

Examining the Influencing Factors and the Most Efficient Point of Broadband Adoption in China

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This paper examines several key factors affecting the adoption rate of broadband Internet access in 31 provinces of China by employing the Stochastic Frontier Analysis Model. It was found that disposable income, penetration rate of fixed phones, number of Internet users, and educational attainment were the most important factors in the adoption of broadband. In addition, we present the relative market potential of each province by exploring the most efficient point for broadband penetration. Our results imply that the market potential is still much greater in the more developed areas of China where the actual adoption rate is high, such as municipalities and the southeast coast region.

Keywords: Broadband adoption; Stochastic frontier analysis; Influencing factors; Most efficient point; China

ACM Classifications: H.m, K.I, K.4

INTRODUCTION

Broadband Internet access has increased dramatically on a global scale over the last few years. The total market for broadband subscription grew from almost zero in 1998 to 298 million subscribers by the end of March 2007. In terms of penetration rate, the number of broadband lines per 100 population reached 5.72 (Chook, 2007). China has become the second largest broadband market after the US with 51.9 million broadband subscribers by the end of 2006 (Chook, 2007). This may be due to the booming economy, rising income, growing PC penetration, increasing Internet users,

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and the Beijing Olympics in 2008, as well as the introduction of new applications (Ng *et al.*, 2004), such as VoIP and IPTV (Arnold, 2004; Mittermayr, 2005).

There are five major broadband operators in China: China Telecom, China Netcom, China Unicom, China Tietong, and Great Wall Broadband, all of which offer services over DSL or FTTx+LAN. Both China Telecom and China Netcom are the dominant operators of broadband access services in China, with a combined broadband market share of 87% (China Broadband Overview, 2007).

DSL is the dominant broadband technology in China. DSL lines accounted for 71% of all active broadband lines, with 32 million subscribers by June 2006. The next important technology is FTTx+LAN access in newer, high-density areas. This has a substantial market share of 26% (China Broadband Overview, 2007), followed by cable modem and wireless technologies that take up a much smaller market share.

Even though the total number of broadband subscribers in China is large, the overall broadband penetration rate stands at only 3.9% of the population. This shows that broadband penetration in China is lagging far behind many countries in the Asia-Pacific region.

Furthermore, the current development of broadband penetration varies greatly across different provinces in China because of the inequality among the regions in terms of economy, education, and infrastructure development. The broadband penetration rates by population at year-end 2006 were 7.64% in the eastern region, 2.47% in the central region, and 1.83% in the western region. Although the broadband penetration rate rose slightly in both the central and western regions in 2006, the gap between the eastern, central, and western regions in terms of penetration rate has not narrowed.

It should also be noted that the total number of Internet users in China reached 162 million by June 2007, and the growth rate was as high as 31.7% (CNNIC, 2007). While Chinese Internet users have increased continuously, the users with dial-up connections have decreased steadily. Therefore, the accelerating growth of the number of Internet users and the low penetration rate of broadband create enormous potential for the future growth of broadband in China.

The purpose of this work was to examine the important factors influencing broadband adoption in 31 provinces of China, and the relative market potential of each province.

The remainder of this paper is organized as follows. In Section 2, a literature review of previous studies on broadband Internet adoption and the factors influencing the adoption of broadband in China is provided. In Section 3, the methodology of stochastic frontier analysis, the data, and our model specifications are explained. Section 4 and Section 5 presents the empirical results and discusses some implications. Finally, some conclusions are presented in Section 6.

LITERATURE REVIEW

Overview of Studies on Broadband Internet Adoption

Various studies have investigated the development of the Internet or broadband Internet adoption at the country level. Falch (2007) proposed that the decisive factors influencing broadband Internet adoption can be categorized according to three different dimensions. The first dimension distinguishes between factors affecting supply and those affecting demand. The second line of division is between content (Lee and Brown, 2008) and infrastructure, though the development of content and infrastructure may stimulate each other. The third line of division distinguishes between technological, economic, and political/cultural factors that affect both the supply and demand conditions for both content and infrastructure development. Kridel *et al.* (2002) identified a number of important factors that influence the decision to adopt broadband services. Their research focused on the factors influencing choice: the price of an Internet service product, income, age, educational attainment,

household size, and geographic location. Income was found to be an important determinant of choice. As income increases, the demand for broadband services also increases. Age is also an important variable. Older generations generally tend to have a lower propensity to adopt high-tech products and services. Households with higher educational backgrounds tend to have a greater propensity to adopt Information Communication Technology (ICT), since household members may have a higher perceived valuation of the usefulness of these products, perhaps induced by their previous educational training (Robertson *et al*, 2007). Dwivedi and Weerakkody (2007) also identified socioeconomic factors, such as gender, age, and education, influencing broadband adoption.

