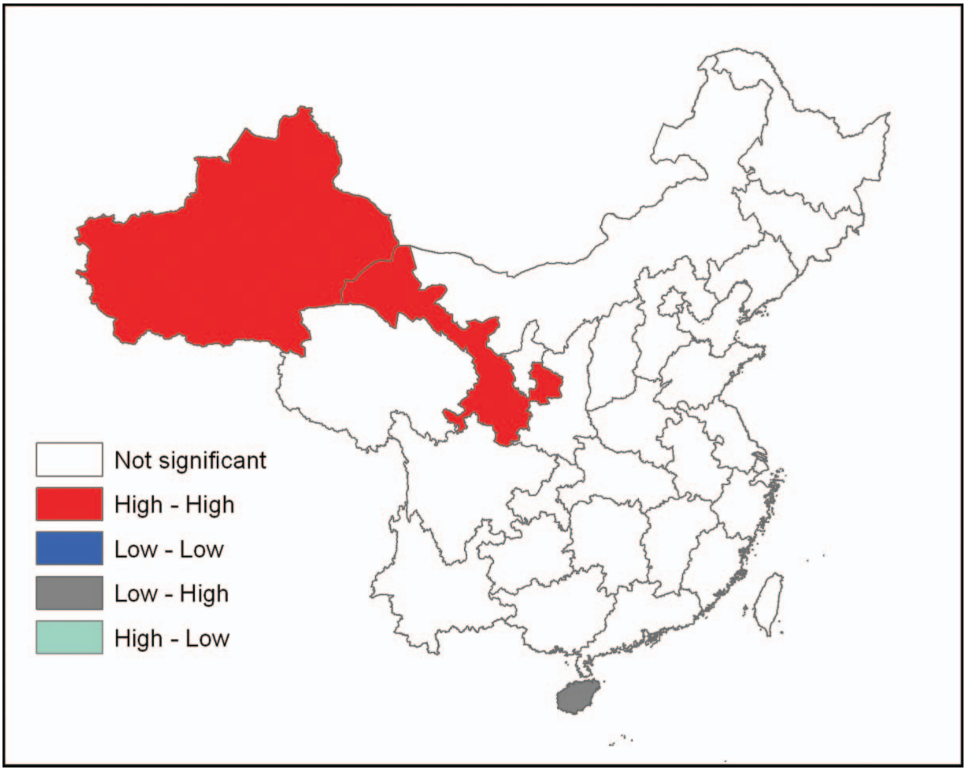

Figure 2 *The local index of spatial association (LISA) cluster map of diffusion speed parameter (b). Note: Tibet, Chongqing, Hong Kong, Macao, and Taiwan are not considered in this analysis.*

the spatial dependence issue was not addressed explicitly. The following discussions are primarily based on our results from Model 1 and Model 2.

For the timing of initial adoption, results from the one-stage estimation show the coefficient of economic development, as represented by GDP per capita (in log), is positive and highly significant. This suggests that wealthy regions lead in adopting cellular technology. This is consistent with Comer and Wikle's (2008) results that GDP per capita is the primary driver of cellular telephone using cross-country data. There is consistent evidence for both models that regions with lower levels of state-owned economy would adopt the cellular technology earlier than those with a higher share of state-owned enterprises. Generally, there are three types of ownership for the Chinese enterprises: state, collective, and private. The private enterprises and collective enterprises, particularly township and village enterprises, are said to have been the most dynamic (Jin and Haynes 1997). Regions with higher shares of non-state-sector activities might have higher demand for mobile telecommunications for business and other purposes and as a result they adopt mobile telecommunications earlier. There is also some evidence that regions with higher levels of FDI adopt mobile telecommunications earlier. This result makes sense because regions that are more "open" to international investment have higher demand for advanced communications technologies to meet the need from increased international trade and investment activities. The level of fixed-line telephone use was found to be insignificant in both models. Generally the results stress the idea that technology adoption starts first in regions with a higher potential demand density, where economic conditions are better and the economies are

Table 5 *Empirical analysis: One-stage estimation results*

	Model 1		Model 2	
Variable	**Coefficient**	***p* value**	**Coefficient**	***p* value**
Location parameters for region characteristics (a)				
FTELE			0.178	0.678
Ln(GDP)	3.457	0.000	1.778	0.002
SOE	−0.012	0.000	−0.007	0.064
FDI	0.086	0.000	0.060	0.000
Diffusion speed parameters for region characteristics (b)				
FTELE			−0.006	0.000
Ln(GDP)	0.057	0.000	0.086	0.000
SOE	0.002	0.000	0.001	0.035
FDI	−0.007	0.000	−0.003	0.010
R^2	0.81		0.91	

Note: The dependent variable is $z_{it} = Ln(\frac{m_{it}}{\gamma_i - m_{it}})$, where m_{it} is the number of cellular subscribers per 100. Ln(GDP) = log value real gross domestic product per capita in 1995 values (in Renminbi); FTELE = number of fixed-line subscribers per 100 inhabitants; FDI = share of foreign direct investment divided by total fixed investment in 1995; SOE = the share of state-owned enterprise in total industrial output in 1995. Region groups have different estimated market potential: $\gamma_i = 0.813$ if a region belongs to the large metropolitan regions, $\gamma_i = 0.437$ if a region belongs to the east China regions, $\gamma_i = 0.254$ if a region belongs to the central and west China region.

more dynamic and more open to new technology from the international environment.