Savage and Waldman (2005) identified speed, service reliability, and always-on access as being important attributes for consumers considering broadband Internet access based on data obtained from a nationwide survey of US residences. The relative importance of the attributes depends on social grouping, as higher income respondents value the attributes more highly than lower income users, and those with a college degree value speed more, always-on access less, and reliability about the same as those without a college degree.

A significant number of studies have been carried out to examine how South Korea became the world leader in broadband Internet services. In the third quarter of 2007, South Korea's broadband penetration was approximately 92.48% of households. We can identify a few factors contributing to this remarkable development. First, the government of South Korea has played an important role in the development of broadband Internet markets (Falch, 2007; Lau *et al*, 2005). The Korean government implemented several national policies to encourage the deployment of broadband Internet, liberalizing the telecommunications industry, and privatizing state-run companies (Lee *et al*, 2005). The collaboration between government, industry, and Internet users is the most important factor accounting for Korea's leadership in broadband adoption (Picot and Wernick, 2007). Second, the penetration rate of personal computers and the presence of highly educated users are also very important. The broadband Internet market in South Korea appears to have developed with a focus on information or content consumption (Hitt and Tambe, 2007; Leea and Sylvia, 2004). Lee *et al* (2003) also pointed out that the matching of demand and supply was the most important factor in the fast diffusion of broadband in South Korea. In particular, fierce infrastructure competition on the supply side led to a high-quality service at a low price and online games on the demand side acted like a killer application.

Choudrie and Dwivedi (2006) implemented the research focusing on the adoption of broadband in the context of a household within the UK. They indicated that broadband adoption was driven by relative advantages such as faster access, utility outcomes such as the uses of broadband for work purpose, and hedonic outcomes such as the uses of broadband for entertainment. Robertson *et al* (2007) assert that adoption patterns in the UK Internet service market can be explained by sociodemographic variables, such as educational attainment, household disposable income, and the presence of children. The prices paid for Internet service products were also found to be useful predictors of adoption. Price elasticity measures indicate that a fall in the subscription price of broadband would significantly increase its adoption (Dwivedi *et al*, 2008).

Noce and McKeown (2007) employed data from the Canadian Internet Use Survey (CIUS) to explore the extent to which demographic variables affected Internet use by individuals in Canada (Sawada *et al*, 2006). The results suggest that educational attainment, income, and geography are particularly strong influencing factors, and that the odds of using the Internet are about three times greater for individuals with some post-secondary education than for those with, at most, a high school education. Geographical location is the second most important determinant of Internet use after education in Canada.

Factors Influencing Broadband Adoption in China

Considering the data from previous studies of several countries that is summarized in Section 2.1, we assumed that educational attainment plays an important role in broadband adoption, since education is widely reported to be one of the most important drivers of broadband adoption (Choudrie and Lee, 2004; Falch, 2007; Kridel *et al.*, 2002; Noce and McKeown, 2007; Robertson *et al.*, 2007). Choudrie and Dwivedi (2005) suggest that household consumers with secondary or tertiary education are more likely to have Internet access. A China Internet Network Information Center (CNNIC) statistical report (2007) also shows that consumers with higher educational attainment, or those working towards higher educational attainment, and postgraduate students are more likely to adopt broadband.

The percentage of Internet users is significant, because a subscriber that accesses the Internet with a dial-up connection is likely to consider switching to broadband if it is available (Garcia-Murillo, 2005; Picot and Wernick, 2007). A percentage increase in dial-up usage may eventually lead to an increase in broadband use (LaRose *et al.*, 2007). This means that an effective way of increasing broadband is simply to expose people to the Internet, since it is likely that a large proportion of them will adopt broadband.

Income has also been consistently recognized as being an important adoption factor. In particular, the average disposable income of each household is generally held to be positively related to broadband adoption (Kridel *et al.*, 2002; Robertson *et al.*, 2007; Savage and Waldman, 2005; Sawada *et al.*, 2006). Choudrie and Dwivedi (2005) also confirm that income drives the general pattern of ICT ownership and usage. Similarly, Carveth and Kretchmer (2002) suggest that in the US, the higher the household income is, then the more likely the members of the household will own a computer and use the Internet. Another study focusing on the determinants of the global digital divide also confirms the importance of the per capita income in explaining the gap in computer and Internet use (Chinn and Fairlie, 2007). Thus, income is an independent variable that explains the difference between adopters and non-adopters of broadband (Choudrie and Dwivedi, 2007).

Badran *et al.* (2007) found that the number of fixed lines per 100 inhabitants, or the teledensity, is considered an infrastructure requirement for broadband penetration in a country. Wire line broadband is especially statistically significant, as it is a major determinant of broadband penetration in the countries being studied, and this is consistent with a priori expectations, as well as the literature. It seems that the deployment of more fixed main lines will increase broadband penetration. Aron and Burnstein (2003) also found that at the state level, the number of telephone lines per square mile is positively associated with broadband adoption in the USA. As DSL lines accounted for 71% of all active broadband lines in China by June 2006, and DSL services (Marcus, 2005) dominate the broadband market in China (China Broadband Overview, 2007), we assumed that the penetration of fixed phones is another factor explaining broadband adoption in China.

Personal computers are the most common platform for accessing the Internet, whether using broadband or dial-up access. Since personal computers are complementary tools for using Internet services (Venkatesh *et al.*, 2000; Leea and Sylvia, 2004; Hoffman *et al.*, 2004), we also assumed that the greater the number of personal computers in a particular province was, then the higher the probability will be that people would subscribe to broadband in China.

According to the official definition of the National Bureau of Statistics of China (NBS), the provinces in China are divided into three regions: eastern, central, and western regions, based on the level of economic development and geographical location. The eastern region consists of 10 provinces and cities: Beijing, Tianjin, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. The central region consists of nine provinces: Hebei, Shanxi, Jilin,

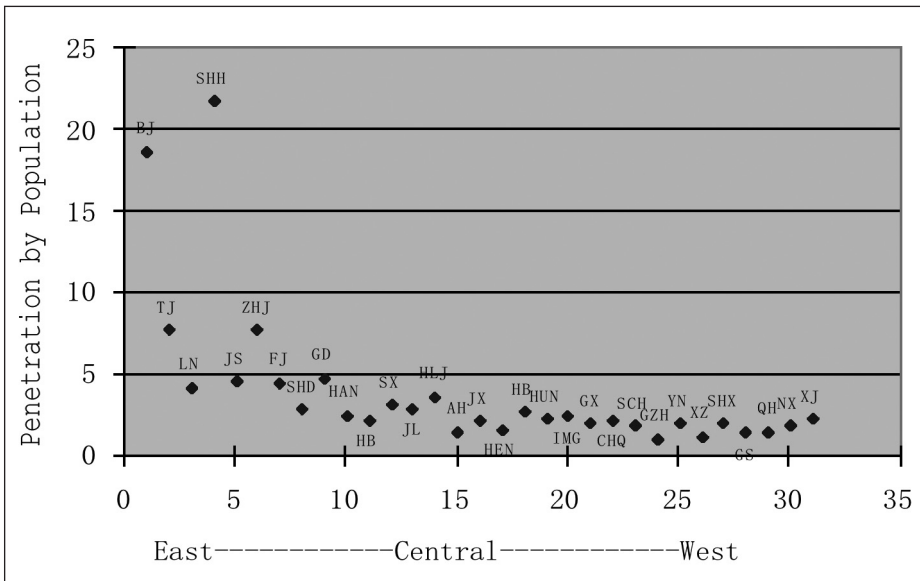


Figure 1: The broadband penetration rate in the 31 provinces of China. The abbreviations for each province or city are as follows: (1) East. BJ = Beijing, TJ = Tianjin, LN = Liaoning, SHH = Shanghai, JS = Jiangsu, ZHJ = Zhejiang, FJ = Fujian, SHD = Shandong, GD = Guangdong, and HAN = Hainan. (2) Central. HB = Hebei, SHX = Shanxi, JL = Jilin, HLJ = Heilongjiang, AH = Anhui, JX = Jiangxi, HN = Henan, HUB = Hubei, and HUN = Hunan. (3) West. IMG = Inner Mongolia, GX = Guangxi, CQ = Chongqing, SCH = Sichuan, GZH = Guizhou, YN = Yunnan, XZ = Xizang(Tibet), SHAX = Shaanxi, GS = Gansu, QH = Qinghai, NX = Ningxia, and XJ = Xinjiang.

Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan. The western region consists of the remaining 12 provinces: Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. The differences in broadband adoption by population among these 31 provinces are shown in Figure 1. The average broadband penetration rate is 7.64% in the eastern region, 2.47% in the central region, and only 1.83% in the western region. The eastern region has a high penetration rate, while the central and western regions have a relatively lower penetration rate. China is often divided into eastern, central, and western parts (Song *et al.*, 2000), and studies have found that the overall regional disparity of the country as a whole can be mostly attributed to the large and increasing gap in economic growth, investment and income between the eastern, central, and western regions (Cai *et al.*, 2002). Thus, we assumed that geographical factors are important in explaining the regional broadband disparity in China.

Table 1 summarizes the possible factors influencing broadband adoption in the 31 Chinese provinces.

METHODOLOGIES

Stochastic Frontier Analysis

Stochastic frontier analysis (SFA) has been applied to various practical problems in management and telecommunication (Thompson and Garbacz, 2007; Uri, 2001). The concept of a frontier was originally used to estimate the production function, where the frontier was defined as maximum output obtainable from a given input. This concept has been applied to other problems, such as estimating profit functions or forecasting market potential. For example, Kim and Kim (1999)

Factor	Symbol	Description
Education	EDU	High school over per 100 population aged 6 years and over.
Internet user	Netizen	Internet users per 100 population.
Income	Income	Average annual household disposable income (1000 RMB).
Fixed phone	Fixed	Fixed phone per 100 population.
Personal computer	PC	Personal computer ownership per 100 population.
Region	D1	A value of "1" if the observed province is located in the Eastern region, "0" if not.
Region	D2	A value of "1" if the observed province is located in the Central region, "0" if not.

Table 1: Factors influencing the adoption of broadband in China.

applied the frontier model to the problem of finding customer potential value. This application differs conceptually from previous research, where the decision-making units are companies. Kim and Kim (1999) considered customers to be response units who made purchase decisions based on their insurance needs and the insurers' sales effort. The frontier was the maximum premium/sale obtainable for each customer, which was not observable to the researchers, but could be estimated using the stochastic frontier model. As noted by Bauer (1990), deviation from the frontier can be regarded as a measure of the inefficiency once we estimate the frontier. At the same time, the factors influencing efficiency can also be examined (Kim and Kim, 1999). Along the same line, this paper also employed SFA in examining the relative market potential of each province in China by exploring the most efficient point for broadband penetration. In other words, the market potential in each province might be measured by comparing the current observed penetration ratio with the maximum feasible penetration ratio in each province.

The original specification involved a production function specified for cross-sectional data which had an error term which had two components, one to account for random effects and another to account for technical inefficiency (Coelli, 1992). This model can be expressed in the following form:

$$Y = f(X;\beta) \cdot \exp(V - U) \tag{1}$$

In this model, Y represents the output, X represents the input, β represents the parameters to be estimated, and $\exp(V - U)$ represents the error term with multiple compositions. The first term, $\exp(V)$, represents the stochastic factors that influence production, where V follows a $N(0, \sigma_v^2)$ distribution with $V \in iid$. The second term, $\exp(-U)$, is assumed to account for technical efficiency (TE) in production with non-negative random variable of U . Thus, a producer's technical efficiency can be specified as $TE = \exp(-U)$. When $U = 0$, TE is equal to 1 and the individual producer is on the production frontier. When $U > 0$, TE is less than 1 and the individual producer is below the production frontier, i.e., it is inefficient.