The measure of the diffusion speed, b_{it}, is equal to the growth rate in the number of adopters, relative to the fraction of potential subscribers who have not yet adopted the technology. The results from both models consistently indicate that GDP per capita is positively correlated with the diffusion rate of cellular technology in that region. Regions with a higher share of state-owned economy are found to have a higher diffusion speed. These regions are found to be slower in the adoption of cellular technology but they have a higher diffusion speed once they adopted the technology. Similarly, we found that although those regions with higher levels of FDI usually adopt mobile telecommunications early, they generally have a slower diffusion speed afterward (Table 5). In other words, FDI has a positive impact on initial penetration level but has a negative impact on the diffusion rate of mobile telecommunications. Whereas economic development level has a consistent positive impact on initial adoption and subsequent diffusion speed, the level of non-state-owned economy and FDI of a region positively affect the time of initial adoption and then affect the diffusion speed negatively. This is consistent with some early studies that found evidence that late adopters diffuse faster and variables that are positively correlated with early adoption are likely to be negatively correlated with the diffusion speed (e.g., Perkins and Neumayer 2005). Interestingly, results from Model 2 confirm that regions with higher levels of fixed-line telephone penetration generally have slower diffusion speeds for mobile telecommunications. In other words, fixed-line telephone use has a negative impact on the diffusion rate of mobile telecommunications. The diffusion speed of regions with higher fixed-line penetration rate would be slower, other things being equal. This could provide some evidence for the argument that the substitution effect, instead of the complementary effect, between mobile telecommunications and fixed-line telephony, is dominant.

Two-stage estimation in Table 6 investigates the determinants of the share of potential adopters among the total population, γ_{it}. Regardless of how inexpensive mobile telephony might become, not all individuals in a region adopt the new technology. Table 6 suggests that the level of potential cellular adopters (share of total population) in a region is significantly and positively correlated to the level of economic development (GDP per capita). Once the level of fixed-line telephone penetration is controlled, however, all other variables become insignificant. It is understandable that residents in wealthy regions have more purchasing power and as a result are less constrained by the affordability of mobile

Table 6 *Empirical analysis: Two-stage estimation results*

	Model 1		Model 2		Model 3	
Variable	**Coefficient**	***p* value**	**Coefficient**	***p* value**	**Coeffcient**	***p* value**
Location parameters (a)						
FTELE			0.129	0.300		
Ln(GDP)	−0.828	0.086	−2.019	0.112	−0.847	0.040
SOE	−0.046	0.001	−0.054	0.002	−0.036	0.001
FDI	0.034	0.076	0.031	0.124	0.027	0.089
Λ					0.899	0.000
R^2	0.53		0.51		0.59	
Diffusion speed parameters (b)						
FTELE			−0.009	0.283		
Ln(GDP)	0.095	0.007	0.181	0.045	0.077	0.005
SOE	0.004	0.000	0.004	0.000	0.003	0.000
FDI	−0.002	0.134	−0.002	0.206	−0.001	0.329
Λ					0.971	0.000
R^2	.56		0.54		0.75	
Potential adopters parameters (γ)						
FTELE			0.037	0.007		
Ln(GDP)	0.379	0.000	0.033	0.798	0.330	0.000
SOE	0.001	0.542	−0.001	0.453	0.001	0.387
FDI	0.000	0.938	−0.001	0.741	0.003	0.125
Λ					−0.806	0.001
R^2	0.64		0.79		0.72	

Note: Ln(GDP) = log value real gross domestic product per capita in 1995 values (in Renminbi); FTELE = number of fixed-line subscribers per 100 inhabitants; FDI = share of foreign direct investment divided by total fixed investment in 1995; SOE = share of state-owned enterprise in total industrial output in 1995; Λ = coefficient of spatial weighting matrix.

telecommunications. Further, it is clear that the regional fixed-line telephone penetration level is the best predictor for the ceiling level of mobile telephony adoption.

These results are consistent with earlier spatial diffusion literature in which economic development level has been found to be the most important factor in explaining the adoption behaviors and level of penetration for mobile communication (e.g., Comer and Wikle 2008). With China changing from a "planned economy" to a more dynamic and "free-market" economy during the past thirty years, the economic structure as represented by the share of economic activities by state-owned enterprises has had a significant impact on the diffusion of mobile telecommunications. Although regions with better economic conditions are found to adopt mobile telecommunications early, there is also some evidence that latecomers that have a higher share of state-owned economy, less FDI, or lower levels of fixed-line telephone adoption have high diffusion speeds. This analysis suggests that compared with prior studies using worldwide country-level data sets, an investigation of spatial diffusion within one country has its own advantage and can make a significant contribution to our understanding of spatial diffusion at a more intermediate level.