From equation 1, since $TE = \exp(-U)$, $Y = f(X;\beta) \cdot \exp(V) \cdot TE$. The stochastic production frontier, $f(X;\beta) \cdot \exp(V)$, consists of two parts: a deterministic part, $f(X;\beta)$ common to all producers and a producer-specific part, $\exp(V)$ which captures the effect of random shocks on each producer. The

deterministic part implies that the structure of best practice production technology is the same as the structure of the central tendency production technology (Kumbhakar *et al*, 2000). Since this implication is too strict, the structure of best practice production technology should be permitted to differ from that of less efficient practice producers, and consequently the producer-specific technical efficiency of $\exp(V)$ is introduced in the model. In this case, technical efficiency can also be defined as $TE = Y / f(X; \beta) \cdot \exp(V)$, the ratio of observed output to maximum feasible output in an environment characterized by $\exp(V)$, which is allowed to vary across producers.

The model used in our SFA study was first proposed by Battese and Coelli (1995), who imposed reasonable restrictions on the model, allowing for the use of panel data, and permitted the simultaneous estimation of the frontier production function with the variables. A panel (repeated observations on each producer) contains more information than does cross section. Panel data will result in estimates of technical efficiency with more statistical properties such as the avoidance of strong distributional assumptions in maximum likelihood estimation (Schmidt *et al*, 1984). Estimation was performed using the Frontier 4.1 Model 2 software package developed and referenced by Coelli, which is an extension of Coelli's earlier work (Coelli, 1992). Specifically, Model 2 estimates a production frontier in the following form:

$$\begin{aligned}
 Y_{it} &= X_{it} \beta + (V_{it} - U_{it}) & i = 1, 2, 3, \dots, N, t = 1, 2, 3, \dots, T \\
 m_{it} &= Z_{it} \cdot \delta \\
 TE_{it} &= \exp(-U_{it}) \\
 \gamma &= \sigma_U^2 / (\sigma_U^2 + \sigma_V^2)
 \end{aligned} \tag{2}$$

Where, U_{it} which are assumed to be independently distributed as truncation at zero of the $N(m_{it}, \sigma_U^2)$ distribution. Z_{it} is the influential factor for technical efficiency, and δ is the parameter that will be estimated, which reflects the influential degree of technical efficiency. The value of γ can be interpreted as an inefficiency indicator. As the value of γ approaches zero, the overall variation in the errors of the production function can be attributed to random elements. Alternatively, as the value of γ approaches unity, more of the estimation errors can be attributed to technical inefficiency.

Data and Model Specification

This study employed a comprehensive panel of data from the period 2004 to 2006 by province, mainly compiled from provincial data between 2004 and 2006 in the People's Republic of China, and the China Statistical Yearbook (2004–2006), published by the National Bureau of Statistics of China (NBS). Data for fixed line penetration and Internet users were obtained from the Ministry of Information Industry (MII) statistical reports (2007) and the CNNIC statistical reports (2007). To obtain a consistent time series, we used panel data from the 31 provinces for the years 2004–2006, and the number of observations used in the model was 93.

The model used in our work considers the provinces of China to be individual units (Tong, 1999). The adoption factors summarized in Table 1 were included in the model as independent variables, and broadband penetration by population was the dependent variable. We ran the following stochastic frontier model:

$$\begin{aligned}
 Y_{it} &= \beta_0 + \beta_1 EDU_{it} + \beta_2 NETIZEN_{it} + \beta_3 INCOME_{it} + \beta_4 FIX_{it} + \beta_5 PC_{it} \\
 &\quad + \beta_6 D_1 + \beta_7 D_2 + v_{it} - u_{it} \\
 TE_{it} &= \exp(-u_{it})
 \end{aligned} \tag{3}$$

where $Y_{it}(i=1,2,..31)$ is the dependent variable of the i th province in the t th period, EDU_{it} , $NETIZEN_{it}$, $INCOME_{it}$, FIX_{it} , PC_{it} , D_1 and D_2 are seven independent variables of the i th province in the t th period, and the value of β was the unknown parameter to be estimated. We used the natural logarithms of all the quantifiable variables in the model.

The point of departure from classical regression analysis was in the specification of the error term, $v_{it} - u_{it}$, which consisted of two components. The symmetrical component, v_{it} , followed the error structure of a standard regression analysis, and was assumed to capture the effect of statistical noise. The other component, $- u_{it}$, was assumed to capture the controllable inefficiency, and is thought to be distributed half-normally and independently of v_{it} .

Therefore, the stochastic frontier model was used to calculate the relative inefficiency in adoption rates. The frontier was the maximum penetration obtainable for each province when the given inputs remained at the same level. While this is not observable to researchers, it can be estimated using Equation (3). As noted by Bauer (1990), deviation from the frontier can be regarded as a measure of inefficiency once the frontier is estimated.

In the analysis of stochastic frontier, the objectives are to obtain estimates of β parameters and estimates of the technical efficiency of each province. Meeting the second objective requires that separate estimates of v_{it} and u_{it} be extracted from estimate ε_{it} of for each province. This is followed by two-step procedure. The first step involves the use of ordinary least squares (OLS) to estimate the slope parameters. OLS provides consistent estimates of all parameters except for the constant intercept term. The second step involves the use of maximum likelihood to estimate the consistent intercept term and the variances of the two error components. Distributional assumptions are used in the maximum likelihood method, and required in estimating the technical efficiency of each province.

After we estimated the model parameter value of β in Equation (3), we were able to derive the observation specific estimate of the inefficiency, u_{it} . The conditional distribution of u_{it} with an estimate of the total error, $\varepsilon_{it} = v_{it} - u_{it}$, was derived by Jondrow *et al* (1982). Two common assumptions about the distribution of u_i include a half-normal and exponential distribution. We used the most common half-normal distribution. The conditional expectation of the inefficiency component has the following form:

$$E(u_i | \varepsilon_i) = \frac{\sigma\lambda}{1 + \lambda^2} \left[\frac{\phi(\varepsilon_i / \sigma)}{1 - \Phi(\varepsilon_i \lambda / \sigma)} - \varepsilon_i \lambda / \sigma \right], \tag{4}$$

where $\phi(\cdot)$ is the density of the standard normal distribution (PDF), $\Phi(\cdot)$ is the standard normal cumulative distribution function (CDF), $\sigma = (\sigma_u^2 + \sigma_v^2)^{1/2}$, and $\lambda = \sigma_u / \sigma_v$. The parameter λ is a different parameterization of the inefficiency component of the half-normally distributed inefficiency term, u_i . Hence, the managerial or potential adoption efficiency in percentage terms can be measured by $[Y_i / (\hat{\beta}x_i + \hat{v}_i)] \times 100\%$. Similarly, the percentage inefficiency can be defined as $[u_i / (\hat{\beta}x_i + \hat{v}_i)] \times 100\%$. For example, assume that $y_i = 15\%$, $\hat{\beta}'x_i = 12\%$, $\hat{v}_i = 6\%$, $\hat{u}_i = 3\%$ for observation i . We say that the observed penetration of this observation is 15%, which can be broken down into three quantities: $\hat{\beta}'x_i = 12\%$ representing the penetration modeled, $\hat{v}_i = 6\%$ representing the penetration increase not expected or modeled, and $\hat{u}_i = 3\%$ representing the penetration decrease due to inefficiency. Thus, a province's adoption rate would be 18% when it reached the most efficient point. However, the actual adoption rate was 15% because of the broadband service provider's inefficient management ($\hat{u}_i = 3\%$). Therefore, in this case, the relative inefficient adoption rate is 16.6% ($3\% \div (12\% + 6\%) \times 100\%$).

EMPIRICAL RESULTS**The Factors Influencing Broadband Adoption in China**

This paper used the Frontier 4.1 software package to make parameter estimations on the model maximum likelihood estimation. The ordinary least squares (OLS) estimates were used to obtain the values for the parameters β , δ^2 , and γ in the specified stochastic frontier model. With the exception of the constant term β_0 , the OLS estimates were consistent, albeit inefficient. Table 2 presents the parameter estimates using the ordinary least squares method and using the stochastic frontier

Variables	Parameter	OLS	Frontier
Constant	β_0	-4.4350 ^a (-10.1956)	-4.3397 ^a (-9.8165)
Education	β_1	0.3282 ^a (3.9518)	0.2983 ^a (4.0091)
Netizen (Internet user)	β_2	0.5807 ^a (4.2333)	0.6971 ^a (8.5327)
Income	β_3	0.7103 ^a (2.3489)	0.7329 ^a (2.6850)
Fixed phone	β_4	0.3564 ^b (2.1297)	0.4603 ^a (3.221)
Personal computer	β_5	0.083 (0.5720)	0.0661 (0.4989)
D1	β_6	-0.0977 (-1.0208)	-0.0504 (-0.3646)
D2	β_7	0.2072 ^a (3.3404)	0.0343 (0.3121)
	δ^2	0.0620	0.0629 ^a (63.4889)
	γ	0.6600	0.9615 ^a (56.0335)
	Mean inefficiency		0.4218
	Log likelihood	4.0917	43.3799

Key: a = Significant at 1%, b = Significant at 5%. The t ratios are given in parentheses.