Generally, the one-stage and two-stage estimation techniques achieve consistent results in this case. The one-stage estimation is able to make full use of the panel data because of the increased degrees of freedom. If the number of spatial units is large and a panel data set is unavailable, however, the two-stage estimation technique using cross-sectional data would also yield acceptable results. This study also demonstrates the importance of considering the spatial dependence issue in diffusion studies.

Conclusions and Future Research

We have analyzed the determinants of mobile telecommunications adoption in twenty-nine regions in China during the period from 1990 to 2005. The regression results suggest that regional socioeconomic characteristics play an important role in determining the timing, speed, and level of mobile telecommunications diffusion in China. Regions with higher levels of economic development are likely to adopt mobile telecommunications earlier and usually have more potential adopters and higher levels of diffusion speed. Foreign investment levels and the non-state-owned-sector activity have positive impacts on early adoption of the mobile network but have a negative impact on diffusion speed, keeping others variables constant. This result also suggests the substitution effect between mobile telecommunications and fixed-line might be more dominant than complementarity. These results stress the idea that technological innovations starts first in regions with a higher potential demand density but that latecomers can catch up with a faster internal adoption speed.

Compared with prior work, this study is characterized by several important differences. First, whereas most of the recent quantitative research into the diffusion of mobile telecommunications has been undertaken by economists and very few empirical studies look at this issue from a geographical or spatial perspective, the focus here is an examination of the diffusion of mobile telecommunications within a single country from a spatial perspective. We investigated the spatial diffusion pattern of mobile telecommunications across different regions and evaluated the impact of spatial dependence. Second, this study investigates the determinants of the diffusion process using a variety of models and estimation techniques. We tried both a cross-sectional data set and a panel data set and estimated the parameters using one-stage and two-stage estimation procedures. We also considered the impact of an alternative telecommunication medium by treating fixed-line telephony penetration as an endogenous variable. By demonstrating the consistency of results across different models, this study tests the robustness of the findings. Finally, different from most recent studies focusing on the diffusion across different countries, an investigation of the spatial diffusion of the mobile communications technology in very different contexts has its own advantage. Considering China's huge size and important regional differences in geography and in natural resource endowments, the diffusion of mobile telephony might help not only the communications between regions, but also with the outside world. China also had a very low penetration rate of telephony during the study period, which allows for a rapid diffusion of mobile telecommunication, regarded as a low-cost, effective alternative to fixed-line telephony. This is in contrast to the situation in many developed countries, where the new innovation had to compete with an effective alternative. This also provides us a great opportunity to understand the role and character of the "first-move advantage" and the "latecomer advantage." We identified that mobile telecommunications was adopted first in regions with a higher potential demand density but there is also some evidence in support of the contention of latecomer catch-up advantage.

By empirically examining the diffusion of mobile telecommunications in China, this study helps researchers and policymakers understand the factors that influence the evolution of mobile communications across different regions in China. On the one hand, the results suggest that economic policy measures leading to greater economic growth are the most important factor in promoting the convergence of the diffusion of telecommunications technologies among regions. On the other hand, the results suggest that regions adopting the technology later generally have a faster diffusion speed, so it is possible that the latecomers can catch up with those early adopters in terms of adoption levels. Therefore, this analysis helps policymakers design appropriate policies to support and facilitate a balanced development of the telecommunications infrastructure, especially for mobile telecommunications. The models outlined in this article also provide a framework for further research when data become available.

Future research would benefit from an examination of the following areas. First, some empirical studies have supported the argument that competition and deregulation have played an important role in countries experiencing rapid network development (Petrazzini 1996; Wallsten 2001). Although China Unicom had entered the mobile telecommunications market as early as 1993, its market was constrained and quite limited before 1999. It was not until the late 1990s that the branches of China Unicom were gradually introduced into other regions across China. In principle, the introduction of competition could have a positive effect on the speed of adoption of cellular technology because it might lead to lower prices and increased demand for mobile services. Further study would benefit from reliable data on competition in the mobile service sector at the regional level to capture the effect of competition on mobile telecommunications diffusion. Second, the impact of some new alternative communication mediums, such as Xiaolingtong,[4] on the penetration of mobile communication services needs to be considered in future studies. Moreover, more complete demographic information, such as age structure, rural and urban access to technology, and income structure would also benefit future studies. ■

Notes

[1] The first mobile communications system was set up in Guangdong Province on 18 November 1987 in support of China's 1987 National Games.

[2] Because there are a relatively large number of parameters that must be estimated, we assume that all regions within a region group have the same location and speed fixed effects. In other words, for regions in each group (LMR, ECR, CWCR), the location fixed effect α_i^0 and the speed fixed effects β_i^0 are the same, respectively.

[3] In fact, a set of other socioeconomic variables have been tested, such as population density, share of value-added by the service sector, and education level. Because they are highly correlated with the variable of GDP per capita, however, they are not included in the final model.

[4] The Xiaolingtong, also called Little Smart or Personal Access System (PAS), is a transitional technology. It functions both as a digital cordless phone indoors and a cellular phone outdoors. It is built into existing fixed-line networks and lures users with low per-minute rates, one-way charges, and cheap monthly fees.

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