Table 2: Estimates of adoption factors.

approach. It is important to note that the log-likelihood was improved from 4.0917 using the ordinary least squares method to 43.3799 using the stochastic frontier model. The value of $\gamma = \sigma_u^2 / (\sigma_v^2 + \sigma_u^2)$ was 0.9615, and this was significant at the 1% level, which means that more of the estimation errors can be attributed to diffusion inefficiency. Thus, a good measure of the residual variation was due to inefficiency effects. All these indicate a good fit and correctness of the specified distributional assumption.

Table 2 shows the results obtained from two different estimations. The results in Column 1 were obtained using a simple OLS, whereas the results in Column 2 were obtained by applying the stochastic frontier approach. As shown in Table 2, several parameters concerning the individual effects are worth mentioning. The variables of Income, Fixed Phone, Internet Users, and Education have a highly significant positive relationship with the broadband adoption rate. This means that a province that has a greater average household disposable income, more fixed phone penetration, more Internet users, and a higher level of educational attainment is more likely to show a higher broadband adoption rate than provinces with lower levels of these variables. As the income of Internet users rises, then the rate of broadband adoption increases. Broadband demand may also be shaped by the number of internet users, including highly educated members of households.

However, regarding PC penetration, the parameters D1 and D2 were estimated not to be statistically significant. Therefore, the idea that regional disparity is associated with broadband adoption is not supported by the data. Perhaps surprisingly, we assumed that there was undoubtedly a correlation between personal computer penetration and broadband penetration, but this expectation was also not supported by the empirical results. This may be because 30.6 % of personal computers were still using dial-up (including ISDN) access in China by the end of 2006 (CNNIC, 2007). In China, the substituting broadband for traditional dial-up access is not adequate, because the advantages of price and content provided by broadband service are not attractive.

Relative Broadband Market Potential in China

When we estimated the frontier model, we were able to derive an estimate of the acceptance inefficiency for each province using the formula given in Equation (3). We calculated these estimates for all the observations. As mentioned previously, we can compute the maximum attainable point that is equal to $y_i - \hat{u}_i = \hat{\beta}'x_i + \hat{v}_i$. Hence, inefficiency as a percentage of the frontier is represented by $[\hat{u}_i / (\hat{\beta}'x_i + \hat{v}_i)] \times 100\%$, which is actually the potential penetration rate of observation i . In Table 2, the mean inefficiency was 42.18%, which shows that there is considerable market potential. We plotted the distribution for each province, shown in Figure 2, which shows the most efficient point of broadband adoption and the actual adoption rate for each province. The gap between the most efficient point of adoption and the actual adoption in Beijing, Tianjin, Shanghai, and Guangdong was 13.5%, 8.5%, 10%, and 8.7%, respectively. However, the gap for other areas was <7%, and the average gap was 2.9%. Interestingly, these findings show that there is a large adoption potential in municipalities, such as Beijing, Tianjin, and Shanghai, as well as in economically developed areas, and southeast coast regions, such as Guangdong and Zhejiang province, even though their actual adoption rates are high.

DISCUSSION

The main contribution of this paper is to examine the relative market potential of each of 31 provinces in China by exploring the most efficient point for broadband penetration utilizing the stochastic frontier analysis, while other papers tried to identify a number of important factors that influence the decision to adopt broadband services in different countries. And the findings of our

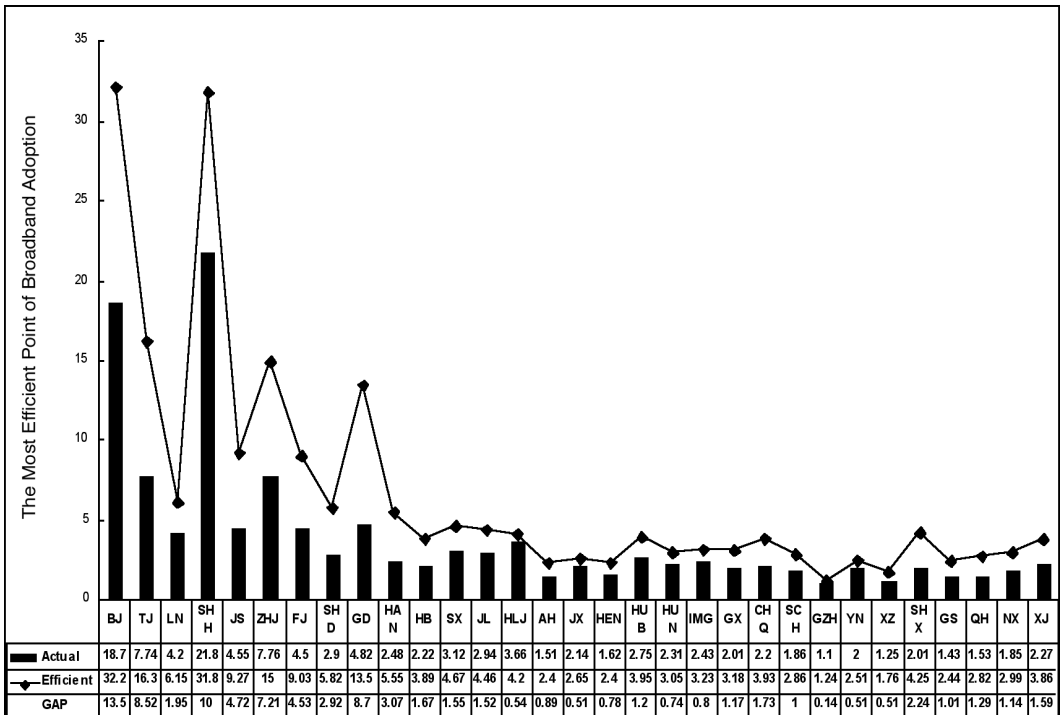


Figure 2. The relative broadband market potential in China.

work also have important implications to policymakers and market planners who wish to understand and quantify the influencing factors and the market potential of broadband access in China. First, there is still unexplored market potential in most provinces in China. Second, the socioeconomic characteristics of each province should be considered as broadband adoption factors when identifying and selecting target markets and constructing networks. For example, telecommunication operators who wish to launch new ICT-related services (Ayres and Williams, 2004) should target customers with higher incomes and stronger educational backgrounds, as this would maximize their return on investment. Third, to set priorities for future investment, policymakers should look at the adoption inefficiency in each province by identifying the gap between the most efficient point of adoption and the actual adoption. The provinces that have a higher adoption inefficiency, such as Beijing, Tianjin, Shanghai, and Guangdong may be good candidates for the first round of 3G and WiMAX implementation and marketing. Beijing and Shanghai are attractive because their market potential is large, even though their current adoption rates are much higher than those of other provinces.

In addition, the results of this study have policy implications for the Chinese government. The potential digital divide problem (LaRose *et al*, 2007) among the provinces should be recognized, because broadband telecommunication operators are expected to invest primarily in the provinces that have more market potential. To resolve the possible digital divide among provinces without sacrificing efficiency of resource allocation, the Chinese government should find ways to encourage investment in provinces with low broadband adoption rates.

CONCLUSION

Most countries are trying to stimulate growth in broadband adoption, since broadband Internet diffusion has become a significant aspect of their economy and society.

We have examined several influencing factors that explain broadband adoption and the relative market potential of broadband in the 31 provinces of China. The findings from our stochastic frontier analysis model show that the factors of disposable income, Internet users, fixed phone penetration, and education are important, and influence broadband adoption in China. In addition, we also found that the average adoption inefficiency in broadband, which indicates market potential, was 42.18%, and differed from province to province. This result implies that there is considerable market potential for broadband operators in China. A more interesting fact is that market potential is much greater in more developed areas of China, such as municipalities and southeast coast regions, where actual broadband adoption rates are high.

Though this is one of only a few studies to empirically examine the broadband market potential of each province in China, it has several limitations. For example, there must be other factors that affect broadband adoption at the provincial level. A useful area of further research would be to expand this study by adding further appropriate factors, such as market competition (Polykalas and Vlachos, 2006) and government policy.

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